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INCOME INEQUALITY IN THE PROCESS OF ECONOMIC DEVELOPMENT: AN EMPIRICAL APPROACH

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As with so many things in life, also this thesis is not a product of linearity. As a teenager I started to work against this goal by choosing ventures of puberty over book smarts. This forced me to choose commercial school over high school, a path which is unlikely to lead to university degree in Finland. Fortunately, during the exuberant economic courses taught by Jussi Hievanen at the commercial school of Hyvinkää, I became greatly interested about economics. Despite the enthusiasm, it still took me several years of, literally, hard labor until the motivation was set for a no-nonsense effort to pass the university entrance examination. The motivation was mostly gathered in working as a packaging machine attendant at the Saint-Gobain Isover Ltd. in Hyvinkää.

My first academic stop was the Department of Economics at the University of Oulu. Winters spent in Oulu taught me the meaning of the phrase "freaking cold", but also under the encouraging care of Professor Mikko Puhakka the idea of writing a doctoral dissertation grew. With the help of Prof. Puhakka the project was also put in motion as, after graduating in late fall 2005, his contacts granted me a mid-term passage to FDPE's first year PhD econometrics course.[1] Personal reasons took me back down south for the rest of my PhD studies and I ended up in the (late) Department of Economics at the University of Helsinki. There Professors Tapio Palokangas and Markku Lanne became my tutors.

Like with most PhD students, this was not the last stop for me, as there is an almost mandatory visit to a foreign university expected at some point of studies. During a road trip through eastern coastal states of the US in the spring of 2008, I became convinced that US would be the place of my

[1]FDPE=Finnish Doctoral Programme in Economics

visit. As our road trip reached New York city, I also knew the exact location of the visit. This was fortunate, as my six month stay at the New York University became the best time of my academic studies, both professionally and personally. The rousing academic environment at the NYU also renewed my interest for economics, which at that point was almost completely lost. After returning to Finland, this thesis was finalized within nine months.

During my academic journey, I have come across many people and institutions that I owe gratitude. First, my humble words of thanks go to my colleagues and co-students in the University of Oulu, HECER and the NYU. This thesis would not have been made final without the overall support that I have received from you. I'm also grateful to Jussi Hievanen for setting this thesis on its way all those many years ago.

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Helsinki, December 2011

Tuomas Malinen

Chapter 1

Introduction

1.1 Background

Income inequality has become one of the closely followed societal subjects in global media within the last few years. For example, the New York Times launched a noticeable campaign on income inequality last year.[1] The Financial times as well as the Economist have also reported on developments in income inequality numerously in recent times.[2]

Why is income inequality causing media interest then? One factor contributing to this interest is that income inequality seems to be increasing in developed economies after contracting for a nearly of a century (see Figure 1 in Section 1.2.2). From history, we know that the concentration of wealth on the hands of those who are already rich can cause social unrest or even *coups d'état* (Acemoglu and Robinson 2001). Income inequality also infringes the ideal of the foundation of (most) western economies, i.e. that all men (and women) are born equal. In addition, income inequality may lower the level of human capital by diminishing education opportunities for lower income households, inflict additional costs to producers by increasing illegal rent-seeking, and cause financial instability by increasing the leverage among the not-so-fortunate citizens (Fishman and Simhon 2002; Kumhof andRanciére 2010; Shaw and McKay 1969). Thus, besides the rather obvious societal ram-

[1] See the New York Times Topics and income inequality.

[2] For the Economist, see the issues of 20th of April and 24th of March 2011. For FT, see issues of 5th and 12th of May 2011.

ifications, income inequality may have a subtler negative effect on the growth prospects of a country.

Within the last two decades or so, the relationship between income inequality and economic growth has been widely debated and it has emerged one of the major fields in economics.[3] At the same time, the literature on this relationship has become concentrated on assessing the effect empirically typically by using data that consists on time series observations from several countries. This has been due to the fact that the theoretical literature has produced results supporting both sides of the "aisle", i.e. both the negative and the positive effect of inequality on growth (Galor and Moav 2004; Stiglitz 1969).[4] Unfortunately, the results of empirical studies have also been controversial (Barro 2000; Banerjee and Duflo 2003; Castelló-Climent 2010; Forbes 2000; Persson and Tabellini 1994).

Many modern studies have used panel data consisting only on a handful of time series observations on several countries, i.e. 'short panels', to study the relationship between inequality and growth (Barro 2000; Forbes 2000; Li and Zou 1998; Persson and Tabellini 1994). This thesis makes an effort to resolve the above mentioned discrepancy by analyzing data from both short panels as well as from panels with long time series from several countries. By using panels with a long time series dimension, this thesis also looks for a possible long-run relationship between inequality and growth, which is a topic that has not been studied almost at all previously. Thesis also contributes on one of the classic questions in economics, i.e. does the propensity to save increase with income? This is another field within the growth literature that tends to lack consensus even on the direction of the effect of inequality (Cook 1995; Leigh and Posso 2009; Li and Zou 2004; Schmidt-Hebbel and Servén 2000).

The rest of this introductory chapter presents the theories and methods applied in this thesis. Summaries of the three studies presented in Chapters 2-4 are also given. Section 1.2 opens with a historical introduction to the distributional aspects advanced by economic theory. It also presents the

[3] A simple search for "income inequality economic growth" on Google Scholar produced over 746.000 results on the 16th of May 2011.

[4] Naturally there is also a third effect or a *non-effect* meaning that inequality could also have no effect on growth. But, such result would lack theoretical interest which returns the question on the (possible) effect of inequality on growth as an empirical one.

measures of income inequality used in this study and gives an overview to the recent global trends in the inequality of income. The modeling of income variation and the distribution of income are discussed in Section 1.3. Section 1.4 presents the general economic theories developed to explain the effect of income inequality on economic growth. Issues related to the analysis of panel data are discussed in Section 1.5. Section 1.6 summarizes the findings of this thesis.

1.2 Income inequality: the wisdom of economic thought and global trends

Money is like muck, not good except that it be spread.
- Francis Bacon (1625)

1.2.1 What determines the division of product among the factors of land, labor, and capital?

The classical query posed in the title of this section has basically governed the economic science throughout its entire existence. This is because economics was, in principle, founded to answer two questions: how can we achieve development and what determines the distribution of product among the factors of land, labor and capital? They were the two main themes discussed in Adam Smith's (1776) seminal book on the wealth of nations and both of them were contributed by several classical authors, including Malthus (1815), Ricardo (1817), and Mill (1845). As it turned out, neither of these questions have been easy to answer. The distribution of product amongst the factors of production has divided the economic sciences for the last two centuries while the literature on economic growth has, during the same period of time, produced only few facts about the factors behind economic development.

As the history of the last 200 years has shown us, economic progress brings in its train an indispensable array of benefits. We know that economic development promotes health, increases the life expectancy, and increases the overall quality of life of individuals (Doepke 2004; Galor and Weil 2000). Most of these gains have been produced by following the idea of market capitalism, namely an economic system where the means of production are privatively owned and used to make profit. However, as put forth by Schumpeter (1942), capitalism is a way of creation through destruction. What this means is that a market economy is engaged in a process of competition which constantly creates new through the destruction of the old and inefficient. This *endogenous* creative process of innovation and economic development enables the growth in productivity and drives the technological progress, which raises our quality of life. What this process also creates, however, is a continuing cycle of creation-destruction-creation, where some individuals and businesses are thrown out of profits and sufficient income for a short or possible extended period of time. This process of capitalist market economy further complicates the issue of distribution, as the individuals who are thrown out of income are no longer factors of production, at least in the strict sense of production, for the time they remain outside the productive workforce. Market economies also tend to go through different phases of development that may increase or decrease the level of inequality accordingly.

Kuznets (1955) constructed a theory to explain the changes in the distribution of income during the process of development in capitalist market economies. According to the so called Kuznet's relation, the inequality of income will first increase and then decrease in the course of economic development. Inequality will increase in the beginning of industrialization due to a growing wage disparity between agricultural and factory pay. Lower mortality rates, greater fertility rates, and investments in new technology will also increase the inequality of income during the first phases of industrialization. Growth of inequality is necessary because an egalitarian agrarian economy cannot accumulate enough savings so that capital creation would be sufficient for production growth. Later on, as the economy industrializes, the distribution of income will even out as a larger portion of people move to a higher industry pay.

Kuznets (1955) made a respectable effort to describe the (natural) division of product among the factors of production in different stages of economic development. Unfortunately, empirical research following his seminal paper on the curvilinear relation between the distribution of income and the level of development has produced some mixed results (Frazer 2006; Gagliani

1987; Nielsen 1994). Moreover, current trends in income inequality in developed economies stand in stark contrast against the Kuznet's relation (see Figure 1 below). So, even if the Kuznet's relation would describe the evolution of the distribution of income during industrialization, it does not seem to fit very well on the *post-industrialized* economies. In economic theory, the "great divide" had also already occurred before Kuznet's published his theory. Growing income inequality in major newly industrialized economies in the late 18th and early 19th century had created a divide within the economic sciences on how societies should determine the distribution of product among its citizens. These two ends of the spectrum where (are) the Socialist economic theory put forth by Marx and Engels (1848) and Marx (1887), and the Austrian school created by Menger (1871).

Marx (1887), as the father of the Socialist economic system, saw the capitalist economy as an exploiter of the working class in benefit of the rich. He argued that stripping down the rights that gave the capitalists the power to oppress the working class, i.e. the right to own capital and land, equality both in income and prominence among individuals would follow suit.[5] However, the fall of the Soviet Bloc in the late 20th century showed that applying Marx's theory to practice was extremely difficult, if not impossible.[6] Marx's idea of collective governance over the production factors led to inefficiency in production due to centrally governed division of product among the factors of production (Walder 1991; Weitzman 1991). Thus, in a Socialist economic system, the redistribution of income was done by government officials, not by market signals. This, naturally, led to a serious incentive problem amongst the workers as returns to their production factor, the labor, was not determined by their effort.[7] Wages and private consumption was also held back which caused the living standard to remain very low (Åslund 2007). In ad-

[5]This refers to the whole production of Marx, not just *The Capital* and *Manifesto of the Communist Party* .

[6]It should be noted, however, that Marx never mentioned revolution (Ekelund and Hébert 1990). It is thus possible that Marx thought that socialism would be the *end-point* of capitalism, meaning that after certain stages of development capitalism would lead to socialism.

[7]In socialistic systems labor force usually included also the land-owners, or the kolkhoz and sovkhoz, because owning of land was prohibited. Government jurisdictions were the owners of the capital (Walder 1991).

dition, centrally planned economies were plagued by shortages of goods and services. Regardless of the obvious problems faced by Communist economies, the actual economic reasons for the collapse of Socialist economic system are still somewhat debated (see Åslund (2007); Easterly and Fischer (1995); Harrison (2002); Zubok (2008)).

At the other end of the spectrum, the Austrian school of economics saw the price mechanism and, thus, the free ownership of the factors of production as the best (the most efficient) way to allocate income among individuals (Hayek 1945; Mises 1969). The economic doctrine of the Austrian school opposed government interventions to the "self-efficient" market mechanism. Therefore, the Austrian school advanced the idea of a free market, or *laissez-faire*, economic doctrine. Despite the fact that the idea of free-market economics has been fairly popular within the economic sciences, no country has actually adopted the economic doctrines of the Austrian school literally (Stringman and Hummel 2010).

Within the last 50 years or so, a model that can be seen as a hybrid of these two ends has also emerged.[8] In accordance with the Stockholm economic school, the so called Nordic economic model, which incorporates free market ideology in a society with a highly developed structures of social insurance, was developed. This "hybrid" has been able to combine relatively high growth rate to reasonably flat distribution of income. Especially within the last 20 years, the Nordic model has also shown its resilience to many shocks commonly associated with capitalist systems, including financial crises and recessions (Aaberge *et al.* 2002; Mayes 2009).

1.2.2 Measuring income inequality

How has the income inequality evolved in countries with different economic systems? In this thesis two different measures of income inequality are used, which can be used to shed some light on this matter. These measures are the

[8]Before the Nordic model was developed, many European countries had also created system that incorporated aspects from both Socialism and free-markets. Nordic model is, however, probably the prime example of a economic doctrine that incorporates the best features, i.e. free market thinking and extensive social security, of both of these economic models.

EHII inequality measure, which is based on the Gini index by Deininger and Squire (1996), and the income share of the top 1% of income earners.

Probably the most common measure of income inequality has been the Gini index or the Gini coefficient. Formally, the Gini coefficient is defined as:

$$Gini = \frac{1}{2n^2\mu}\Sigma_{i=1}^{n}\Sigma_{j=1}^{n}|y_i - y_j|, \tag{1.1}$$

where n is the number of households, μ is the mean household income, and y_i and y_j are income of any two of the n households (Culyer 1980). Thus, the Gini index gives the relative position of different households within the income distribution. One of the problems of the Gini index is that it requires quite a lot of information. To calculate it accurately one needs the mean household (or person) income within a country, which in many cases is very hard to come by. This has also caused problems with the comparability of the data, as income data is usually gathered differently in different countries. Some countries, for example, gather income data from households while others gather it from individuals. This, naturally, can lead to serious comparability problems across countries.

To overcome these problems there has been a growing interest towards using taxation statistics to estimate the level of income inequality within the last decade or so. This has opened up a possibility to construct lengthy time series on the evolution of the top income shares of population from several different countries. Top income share data uses the same raw data from all countries and it is constructed using the same methodology for every country (Piketty 2007). This should make the series comparable. The long time series also makes it easier to assess possible structural changes. However, some disadvantages remain. First and foremost, fully homogenuous cross-country data just does not exist, although the tax statistics may be the closest we can get to a data that is homogeneous across countries. It is also possible that the top income shares follow different *processes* in time than the overall inequality does. Furthermore, the possibility of tax avoidance may have biased the results. Nevertheless, top income shares have been found to track broader measures of income inequality, like the Gini index, very well (Leigh 2007).

Figure 1 presents the evolution of the top 1% income share within 11 developed economies during the 20th century. In spite of somewhat different

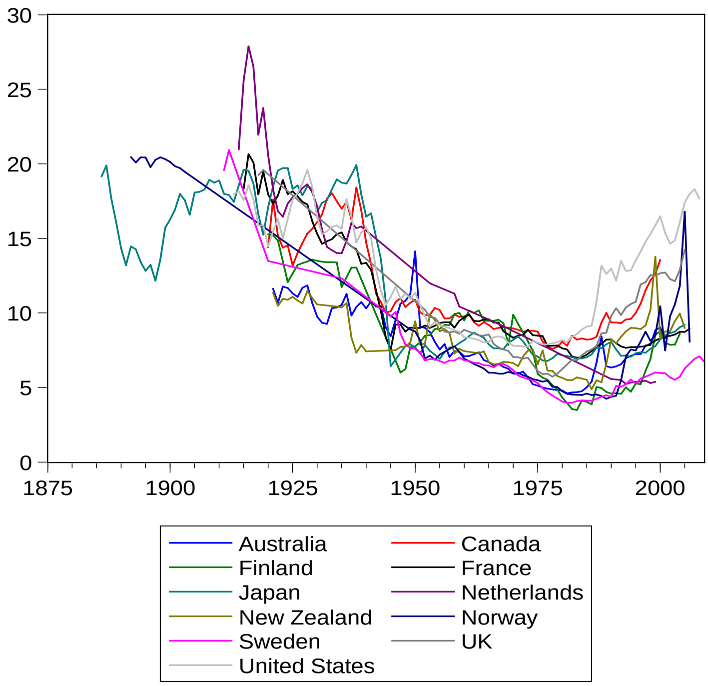

Figure 1. The share of income of the top 1% of population in 11 developed countries 1880-2009. Source: Alvaredo *et al.* (2011)

social policies among these 11 developed nations, income inequality has followed a strikingly similar pattern during the last century or so. In accordance with the Kuznet's relation, income inequality has followed a falling trend almost all countries through the 20th century, but in the end of the 20th century the trend seem to have reversed. Roine and Waldenström (2011) have examined the question that does the series of top income of developed countries include structural breaks, i.e. breaks in the mean and/or trend of the series. They found that there is evidence of a common trend-break in the series of top 1% income share in the years 1945 and 1980.[9] The break in 1945 shows a shift from faster decline of income inequality to a more slower decline. The break in 1980, however, constitutes a shift after which the declining trend either changes to increasing trend or to a stable non-increasing/-decreasing trend. That is, in this *sub-sample* of developed countries, the share of income of the top 1% has been growing or remained stable since the 1980s.

To get a bigger picture of what has happened within the last 20 years, Figure 2 presents the mean value of the EHII2008 inequality measure for 96 countries.[10] This measure is created using the Gini index by Deininger and Squire (1996), the annual data on wages on the manufacturing sector and the manufacturing share of population published by the United Nations Industrial Development Organization (Galbraith and Kum 2006).[11] The figure

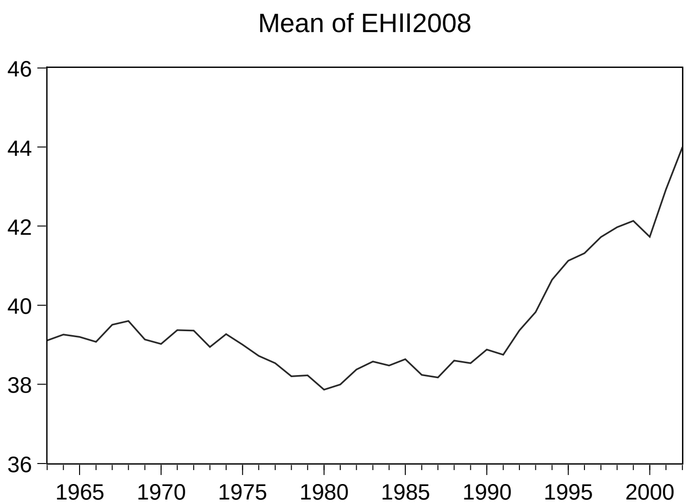

Figure 2. The mean of the EHII2008 inequality measure for 96 countries 1963-2002. Source: Galbraith and Kum (2006)

[9]The number of countries included in the stydy by Roine and Waldenström (2011) was 9.

[10]EHII stands for Estimated Household Income Inequality.

[11]For more detailed description of the EHII2008 inequality measure see Section 2.3.1.

endorses the finding by Roine and Waldenström (2011). The mean of income inequality has clearly increased since the 1980.

What countries then have contributed the most for the increase of the mean after the 1980s? Figure 3 presents the mean values of the EHII2008 inequality measure for groups of former Communist and Nordic countries, the mean values for the group of 9 out of the 11 developed countries presented in Figure 1, and the mean values for the remaining 69 countries presented in Figure 2.[12] According to Figure 3, the biggest increases in income inequality

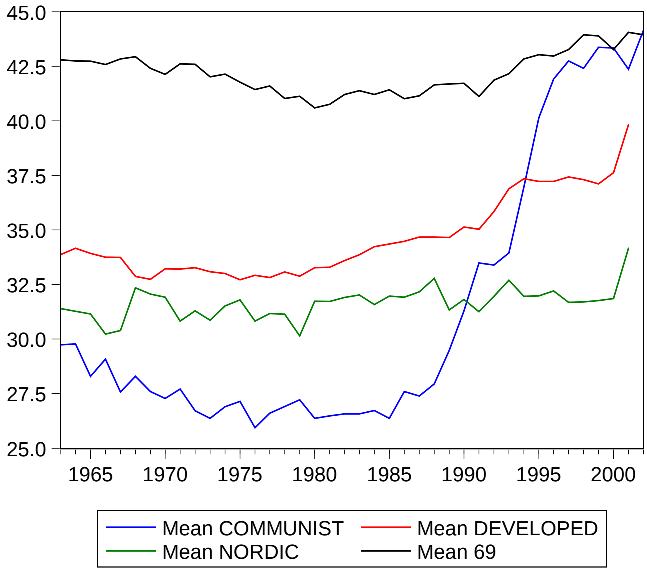

Figure 3. The mean values of the EHII2008 inequality measure for Communist, Nordic, and developed countries 1963-2002. Source: Galbraith and Kum (2006)

have occurred in the former Communist countries, where the inequality also

[12]Former Communist countries include: Bulgaria, China, Croatia, Cuba, Czech Republic, Hungary, Kyrgyz Republic, Macedonia, Poland, Romania, Slovenia, Soviet Union/Russia, and Yugoslavia. Values of Croatia and Slovenia overlap with the values of Yugoslavia for three years from 1986 to 1989. Nordic countries include: Denmark, Finland, Iceland, Norway, and Sweden.

seems to have been at the lowest level during the Communist era.[13] In Nordic countries, the trend seems quite stable although there is an upward kink in the graph in 2001. Income inequality in the remaining 69 out of 96 countries seems quite stable although it also has risen from the 1980s. Thus, the reversal of the downward trend in inequality in developed economies and the raise in income inequality in transition economies seem to have contributed the most on the global trend of increasing inequality during the last two decades.

1.3 The process of income variation and the distribution of income

> *The forces determining the distribution of income in any community are so varied and complex, and interact and fluctuate so continuously, that any theoretical model must either be unrealistically simplified or hopelessly complicated.*
> -D. G. Chambernowne (1953)

The very first formal models on the distribution of income by Chambernowne (1953) and Mandelbrot (1961) were based on the assumption that the process of income variation is stochastic. Intuitively this seems like a very reasonable assumption as, at least, some part of the individual income is usually deemed to fluctuate randomly from year to year.

Later on, for example, Deaton (1991) has used random walk to approximate the developments in labor income through time in his study on how liquidity constraints affect national savings. Deaton assumed that the labor income of an individual follows an $AR(1)$ process of the form:

$$log(y_{t+1}) = \delta + log(y_t) + log(z_{t+1}), \tag{1.2}$$

[13]It should be noted that due to data quality and political issues concerning income distribution, the income distribution data obtained under the Communist rule is likely to be quite unreliable (Åslund 2007). However, it is also true that in many transition economies poverty rose after transition due to falling output and wages. At the same time, the middle-class emerged. These two contracting developments have been likely to contribute to the rapid rise of income inequality in the former Communist countries. Still, the actual magnitude of the dispersion of income is more or less unclear.

where y_t is labor income, z_{t+1} is stochastic random variable, and $\delta > 0$ is a constant. When z_{t+1} is assumed to be identically and independently distributed, the labor income process, $log(y_t)$, is $I(1)$ non-stationary and, specifically, it follows a *random walk* with drift (see Section A.1 for a more detailed definition of the random walk and $I(1)$ nonstationary processes). An $I(1)$ nonstationary processes have a infinite memory, i.e. they are highly persistent. Assuming some degree of persistence in the evolution of the income series (y_t) of an individual is quite intuitive, as shocks (e.g., wage raise) to the income process of an individual may have permanent effects on the future income of the individual. Therefore, the random walk model (1.2) appears to be a good description of labor income.

However, it is also likely that some deterministic factors like education affect on the labor income. In a recent study on the evolution of consumption and income inequality, Blundell *et al.* (2008) model the income of households to be varying according to:

$$logY_{it} = Z_{it}\delta_t + P_{it} + v_{it}, \tag{1.3}$$

where Z_{it} is a set of income characteristics that are observable and known by consumers at time t,[14] v_{it} follows a moving average process of order q (a $MA(q)$ process), and $P_{i,t} = P_{i,t-1} + \epsilon_{it}$ with ϵ_{it} serially uncorrelated, indicating that the process $\{P\}$ is $I(1)$ nonstationary. Several studies in the micro literature tend to find that also empirically the permanent component P_{it} is a random walk, and hence it can be modeled as an $I(1)$ nonstationary process (Meghir and Pistaferri 2004; Hall and Mishkin 1982; Blundell *et al.* 2008).

When individual income series are affected by a random walk component, their aggregated time series is likely to be characterized by a random walk (Rossanan and Seater 1995). However, the distribution of income is often measured using some bounded measure, like the Gini index or the share of income. This issues a question on the random walk hypothesis, as any measure that varies within some boundaries like the income share, cannot, by definition, be an $I(1)$ nonstationary process. This is because the variance of

[14]These include demographic, education, employment status, ethnic, etc. factors (Blundell *et al.* 2008)

such a series cannot grow infinitely, which is one property of the random walk process. However, it is possible that the distribution can have stochastic trend in its other moments, like the mean, skewness, and kurtosis, than variance (White and Granger 2010). This way the measure of income inequality, being a functional of some income distribution having a stochastic trend in one or several of its higher moments, may exhibit such high levels of persistence that it is better approximated by an $I(1)$ process than a stationary process.

1.4 Theoretical effects of income inequality on economic growth

You cannot have the benefits of capitalist market growth without the support of, virtually, all the people.
-Alan Greenspan (C-Span, September 2007)

1.4.1 The origins

The question, how does the distribution of product affect the production was, for some time, a more infrequently studied subject in economics, although the relation between the distribution of income and income growth was commented already by Smith (1776). Smith argued that because national savings govern the accumulation of capital, and because only the rich people saved, the accumulation of capital required that there were enough rich people in the society. However, Smith also argued that production growth would not be possible without sufficient demand. He stated that every man should be able to provide for himself and his family. This would constitute the threshold of sustainable inequality, and it would also assure a sufficient level of demand in the economy.

Despite the fact that the classical doctrine generally argued that investment was a result of savings, not much emphasis was put on how the distribution of income would affect savings after Smith (1776). This was because classical economic thought relied quite often to the *Say's law*. What Say's law states is that supply creates its own demand, implying that saving is the potential demand (a "promise" of consumption) that is just working through investments. There was, however, one loud critic of the Say's law among the Classics. Malthus (1836) argued that savings *ex ante* need not to always equal investments *ex ante*. That is, consumption can exceed production resulting to an over-demand, which will lead to diminished wealth of a nation due to excessive use of productive capital. But, Malthus (1836) never developed his critique to explain how market forces maintain the optimum rate of savings, and the monetary causes of overproduction (Ekelund and Hébert 1990). Thus, Say's law remained the cornerstone in classical economic thinking.

It took a century before Keynes (1936) finalized the critique of the Say's law put forth by Malthus (1836).[15] Keynes presented his theory of aggregate demand and consumption in his principal work, *The General Theory of Employment, Interest, and Money*, which also stated that inequality of income will lead to slower economic growth. Keynes argued that marginal consumption decreases as the income of an individual increases, and thus aggregate consumption depends on changes in aggregate income. According to Keynes, demand is the basis of investments, and because inequality lowers aggregate consumption, the inequality of income will diminish economic growth by diminishing investments.

Stiglitz (1969) summarizes the findings of the classical economic theory as follows. In classical economic theory, inequality of income was assumed to influence economic growth rates through savings and consumption. When the saving function is linear, e.g. $s_i = my_i + b$, where y_i is output per capita, m is the marginal propensity to save, and b is the per capita savings at zero income, aggregate saving behavior in an economy is not affected by the distribution of income. However, if the saving function is nonlinear, aggregate savings become dependent on the distribution of income.

When the saving function is linear or concave, distribution of income and wealth converge toward equality (Stiglitz 1969). If the saving function is convex, i.e. the marginal propensity to save increases with income, more unequal distribution of income results in higher capital intensity through greater aggregate savings. Thus, in a steady-state equilibrium, where income is distributed unevenly, the wealth of a nation is greater than in the steady-

[15]Note: the second edition of *Principles of Political Economy* generally cited from Malthus, was published posthumously.

state equilibrium, where income is distributed evenly. However, these steady-state equilibria exist only when all individuals have positive wealth. Thus, result may not apply, for example, to developing countries.

1.4.2 Modern theories

There are basically three main strains of modern theories on the effect of income inequality on economic growth. These include the political economy model by Perotti (1993), a model of division of labor and specialization by Fishman and Simhon (2002), and the two-regime model by Galor and Moav (2004), which combines the classical approach with human capital theory by Becker (1965) and Mincer (1974). All these strands of theoretical literature rely on the human capital theory and on the assumption of credit restrictions. Human capital theory explains the role of human capital in the production process as specialization (schooling) and on-the-job investments (training) (Acemoglu 2009). Credit-market imperfections refer to the situation in which people's access to credit is restricted. These restrictions can originate from the regulations of legislative institutions, credit rationing imposed by central banks, or from underdeveloped banking sector. Further, credit-market imperfections are present when acquiring credit in return for expected future profits is gravely limited.

Political economy models assume that preferences of individuals are aggregated through political process. Therefore, redistribution of income and economic growth are driven by the political process. Political process can be driven by a *median* voter or by organized social groups. In the model by Perotti (1993), the equilibrium reached by the economy depends on the initial distribution of income. If the aggregate capital is very small, redistribution of income through taxes and subsidies will result in a poverty trap where no one is able to acquire education. In this case, a more unequal distribution of income will support the economy because at least some individuals are able to acquire education and increase the level of human capital. As economy becomes more developed, very unequal income distribution may diminish growth because the accumulation of human capital would require that middle-income and poor individuals acquire education, as the rich have already educated themselves. In a rich economy, only the poor may increase the level of human capital, and therefore higher steady-state growth path requires that income is distributed evenly.

If an economy's aggregate capital is small, unevenly distributed income urge capital owners to invest in specialization (Fishman and Simhon 2002). In this case, inequality results to a higher level of human capital, a higher division of labor, and thus to faster economic growth. When an economy's aggregate capital is large, the more equal distribution of income encourages households to invest in specialization and entrepreneurship. In this case, equality of income will create a more risk-free environment and wide-based demand for goods. This will lead to higher employment, greater division of labor, and to faster economic growth.

In the model by Galor and Moav (2004), the engine of economic growth changes from physical capital to physical and human capital in the process of economic development. The process of economic development is divided into two regimes, which have their own steady-state growth paths. Economies in the first regime are underdeveloped, aggregate physical capital is small, and the rate of return to human capital is lower than the rate of return to physical capital. In this regime inequality increases aggregate savings by increasing the income of the rich and greater aggregate savings fuel physical capital accumulation.

In the second regime, economies are rich and the rate of return to human capital is so high that it induces human capital accumulation (Galor and Moav 2004). Therefore, both human and physical capital are engines for economic development. Since individuals' investment in human capital is subjected to diminishing marginal returns, the return to human capital investments is maximized when investment in human capital is widely spread among the population. Because access to credit is constrained, human capital investment is maximized when income in the economy is distributed evenly.

1.5 Analyzing panel data

I am obliged at the outset to draw attention to the fact that analysis of variance can be, and is, used to provide solutions to problems of two fundamentally different types. These two distinct

classes of problems are: class I: detection and estimation of fixed (constant) relations among the means of sub-sets of the universe of objects concerned; class II: detection and estimation of components of (random) variation associated with a composite population.
- Churchill Eisenhart (1947)

A *panel* or a *longitudinal* data set consists of several time series, indexed $t = 1, ..., T$, for several cross-sectional units, indexed $i = 1, ..., n$, where i can be country, a municipality, a firm, and so on. Therefore, the observations can be collected to a single vector, for example:

$$\begin{aligned} Y_i &= (y_{i,1} \quad ... \quad y_{i,Ti})' \quad i = 1, ..., n \\ Y &= (Y_1' \quad ... \quad Y_n')', \end{aligned}$$

where the vector $(Y_1'...Y_n')$ includes the time series observations of the n statistical units or individuals.

The use of panel data posses several major advantages over cross-sectional or time-series data. Panel data usually gives a larger number of data points, which increases the degrees of freedom and reduces collinearity among explanatory variables, thus improving the efficiency of estimates. Dynamics of change or the dynamic coefficients cannot usually be estimated using cross-sectional or single time series data (Hsiao 2003). Cross-section estimations also usually fail on making inference about the dynamics of change as their estimates tend to reflect inter-individual differences inherent in comparisons of different people, firms, or countries. That is, cross-sectional data is unable to distinguish between individuals or countries in different regions, for example, as it cannot use the information on subjects that change between regions. With panel data, this can be done, as it includes information on the subjects from a long(er) period of time.

In time series analysis, analyzing some dynamic models requires that the lag coefficients needs to be assumed, a priori, to be a function of only a very small number of parameters (Hsiao 2003). Otherwise, multicollinearity can be a problem.[16] If panel data would be available, the interindividual

[16]Consider a distributed lag model of the form:

$$y_t = \Sigma_{k=0}^{h} \beta_k x_{t-k} + \epsilon_t, \quad t = 1, ..., T,$$

diffences in the (exogenous) explanatory variables could be used to reduce the problem of collinearity. Panel data also allows one to control for one of the crucial problems arising in cross-sectional of time series data, namely the omitted variables bias. If individual- or some group-specific factors affect on the dependent variables, explanatory variables can capture the effects of these factors, and parameter estimates will not represent the true effects of the explanatory variables *per se*. With panel data, one can utilize the intertemporal dynamics and the individuality of the subjects being studied. Consider, for example, a simple time series regression:

$$y_t = \alpha + \beta' x_t + \gamma z_t + \epsilon_t \tag{1.4}$$

where x_t and z_t are exogenous variables, α is a constant and the error term ϵ_t is independently and identically distributed over t with mean zero and variance σ^2. If z_t are observable, there is no problem and the coefficients of β and γ can be consistently estimated using OLS. However, if z_t are unobservable and the covariance between x_t and z_t is nonzero, the OLS estimator of coefficients on x_t is inconsistent. If we would be able to use repeated observations from the same individual, model (1.5) would be given as:

$$y_t = \alpha + \beta' x_{it} + \gamma z_{it} + \epsilon_{it}, \tag{1.5}$$

where ϵ_{it} is now identically, independently distributed over i and t with mean zero and variance σ_ϵ^2. Now, if $z_{it} = z_t$ for all i meaning that the values of z stay constant across individuals, one is able to take deviation from the mean across individuals at a given time yielding:

$$y_{it} - \bar{y}_t = \beta'(x_{it} - \bar{x}_t) + (\epsilon_{it} - \bar{\epsilon}_t). \tag{1.6}$$

Thus, the (unobserved) effect z_t is eliminated and OLS can be used to obtain consistent and unbiased estimates of β from (1.6).

The limitations of the panel data analysis include the possible heterogeneity bias and cross-sectional dependence. Even though the panel data can cope with heterogeneity of the data better than the cross-sectional or time

where x_t is an exogenous variable and ϵ_t is random disturbance term. Now, obviously, x_t is near x_{t-1}, and still nearer $2x_{t-1} - x_{t-2} = x_{t-1} + (x_{t-1} - x_{t-2})$ (Hsiao 2003). Thus, a fairly strict multicollinearieties appear among $h+1$ explanatory variables.

series data, ignoring the individual or time-specific effects that exists among cross-sectional or time series units can still lead to parameter heterogeneity in the panel model specification (Hsiao 2003). If, for example, the slopes of the estimated parameters in the model (1.5) would differ, i.e. $\beta_i \neq \beta_j$, straightforward pooling of all observations from different individuals could lead to nonsensical pooling, as it would just give a average of coefficients that differ across individuals. Furthermore, time-varying intercepts and coefficients would also be likely to cause bias.

Large macro panels including long time series from several countries, which all possible belong to some group, like the OECD countries, may be affected by cross-sectional dependence. The cross-sectional dependence arises when, for example, the GDP series of several countries are correlated with each other. This may lead to biased inference if not accounted for. Especially, in cointegrated panels cross-sectional dependence can bias the results of the tests and estimators considerably (Baltagi 2008; Mark and Sul 2003).

1.5.1 Basic estimators of panel data

In panel data models, the conditional expectation of y given x can be examined by using the linear regression:

$$y_{it} = \alpha_i + \beta X'_{it} + \epsilon_{it}, \quad \epsilon_{it} \sim N(0, \sigma^2), \quad \epsilon_{it} \perp\!\!\!\perp X_{it}. \tag{1.7}$$

where β is a $K \times 1$ vector of parameter coefficients (excluding intercept). Now, if $u_i \perp\!\!\!\perp X_{it}$, but $\alpha_i \neq \alpha \ \forall i$, a *random effects* estimator can be used to estimate model (1.7). It is based on a model:

$$y_{it} = \alpha + \beta X'_{it} + u_i + \epsilon_{it}, \quad u_i \sim N(0, \sigma_u^2), \quad \epsilon_{it} \sim N(0, \sigma_\epsilon^2), \tag{1.8}$$

where following assumptions must hold:

$$Eu_i = E\epsilon_{it} \equiv 0, \tag{1.9}$$

$$Eu_i u_j = \begin{cases} \sigma_u^2 & \text{if} \quad i = j \\ 0 & \text{if} \quad i \neq j, \end{cases} \tag{1.10}$$

$$E\epsilon_{it}\epsilon_{jt} = \begin{cases} \sigma_\epsilon^2 & \text{if} \quad i = j, t = s \\ 0 & \text{otherwise}, \end{cases} \tag{1.11}$$

and

$$u_i \perp\!\!\!\perp X_{it}, \tag{1.12}$$

$$\epsilon_{it} \perp\!\!\!\perp X_{it}, \tag{1.13}$$

$$\epsilon_{it} \perp\!\!\!\perp u_i. \tag{1.14}$$

In the case of random effects, the OLS estimator is no longer the BLUE, i.e. the *best linear unbiased* estimator. Thus, in the case of random effects, the estimation must be conducted with *generalized least squares* estimator, or GLS.

However, if $u_i \not\perp\!\!\!\perp X_{it}$, the GLS random effects estimator will be inconsistent. In this case, the *fixed effects* estimator can be used. Fixed effects estimator is based on the model:

$$\begin{aligned} &y_{it} = \alpha_i + \beta' X_{it} + \epsilon_{it}, \qquad \epsilon_{it} \sim N(0, \sigma^2), \quad \epsilon_{it} \perp\!\!\!\perp X_{it} \\ &i = 1, ..., n, \quad t = 1, ..., T, \end{aligned}$$

where α_i is a scalar of constants representing the effects of those variables specific to the ith individual. The OLS estimator of fixed effects is also called the *least-squares dummy variables*, or the LSDV estimator. The LSDV estimator removes the individual effects effects, usually by assuming $\Sigma_{i=1}^{n} \alpha_i = 0$ (Hsiao 2003). This way the individual effects α_i represent the deviation of the ith individual from the common mean, and they are eliminated from estimation.

One can also use instrumental estimation methods to control for the possible endogeneity problem. Endogeneity arises when some or all of the explanatory variables are correlated with some part of the error term. With panel data this often refers to the situation presented above where $u_i \not\perp\!\!\!\perp X_{it}$. Although LSDV estimator can be used to control for this problem, it is biased and inconsistent estimator, if explanatory variables include lagged values of the dependent variable.[17] Dynamic panel data models are of the form:

$$y_{it} = \alpha + \gamma y_{i,t-1} + u_i + \epsilon_{it}, \quad u_i \sim iid(0, \sigma_u^2), \quad \epsilon_{it} \sim iid(0, \sigma_\epsilon^2) \tag{1.15}$$

In this case, clearly, $u_i \not\perp\!\!\!\perp y_{i,t-1}$. Now, the general method of moments (GMM) estimator can be used to consistently estimate model (1.15). For the instrumental variables, denoted as Z_{it}, it is required that $u_i \perp\!\!\!\perp Z_{it}$. In the case of

[17]However, with $T \longrightarrow \infty$ the LSDV estimator becomes consistent.

(1.15), lags of differences of explanatory variables can be used as instrumental variables for y_{it} as first differencing eliminates the individual time-invariant variables u_i. So, for example, $(y_{i,t-1} - y_{i,t-2})$ and $(y_{i,t-2} - y_{i,t-3})$ can be used as instruments for $y_{i,t-1}$, $(y_{i,t-2} - y_{i,t-3})$ and $(y_{i,t-3} - y_{i,t-4})$ can be used as instruments for $y_{i,t-2}$, etc.

1.5.2 Estimation in cointegrated panel data

Estimators presented above are consistent and/or asymptotically unbiased only when the underlying data is not *cointegrated* (Baltagi 2008; Kao and Chiang 2000). Cointegration refers to a stationary linear combination of *integrated* variables. Cointegration thus implies that there is a long-run *equilibrium* relation between the integrated variables. Integration, or $I(1)$ nonstationarity of a variable means that a stochastic trend affects the evolution of the series through time. Such series are described in A.1. Integrated variables have a infinite memory and they are highly persistent meaning that they are described by strong autocorrelation between successive observations of the time series.

Assume, for example, that we have a two-dimensional time series of the form:

$$\begin{cases} y_{1t} & = \beta x_t^* + \epsilon_{1t} \\ y_{2t} & = x_t^* + \epsilon_{2t}, \end{cases} \tag{1.16}$$

with $x_t^* \sim I(1)$ and $\epsilon_{1t}, \epsilon_{2t} \sim I(0)$, then

$$(1 - \beta) \begin{pmatrix} y_{1t} \\ y_{2t} \end{pmatrix} = \beta(x_t^* - x_t^*) + (\epsilon_{1t} - \beta\epsilon_{2t}) \sim I(0), \tag{1.17}$$

Thus, the series $Y_t = (y_{1t} \quad y_{2t})'$ is said to be cointegrated and the cointegration vector is $[1 \quad -\beta]$. The result presented in (1.17) can also be used to test for cointegration between $I(1)$ nonstationary variables, i.e. we can test are some of the *linear combinations* of the variables stationary.

Mark and Sul (2003) consider a dynamic OLS (DOLS) estimator with fixed effects, heterogenous trends, and common time effects for cointegrated panel data. The last model accounts for cross-sectional dependence by introducing a common time effect. Mark and Sul's model assumes that observations on each individual i obey the following triangular representation:

$$y_{it} = \alpha_i + \lambda_i t + \theta_t + \gamma' x_{it} + u_{it}, \tag{1.18}$$

where $(1, -\gamma')$ is a cointegrating vector between y_{it} and x_{it}, which is identical across individuals, α_i is a individual-specific effect, $\lambda_i t$ is a individual-specific linear trend, θ_t is a common time-specific factor, and u_{it} is a idionsyncratic error term that is independent across i, but possibly dependent across t. Model (1.18) allows for a limited form of cross-sectional correlation, where the equilibrium error for each individual is driven in part by θ_t.

Panel DOLS eliminates the possible endogeneity between explanatory variables and the dependent variable by assuming that u_{it} is correlated at most with p_i leads and lags of $\triangle x_{it}$ (Mark and Sul 2003). The possible endogeneity can be controlled by projecting u_{it} onto these leads and lags:

$$u_{it} = \Sigma_{s=-p_i}^{p_i} \delta'_{i,s} \triangle x_{i,t-s} + u_{it}* = \delta'_i z_{it} + u^*_{it}. \tag{1.19}$$

The projection error u^*_{it} is orthogonal to all the leads and lags of $\triangle x_{it}$ and the estimated equation becomes:

$$y_{it} = \alpha_i + \lambda_{it} + \theta_t + \gamma' x_{it} + \delta_i z_{it} + u^*_{it}, \tag{1.20}$$

where $\delta'_i z_{it}$ is a vector of projection dimensions. The consistent estimation of (1.20) is based on sequential limits, meaning that the convergence occurs in *sequential* fashion, where first $T \to \infty$ after which $n \to \infty$. Equation (1.20) can be feasibly estimated in panels with small to moderate n.

An alternative to the panel DOLS estimator is the panel VAR estimator by Breitung (2005). He proposes a panel VAR(p) model which can be presented as a panel vector error-correction model (VECM) as

$$\triangle y_{it} = \psi_i d_t + \alpha_i \beta'_{y,t-1} + \Sigma_{j=1}^{p-1} \Gamma_{ij} \triangle y_{i,t-j} + \epsilon_{it}, \tag{1.21}$$

where d_t is a vector of deterministic variables and ψ_i a $k \times k$ matrix of unknown coefficients, Γ_{ij} is unrestricted matrix, and ϵ_{it} is a white noise error vector with $E(\epsilon_{it}) = 0$ and positive definite covariance matrix $\Sigma_i = E(\epsilon_{it}\epsilon'_{it})$. The model is estimated in two stages. First, the models are estimated separately across n cross-section units. Then cointegration vectors are normalized so that they do not depend on individual specific parameters. Second, the system is transformed to a pooled regression of the form:

$$\hat{z}_{it} = \beta' y_{i,t-1} + \hat{v}_{it}, \tag{1.22}$$

where $\hat{z}_{it} = (\hat{\alpha}_i' \hat{\Sigma}_i^{-1} \hat{\alpha}_i)^{-1} \hat{\alpha}_i' \hat{\Sigma}_i^{-1} \bigtriangleup y_{it}$ and $\hat{v}_{it}$ is defined in similar fashion. The cointegration matrix, β, can now be estimated from (1.22) using the OLS estimator. It is assumed that the statistical units included in the panel have the same cointegration rank. Consistent estimation is based on sequential limits. Cross-sectional correlation is accounted by using an estimated asymptotic covariance matrix.

1.6 Contributions of the thesis

This thesis concentrates on the panel econometric analysis of the relationship between inequality and growth. The relationship is studied from three different angles. First, the short-term effect of inequality on growth is studied. Next, the long-run (equilibrium) relationship between inequality and economic development is analyzed. The third chapter concentrates on the effect that inequality may have on the factors of economic development, namely on its possible effect on savings.

1.6.1 The effect of income inequality on economic growth in the short run

In Chapter 2, the effect of inequality on growth is studied by using macroeconomic data on a panel of 70 countries. Chapter contributes on two sets of problems that panel econometric studies have recently encountered. These are the comparability problem associated with the commonly used Gini index by Deininger and Squire (1996), and the problem relating to the estimation of group-related elasticities in panel data.

Many recent studies assessing the effect of inequality on growth have used the Gini index by Deininger and Squire (1996) as a measure of income inequality. However, the "high quality" dataset of Deininger and Squire has received serious criticism concerning the accuracy, consistency, and comparability of the data (Atkinson and Brandolini 2001; Galbraith and Kum 2006). Galbraith and Kum (2006) have created a new improved measure of income inequality called the EHII2008. They have obtained their inequality measure by regressing Deininger and Squire's Gini coefficients on the values of explanatory variables, which include the different income measures of Deininger and Squire's data set, the set of measures of the dispersion of pay in the manufacturing sector, and the manufacturing share of the population. This should make the values of EHII2008 consistent and comparable as the data on wages on the manufacturing sector should be comparable across countries. The EHII2008 inequality measure also has a large data coverage on different countries, which diminishes the small sample bias and the possibility of systematic errors in estimation.

Many of the theories presented in Section 1.4 assume that the effect of income inequality on economic growth would differ between countries according to their level of economic development. Estimation of such income group elasticities in panel data with parametric methods would require that some group-specific constants are added to the estimated model. This creates a statistically dubious estimation configuration, and the inference of such estimations is likely to be conditional on the sample (Hsiao 2003; Baltagi 2008). The general way to avoid the vagueness relating to the use of group- or individual-related constants has been to use non-parametric methods (Lin et al. 2006; Banerjee and Duflo 2003). The problem with non-parametric methods is that they are known to lack statistical power compared with parametric methods in smaller samples generally used in growth literature.

It is shown in this chapter that there is a simple way to 'bypass' the vagueness related to the use of parametric methods to estimate group-related parameters. The idea is to estimate the group-related elasticities implicitly using a set of group-related instrumental variables. This can be done by grouping the individuals in the sample, creating group-related explanatory variable by linking each explanatory variable to each group, and attaching some group-related instrumental variable to each of the group-related explanatory variables. Although the method is rather simple, the inference drawn from these estimations should be unconditional or marginal with respect to the population.

The results obtained using the estimation method described above indicate that the relationship between income inequality and growth is likely to be non-linear. This result is rather well in line with the results obtained with non- or semi-parametric methods (Banerjee and Duflo 2003; Lin et al. 2006).

1.6.2 The long-run relationship between income inequality and economic development

Findings in Chapter 2 give only the short- or medium-term effects of inequality on growth. Potentially more interesting question is, how does inequality affect economic growth or development in the long-run? Chapter 3 extends the analysis by studying the possible long-run dependence between inequality and development.

Chapter 3 incorporates the EHII2.1 inequality measure and a panel data on macroeconomic variables with annual time series observations from 38 countries to test the existence of long-run equilibrium relation between inequality and the level of GDP. According to the panel unit root tests, both the logarithmic EHII2.1 inequality measure and the logarithmic GDP per capita series seem to follow an $I(1)$ nonstationary process.[18] They are also found to be cointegrated of order one using panel cointegration tests by Pedroni (2004) and Banerjee and Carrion-i-Silvestre (2006), which implies that there is a long-run equilibrium relation between them.

The effect of inequality on the level of GDP is estimated with panel dynamic OLS and panel dynamic SUR estimators using a simplified production function including just two factors, namely physical capital and income inequality. In accordance with the theory presented by Fishman and Simhon (2002), the estimated model assumes that the coefficient of inequality reflects the effect of human capital on production growth (see Section 1.4.2). Estimation is based on the following model:

$$\begin{aligned} log(GDP_{it}) = \alpha_i + \gamma_1' log(investments_{it}) + \gamma_2' log(inequality_{it}) \\ + \lambda_i t + \theta_t + u_{it}, \end{aligned}$$

[18]In unit root testing, the data on the total of 53 countries was used.

where α_i are individual constants, $\lambda_i t$ are individual trends, θ_t is the common time effect, $(1, -\gamma_1', -\gamma_2')$ is a cointegrating vector between GDP, investments and inequality, and u_{it} is an idiosyncratic error.

As mentioned above, many of the theoretical models presented in Section 1.4 imply that the growth elasticity of inequality might differ between developing and developed economies. To take this into account in estimation, countries in the dataset are divided into three income groups. To make the estimation of income groups asymptotically feasible, i.e. to make the groups large enough, countries are divided into three equally sized groups. According to the results of income group estimations, the long-run growth elasticity of inequality is negative in the middle-income and rich economies. Results for developing economies are inconclusive.

These findings imply that the distribution of income and economic development have a steady-state equilibrium relation, or relations, as commonly predicted by theoretical models. Findings also imply that this relationship between income inequality and economic growth is negative in developed economies.

1.6.3 The relationship between inequality and savings

As presented in Section 1.4, the effect of savings on capital accumulation and growth has always been one of the fundamental research topics in economics. In addition to the theories presented in Section 1.4, there are several theoretical models explaining the effect of inequality on savings.

The permanent income hypothesis by Friedman (1957) states that individuals with low income have a higher propensity to consume, and small changes in income, or its distribution, do not affect the consumption decisions of households. The life-cycle hypothesis argues that, if bequests are luxury, the saving rate should be higher among wealthier individuals (Kotlikoff and Summers 1981). Deaton (1991) finds that when income follows a random walk process and borrowing constraints are binding, it is undesirable for households to undertake any smoothing of consumption implying that consumption equals income. In political-economy models, more unequal income distribution may create demand for more redistribution through taxation and income transfers. If the saving function of individuals in the economy is convex, i.e. the rich save more, this will diminish aggregate savings through the diminished incomes of the rich (Alesina and Perotti 1994).

Although theoretical research spans several decades, the effect of income inequality on savings remains an open empirical question. This is due to the fact that empirical cross-country studies have produced controversial results on the effect of income inequality on savings (Cook 1995; Leigh and Posso 2009; Li and Zou 2004; Smith 2001). Generally all the empirical studies have assumed that income inequality, measured either by the Gini index or by the share of income earned by different income classes, is a stationary variable. However, according to the results presented in Chapter 2, income inequality may be driven by a stochastic trend indicating that inequality would be an $I(1)$ nonstationary variable. If this result held in general, it would offer an explanation to the ambiguous results of the previous empirical studies, because regressing a stationary variable on an $I(1)$ variable(s) can lead to a spurious regression (Stewart 2011). In empirical studies, savings is usually measured as a percentage of the GDP. If both the logarithmic savings and the logarithmic GDP are $I(1)$ variables and cointegrated, their difference results, by construction, in a stationary variable, namely savings as a percentage of the GDP. Thus, if inequality were an $I(1)$ variable and savings as a ratio of the GDP a stationary $I(0)$ variable, regressing savings on inequality would give spurious results.

In Chapter 4, macroeconomic data on nine developed economies spanning across four decades starting from the year 1960 is used to study the effect of the changes in the top income share to national and private savings. The income share of the top 1 % of population is used as a proxy for the distribution of income. According to panel unit root tests, the logarithmic income share of the top 1%, logarithmic gross national savings and logarithmic private consumption are all $I(1)$ variables. The income share of the top 1% is also found to be cointegrated with private consumption, which implies that there is a long-run dependency relation between them. The effect of inequality on private consumption is found to be negative in the Nordic and Central-European countries, but for the Anglo-Saxon countries the direction of the effect (positive vs. negative) remains ambiguous. The results of the panel cointegration tests are inconclusive on the possible cointegration relationship between gross savings and the top 1% income share. The real GDP per capita and gross savings as well as the real GDP per capita and private consumption are also found to be cointegrated. This implies that the ratios of savings and private consumption to GDP would be stationary variables and hence previous research is likely to have produced biased results on the effect of inequality on savings.

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Appendix A

Random walk and $I(1)$ nonstationary processes

When random variables $\epsilon_1, ..., \epsilon_n$ are identically and independently distributed with $E[\epsilon_t] = 0$, the sums

$$y_t = \epsilon_1 + ... + \epsilon_t, \quad t = 1, 2, ... \tag{A.1}$$

are called *random walk* -processes. The name comes from the fact that the time series of random walk processes (A.1) tends to wonder through time with increasing variance. The process of (A.1) can also be defined using a $AR(1)$ model of the form

$$y_t = y_{t-1} + \epsilon_t, \quad \epsilon_t \sim i.i.d, \tag{A.2}$$

which is now also called an $I(1)$ nonstationary process. When a constant term ($\delta \neq 0$) is added to equation (A.2)

$$y_t = y_{t-1} + \delta + \epsilon_t, \quad \epsilon_t \sim i.i.d. \tag{A.3}$$

the process is called as *random walk with drift.*

Chapter 2

Inequality and growth: another look at the subject with a new measure and method

Abstract[1]

Recent empirical research on the relationship between income inequality and economic growth has provided controversial results. Some studies predict a negative, and some a positive effect of inequality on growth. Answers to the controversy have usually been sought from problems in the estimation technique, the measure of inequality, or from some form of non-linearity in the relationship between inequality and growth. This study accounts these problems by using an improved measure of income distribution and parametric group-related panel estimation. In conclusion, we find that the effect of inequality is likely to be non-linear.

[1]A paper based on this chapter is forthcoming in the *Journal of International Development.*

2.1 Introduction

The effect of income inequality on economic growth has been under intensive study for several decades, but no clear empirical regularity has emerged. Empirical research on the subject commenced in 1955 when Simon Kuznets released his study. Kuznets argued that income inequality will first increase at the beginning of industrialization, but will even out as the economy becomes more developed. Although Kuznets' data did provide some evidence of the existence of such a relation, the subject was only infrequently investigated during the next four decades. The main reason for this was the lack of data on income distribution. In 1996, Deininger and Squire released their Gini index, which quickly became the most used estimate for the income distribution in growth studies.

After the release of the Gini index, panel data analysis has become somewhat of a standard in studies trying to assess the effect of inequality on growth, mostly because a simple cross-country estimation can suffer from an omitted-variables bias. If region-, country-, or some group-specific factors affect economic growth rates, explanatory variables can capture the effects of these factors, and parameter estimates will not represent the true effects of the explanatory variables *per se*.[2] This problem can be diminished using panel data. Unfortunately, the results of panel data studies have been controversial.

In one of the first panel data studies on the topic, Persson and Tabellini (1994) found that income inequality has a negative effect on economic growth rates. Li and Zou (1998) found that income inequality is positively associated with economic growth, a view supported by Forbes (2000). Deininger Squire (1998) found that initial inequality in the asset distribution has a strong negative effect on growth, a finding which has been supported by Lundberg and Squire (2003). Recently, Banerjee and Duflo (2003), Barro (2000), Chen (2003), and Lin et al. (2006) have found evidence that the relationship between income inequality and growth might be non-linear.

[2]There are, for example, clear indications of this in the study by Deininger Squire (1998, p. 270), where country dummies affected the inequality elasticity of growth. More detailed analysis of problems relating to the omitted-variable bias in growth regressions with inequality as an explanatory variable can be found in Forbes (2000).

Recent panel econometric studies have generally encountered two sets of problems. First, the Gini index of Deininger and Squire (1996) has attracted serious criticism concerning its consistency and accuracy (Atkinson and Brandolini 2001; Galbraith and Kum 2006). If the values of Deininger and Squire's Gini index are flawed, then the majority of the econometric studies on the topic are subject to errors.[3] Second, estimation of income group elasticities in panel data with parametric methods requires that some group-specific constants be added to estimation, which may cause the inference to be conditional on the countries in the sample. Non-parametric methods have been used to avoid this problem (Lin et al. 2006, Banerjee and Duflo 2003). The problem with non-parametric methods is that they are known to lack statistical power compared with parametric methods. Therefore, cross-country estimation and *group-specific* fixed effects estimation have usually been used to estimate the income group elasticities with parametric methods (see, e.g., Chen (2003) and Forbes (2000)). This has, unfortunately, led to questionable results because many of the estimated models have included a lagged dependent variable which renders the fixed effects estimator inconsistent with small time dimensions of data.

This study uses a new inequality measure compiled by Galbraith and Kum (2006) to correct for the possible bias created by the Deininger and Squire (1996) Gini index. This study also presents a simple parametric way to robustly estimate group-specific elasticities using full data coverage in a panel setting. The results based on non-linear GMM estimation imply that income inequality has had a negative effect on growth, but that the relation may also include non-linearities.

This paper is organized as follows. Section 2 presents the basic theories that have been suggested to provide the causal relationship of income inequality on economic growth. Section 3 gives more detailed description of the problems encountered in previous studies, and presents some solutions for these problems. Section 4 introduces the data, and section 5 gives estimation details and results. Section 6 concludes the findings of this study.

[3] For example, Barro (2000), Banerjee and Duflo (2003), Forbes (2000), and Chen (2003) have used the dataset by Deininger and Squire (1996).

2.2 The theoretical effect of inequality on growth

Several theories have been proposed on how income inequality might affect economic growth rates. Some theories describe the long-run and others a short- or medium-term causal relationship of inequality on growth. Because this study assesses the short- and/or medium-term effect of inequality on growth, the long-run effects are not discussed here. The theories regarding the short- and medium-term effects of inequality on growth can be classified into four broad categories: credit market imperfections, political economy, social unrest, and saving rates, which we discuss next.

2.2.1 Credit market imperfections

Given credit market imperfections, the inequality of incomes is usually assumed to restrict households' opportunities for education.[4] If an economy's aggregate capital is small, unevenly distributed incomes urge capital owners to invest in specialization (Fishman and Simhon 2002). In this case, inequality results in a higher level of human capital, a greater division of labor and faster economic growth. When an economy's aggregate capital is large, more equal distribution of incomes encourages households to invest in specialization and entrepreneurship. In this case, equality of incomes creates a more risk-free environment and a broadly-based demand for goods, which will lead to higher employment, greater division of labor, and faster economic growth.

2.2.2 Political economy

In a society where the mean income exceeds the median income, the idea of evening out the distribution of incomes through the political process may arise (Bénabou 1996). In such cases, taxation and transfer payments are commonly used to redistribute incomes. Higher taxes can lead to diminished investments and/or consumption.

[4] To be more precise, when access to credit is limited, households' investment opportunities depend on their assets and incomes. Thus, given credit-market imperfections, poor households usually forgo investment in human capital (Barro 2000).

When incomes are distributed unevenly, the wealthier portion of the population may try to influence politicians not to increase taxes and income transfers, which can lead to a corrupt government. Corrupted administration causes inefficiencies in the distribution of licenses, social benefits, etc. Because the demand for licenses is usually high and inflexible, a rise in license prices lowers the profits of producers and investors, which is likely to reduce investment (Murphy *et al.* 1993).

2.2.3 Unrest related to social policy

Income inequality may motivate individuals to commit crime, illegal rent-seeking activity or other acts that disturb the stability of society (Bénabou 1996; Merton 1938). Inequality can also increase social disorganization when social networks are disrupted in residential areas (Shaw and McKay 1969). Social disorganization may lower social capital and increase crime and delinquency rates. Crime and illegal rent-seeking activities may inflict additional costs on producers and investors, which lowers the incentive to invest (Hall and Jones 1999; Murphy *et al.* 1993). Low social capital can also increase the bargaining and enforcement costs of contracts as the parties have less trust in each other (Ostrom 1990). Low social capital also usually means a more risk-averse society.

2.2.4 Saving rates

High saving rates are thought to be especially important for developing economies, because raising an economy to a higher growth path requires substantial investment (Sachs *et al.* 2004; Stiglitz 1969). Funds for investments come from aggregate savings and/or loans from abroad. Domestic investment can also be replaced by direct foreign investment. These options are not equal in risk. Large-scale lending can lead to a balance of payments deficit and to a debt circle if the higher growth path remains unattained. Direct foreign investment creates jobs and raises income in the region, but also supersedes domestic supply. A major portion of the profit of foreign firms is also usually repatriated to a foreign country, which affects the balance of payments and hinders the exercise of an independent monetary policy. Foreign investment is also usually highly sensitive to economic fluctuations and speculation, which may cause uncontrollable shifts in the balance of capital.

Thus, increasing aggregate savings may be the safest way for a developing country to finance its structural investment. Many theories argue that savings rates would increase with income. These include the permanent income hypothesis of Friedman (1957), life-cycle hypothesis of Ando and Modigliani (1963), which was augmented with intergenerational transfers by Kotlikoff and Summers (1981), and savings under liquidity constraints of Deaton (1991) and Seater (1997). Inequality may therefore enhance growth indirectly through increased aggregate savings and investment.

2.3 Summary of the main problems encountered in the field of study

In this section, we present the problems associated with the Deininger and Squire (1996) Gini index that has been intensively used in income inequality studies within the last 15 years. We also offer a simple parametric way to estimate group-related elasticities in panel data.

2.3.1 Problems with the Deininger and Squire (1996) Gini index

Many modern studies on the relationship between inequality and growth have used the Deininger and Squire (1996) Gini index as a measure of income distribution. Most of these studies rely on the "high quality" part of the data. However, the "high quality" dataset of Deininger and Squire has attracted serious criticism concerning its accuracy, consistency, and comparability.[5] According to Atkinson and Brandolini (2001), Deininger and Squire's Gini index includes so many different datasets that in many cases the "high quality" time series cannot be viewed as a continuous series. The different datasets may not be comparable between countries either. These are serious

[5]All this criticism also naturally applies to the "low" quality part of Deininger and Squire's data.

problems for estimation, because statistical inference requires that observations are from the same parent population. If the observations are not comparable even within a country, there is no one parent population, and the parameter estimates may be spurious. Galbraith and Kum (2006) have also shown that the income distribution estimates given by Deininger and Squire's Gini index are biased in many cases.

The problems concerning the accuracy and consistency of Deininger and Squire's (1996) "high quality" estimates can best be demonstrated with the help of an example.[6] The time series of Deininger and Squire's "high quality" Gini index for France, Norway, and India are presented in Figure 1. The first thing that attracts attention are the abrupt changes in the values of the Gini in Norway. The value of the Gini drops by 6 points between 1976 and 1979 and rises almost 3 points between 1984 and 1986. Why would a Nordic welfare state have experienced such violent changes in its income distribution when there were no major economic or societal developments or crises during these periods? There is, however, a far stranger result present

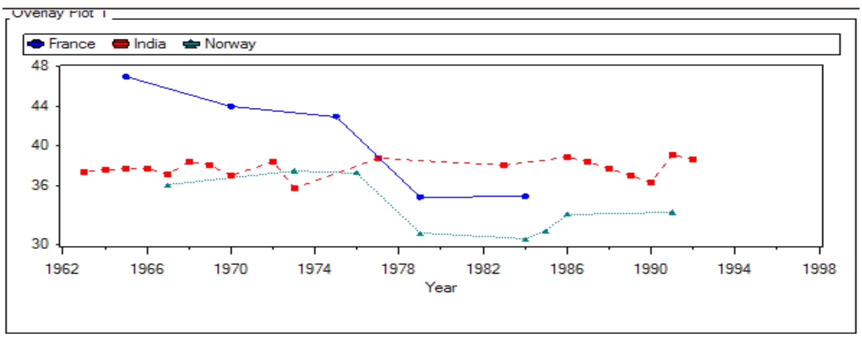

Figure 1. Values of Deininger and Squire's "high quality" Gini index for France, Norway, and India. Source: Deininger and Squire (1996)

in Figure 1. According to the Deininger and Squire (1996) Gini index, India had a more equal income distribution than Norway in 1973 and a more equal income distribution than France in the 1960s and 1970s. This result is highly

[6] All the values here are from the updated version of Deininger and Squire's dataset. As recommended by Deininger and Squire (1996), 6.6 Gini points are added to all the Gini values that are from the "expenditure" series.

questionable, because the poverty rate in India was one of the highest in the developing economies in the 1990s, and the level of poverty had clearly declined from the 1970s (Justino 2007). Both Norway and France also had progressive taxation and extensive publicly financed social services by the 1970s.

For comparison, the time series of the EHII2008 Gini index for France, Norway, and India are presented in Figure 2. The changes in series are grad-

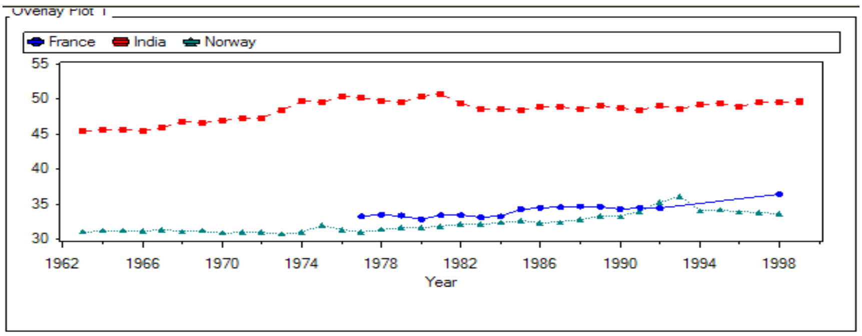

Figure 2. Values of EHII2008 Gini index for France, Norway, and India. Source: Galbraith and Kum (2006)

ual, as should be the case with a slowly-changing societal variable like income distribution in the absence of economic or other crises. The values of the Gini index for India are also clearly above those of France and Norway, which is reasonable considering the differences in the level of economic development and poverty (Justino 2007). The effect of the economic downturn on income distribution in the Nordic countries at the beginning of the 1990s is also present in the series for Norway. [7] As pointed out by Atkinson and Brandolini (2001), the most severe problem in the "high quality" dataset of Deininger and Squire (1996) is its inconsistency. Like Norway, there are several other countries which, according to Deininger and Squire's Gini index,

[7] Aaberge *et al.* (2002) argue that very generous unemployment benefits, a different type of unemployment compared to many previous economic downturns, and the methods used to calculate the Gini index have probably contributed to the small changes in the income distribution in Norway during the economic downturn at the beginning of the 1990s. In other Nordic countries, e.g. Finland and Sweden, the economic downturn and the growth of unemployment were more severe.

exhibit some rather aggressive changes in their income distribution within relatively short time periods without a clear economic rationale.

These problems in the widely-used Deininger and Squire (1996) Gini index have some profound implications. In the worst case, all previous studies on the topic using this Gini index have produced nonsense estimates for the effect of income inequality on growth. Even if the parameter estimates of income inequality had not been spurious, they still could not be trusted because the values of Deininger and Squire's index may have been erroneous. It is thus likely that we have only a few studies on the subject whose results we can trust, i.e., those studies that have not used their index as a measure of income distribution.[8] These include Castelló-Climent (2010), who finds that inequality has a negative effect on growth in low and middle-income economies, Frazer (2006), who does not find general support for the Kuznets hypothesis of an inverted relation between inequality and growth using non-parametric methods, and Lin et al. (2006), who find support for the Kuznets hypothesis using semi-parametric methods.

The EHII2008 inequality measure used in this study has been built "on top" of the Deininger and Squire (1996) Gini index, a method suggested by Atkinson and Brandolini (2001) (Galbraith and Kum 2006). Galbraith and Kum have estimated their inequality measure using the various income measures of Deininger and Squire's data set, the set of measures of the dispersion of pay in the manufacturing sector, and the manufacturing proportion of the population as explanatory variables.[9] According to Galbraith and Kum, the EHII2008 inequality measure has three clear advantages over Deininger and Squire's Gini index. It has more than 3000 estimates, while Deininger and Squire have only about 700 "high quality" estimates. The EHII2008 gets its

[8] It is of course possible that measures of income distribution used in these studies have also been flawed, but, for example, Frazer (2006) uses the UNU-WIDER (World Institute for Development Economics Research of the United Nations University) dataset, which is considered to be clearly more reliable than the dataset of Deininger and Squire (1996).

[9] First, Galbraith and Kum (2006) regressed the Deininger and Squire (1996) Gini index on the explanatory variables to see which are the most important explanatory variables and then used them to estimate the EHII2008 inequality measure. The large unexplained (residual) variation, which was the problem in the index of Deininger and Squire, was thus eliminated from the EHII2008 measure.

accuracy from the industrial data published annually by the United Nations Industrial Development Organization (UNIDO). Changes over time and differences across countries in pay dispersion are thus reflected in income inequality. All estimates are also adjusted to household gross income, which makes them more congruent. Values of the EHII2008 also correspond to the estimates for income distributions of other research institutes, such as the OECD and the UNU-Wider,[10] better than those of the Deininger and Squire Gini index (Föster & Pearson 2002, Galbraith & Kum 2004).

2.3.2 Estimation of group-related elasticities

Various modern studies have used non-parametric methods to assess the possible non-linearity in the relation between inequality and growth (e.g., Banerjee and Duflo (2003); Lin et al. (2006)). The problem with non-parametric methods is that they are known to lack statistical power compared with parametric methods, especially in the mid-sized samples typically used in growth studies. That is why many studies have tried to avoid the use of non-parametric methods by imposing some restrictions on the data. For example, Forbes (2000) has conducted a sensitivity analysis using fixed effects to estimate the elasticity of growth with respect to inequality separately in different income groups. Her results show that the inequality elasticity of growth is positive and does not vary between different income groups of countries. But Forbes uses fixed effects in a model that includes a lagged dependent variable, which leads to biased parameter estimates when the time dimension of the data is fixed.[11] This creates a problem facing the study of non-linear relations in the dynamic panel setting using the parametric approach. Specifically, the group-specific constants are likely to lead to inference that is conditional on the particular countries included in the data, and there are usually not enough observations among different groups for feasible group- or country-specific instrumental estimation.[12]

[10] World Institute for Development Economics Research of the United Nations University.

[11] For consistency, it is required that the time dimension of the data tends to infinity.

[12] For example, the smallest groups of Forbes (2000, p. 883) have only 48 and 54 observations, which are clearly too few to obtain asymptotic efficiency in instrumental variable

Some econometricians argue that the statistical inference, when using individual constants in panel data, is *conditional* on the individuals included in the sample (Baltagi 2008, p. 14). This is because the model using individual constants is thought to include only the information confined to the individual effects present in that particular sample (Hsiao 2003, p. 43). In other words, if we used dummy variables to "earmark" each individual country or group in our dataset, our inference would be restricted to just those individuals, not the population. This problem is closely linked to fixed effects, or the least squares dummy variables estimator, as the individual effects are treated as parameters to be estimated.

If we wanted to study the possible non-linearities in the relationship between inequality and growth with respect to the level of economic development, for example, we would need to classify the countries in our dataset in some way (e.g., as poor, middle-income, and rich) by using a set of dummy variables. As mentioned above, this may restrict our inference to just the sample employed. However, this problem can be 'bypassed' quite easily by using a non-linear (instrumental variables) estimator like the GMM. The idea is to estimate group-related elasticities implicitly using a set of group-related instrumental variables. This can be done by grouping the individuals in the sample, creating a group-related explanatory variable by linking each explanatory variable to each group, and attaching some group-related instrumental variable to each of the group-related explanatory variables. The new group-related variables are used to estimate some set of unknown parameters drawn from the parameter space. Estimation is carried out implicitly with the non-linear instrumental variables estimator using a set of group-related instrumental variables, making the inference unconditional or marginal with respect to the population.

In practice, however, there is a problem with this method. The number of estimated parameters, p, is of the order of the product of the number of groups, n_g, and the number of explanatory variables, K, namely $p = Kn_g + 1$. So if the number of individuals in the data is larger than the time dimensions of the data, we end up with a very small number of degrees of freedom rather

estimations. Thus, Forbes is forced to use a fixed effects estimator, which is not likely to be consistent (see previous footnote).

quickly. Thus, in order for the method to work we need to have a sufficiently small number of groups with respect to the time dimension.

2.4 Data

The data used in this study consists of the following variables: real GDP per capita with the base year of 1996, change in real GDP per capita, gross investments as a portion of real GDP per capita, average years of schooling, the Gini index of Deininger and Squire (1996), and the EHII2008 inequality measure of Galbraith and Kum (2006). The data covers the years 1965 - 2000, and is mostly compiled from the Penn-World tables (Heston et al. 2006). Exceptions are the EHII2008 inequality measure, which is acquired from the University of Texas Inequality Project, the estimate for average years of schooling which is acquired from the dataset of Barro and Lee (2000), and the Gini index, which is acquired from the World Bank's Measuring Income Inequality Database. The list of countries is presented in the appendix.

Table 2.1: Descriptive statistics

variable	mean	std. deviation	min.	max.
GDP	6001.12	6787.93	115.19	34364.50
GDP growth (%)	2.076	5.408	-53.119	27.254
D&S Gini index	37.414	8.574	20.917	57.900
EHII2008 ineq. measure	40.828	6.651	24.156	57.213
investments (%)	17.321	8.869	2.237	69.523
average schooling	5.293	2.795	0.380	12.250

2.5 Estimation

Several model specifications have been suggested in econometric growth studies using the Gini index as an explanatory variable.[13] Here, a basic Barro-type extended version of the neo-classical growth model is used to make the results

[13] See, for example, Forbes (2000), Barro (2000) and Persson and Tabellini (1994).

comparable. Estimation is based on the following model:

$$\begin{aligned} log(growth_{it}) &= \alpha + \beta_1 log(GDP_{i,t-1}) + \beta_2 log(investment_{i,t-1}) \\ &+\beta_3 log(education_{i,t-1}) + \beta_4 log(inequality_{i,t-1}) + \kappa_{it} \end{aligned} \tag{2.1}$$

where κ_{it} is the residual, which includes both the possible country-specific effect, μ_i, and the error term, ϵ_{it} ($\mu_i \sim i.i.d.(0, \sigma_u^2)$, $\epsilon_{it} \sim i.i.d.(0, \sigma_\epsilon^2)$). Growth is measured as five-year averages to control for short-run economic fluctuations as in Islam (1995). The average growth rate during each five-year period is regressed on the values of the explanatory variables in the year immediately preceding each period.[14] The use of five-year intervals means that there are, at most, eight observations available for each country. Since the instrumentation of endogenous variables will drop the maximum number of observations in the estimation to five for each country, the estimation covers the years from 1975 to 2000 in practice.

As shown by Forbes (2000), the estimation of equation (2.1) is complicated by the endogeneity of the GDP, which can be demonstrated by writing the GDP growth as the difference in levels of income and adding $income_{i,t-1}$ to both sides:

$$\begin{aligned} log(income_{it}) &= \alpha + \gamma log(income_{i,t-1}) + \beta_2 log(investment_{i,t-1}) \\ &+\beta_3 log(education_{i,t-1}) + \beta_4 log(inequality_{i,t-1}) + \kappa_{it}, \end{aligned} \tag{2.2}$$

where $\gamma = \beta_1 + 1$. Clearly $E(\kappa_{it} income_{i,t-1}) \neq 0$. In panel data, all explanatory variables can correlate with the (possible) country-specific effect, and this has to be taken into account in the estimation. Because of this, and because model (2.1) is dynamic by nature, estimation is done with the generalized method of moments estimator (GMM) (Arellano and Bond 1991). The benefits of the GMM include heteroskedasticity not affecting it and its being easily equipped to withstand autocorrelation.

In this paper, the first and second lags of the first differences of all explanatory variables are used as instruments for the explanatory variables in levels (Arellano and Bower 1995).[15] Thus, $(\mathbf{X}_{i,t-2} - \mathbf{X}_{i,t-3})$ and $(\mathbf{X}_{i,t-3} - \mathbf{X}_{i,t-4})$ are used as instruments for $\mathbf{X}_{i,t-1}$, and $(\mathbf{X}_{i,t-3} - X_{i,t-4})$ and $(\mathbf{X}_{i,t-4} - \mathbf{X}_{i,t-5})$

[14] The averaged growth rate in 1986 to 1990, for example, is regressed against the values of the explanatory variables in 1985.

[15] The correlation between difference and level commonly diminishes rapidly after the

are used as instruments for $\mathbf{X}_{i,t-2}$, etc. It is therefore assumed that all the explanatory variables are predetermined such that $E(\epsilon_{it}\mathbf{X}'_{is}) = 0 \ \forall \ t > s$, where $\mathbf{X}$ is the matrix of explanatory variables.

The reason for estimating equation (2.1) in levels is the fact that transforming the data with first differencing or orthogonal deviations to eliminate the unobserved individual effects also eliminates the individual country-related information in those effects.[16] By eliminating individual effects, we may actually create a spuriously better fit for our data, because we also remove some of the individual variation present in the data.

Table 2 presents the mean and standard deviation of the five-year average growth rate and simple correlation coefficients between the five-year growth rate and the EHII2008 inequality measure in levels and in first differences. According to the means and standard deviations shown in table 2.2,

Table 2.2: Summary statistics for 5 year average growth rate and the EHII2008 inequality measure

variable	mean	s.d.
5 year average growth rate in levels	5.951	3.478
5 year average growth rate in first-diff.	-0.514	3.998

variable	corr.	p-value
5 year aver. gr. and EHII2008 in levels	-0.1694***	0.0005
5 year aver. gr. and EHII2008 in in first diff.	0.1006	0.0656
5 year aver. gr. in levels and EHII2008 in first diff.	-0.217***	$<.0001$
5 year aver. gr. in first-diff. and EHII2008 in levels	0.079	0.1322

S.d. stands for the standard deviation of the variable. Corr. gives the value of the simple correlation coefficient between the growth rate and the EHII2008 inequality measure in levels and in first differences. P-value gives the p-value of the simple correlation coefficient.

not much variation would be lost in differencing the five-year average growth rate. However, the simple correlation coefficients tell a different story. When the average growth rate is given in levels, the correlation coefficient with the

second lag. Thus, only the first two lags of differences are usually relevant for the identification. Using too many moment conditions could also result in bias in the GMM estimator (Ziliak 1997).

[16]These unobserved country effects reflect, among other things, the differences in the initial level of efficiency (Bond *et al.* 2001).

EHII2008 inequality measure is negative regardless of the form in which the EHII2008 is given (i.e., in first differences or levels). The correlation coefficient is positive if the average growth rate is presented in first differences. This indicates that, although the external variation does not seem to change much in first-differencing, some information is clearly lost, which is very likely to affect the inference drawn from the data. That is, the results of our estimation could be totally different if we used first-differenced data. The results in table 2.2 thus indicate that removing individual effects by first-differencing runs the risk of causing erroneous inference.

The estimation results of equation (2.1) are presented in table 3. The Newey-West estimator with lag one is used as the GMM estimator's weight matrix to account for autocorrelation in the variables appearing in the orthogonality conditions. Hansen's J test is used to evaluate the validity of extra instruments. According to the test, the orthogonality conditions seem quite realistic for the chosen set of instruments. According to the results of GMM estimation presented in table 2.3, only lagged GDP per capita is statistically significant at the 5% level. However, the result may have been affected by the small sample bias, because the GMM estimator may exhibit substantial bias in dynamic panel data model estimations with small samples (Hayakawa 2007).

To diminish the possible bias, we estimate the equation (2.1) using only the EHII2008 as a measure of income distribution. This increases the number of countries included in estimation to 70 and the number of observations to 263.[17] According to results presented in table 2.4, the elasticity of growth with respect to inequality is about -0.014. The elasticity of growth with respect to lagged GDP is approximately -0.007. The elasticity of growth with respect to investments was about 0.028. The elasticity of growth with respect to average years of schooling was approximately 0.008.

The GMM estimation results in table 2.4 are in line with general economic theory, contrary to those in table 2.3, where, for example, the coefficient of investments was not statistically significant. Although there are several

[17] Countries that have observations in 4 consecutive estimation periods are included in the estimation. This is the minimum number of observations because 3 time series observations are lost due to instrumentation.

Table 2.3: Estimation results for growth rate I

Estimator:	FE-OLS	FE-OLS	GMM	GMM
Constant	0.0173	0.0303**	0.0588*	0.0719***
	(0.0077)	(0.0106)	(0.0281)	(0.0188)
$\text{GDP}_{i,t-1}$	-0.0031****	-0.0032****	-0.0044***	-0.0054
	(0.0004)	(0.0003)	(0.0012)	(0.0031)
$\text{investments}_{i,t-1}$	0.0025	-0.0086	0.0091	0.0041
	(0.0076)	(0.0073)	(0.0140)	(0.0124)
$\text{years of schooling}_{i,t-1}$	0.0030*	0.0016	0.0035	0.0048
	(0.0014)	(0.0012)	(0.0024)	(0.0059)
$\text{D\&S gini index}_{i,t-1}$	-0.0027	-	-0.0628	-
	(0.0021)		(0.0572)	
$\text{EHII2008}_{i,t-1}$	-	0.0034	-	-0.0079
		(0.0027)		(0.0055)
countries	34	34	34	34
observations	183	203	103	136
Hansen test	-	-	0.27 (8)	0.92 (8)

* = $p<.05$, ** = $p<.01$, *** = $p<.001$, **** = $p<.0001$. Standard errors are presented in parentheses. Hansen stands for Hansen's test for overidentifying restrictions and the number of instruments is presented in parentheses. All OLS estimations are done using White heteroskedasticity-consistent standard errors and covariances. First and second lags of first difference are used as instruments for explanatory variables in GMM estimation. A Newey-West estimator with lag one is used as the GMM estimator's weight matrix to account for autocorrelation in the variables appearing in the orthogonality conditions.

Table 2.4: Estimation results for growth rate II

Estimator:	FE-OLS	GMM
Constant	0.0336****	0.0979***
	(0.0087)	(0.0274)
$\text{GDP}_{i,t-1}$	-0.0026****	-0.0070**
	(0.0003)	(0.0023)
$\text{investments}_{i,t-1}$	-0.0055	0.0277*
	(0.0042)	(0.0137)
average $\text{schooling}_{i,t-1}$	-0.0014	0.0082*
	(0.0009)	(0.0037)
$\text{EHII2008}_{i,t-1}$	-0.0010	-0.0142*
	(0.0023)	(0.0065)
countries	70	70
observations	413	263
Hansen test	-	4.61 (8)

* = p<.05, ** = p<.01, *** = p<.001, **** = p<.0001. Standard errors are presented in parentheses. Hansen stands for Hansen's test for overidentifying restrictions and the number of instruments is presented in parentheses. All OLS estimations are done using White heteroskedasticity-consistent standard errors and covariances. First and second lags of first difference are used as instruments for explanatory variables in GMM estimation. A Newey-West estimator with lag one is used as the GMM estimator's weight matrix to account for autocorrelation in the variables appearing in the orthogonality conditions.

possible reasons for this strange result, including sample selection, one likely explanation is that the results in table 2.3 may have suffered from small sample bias.

The results in table 2.4 thus imply that the inequality elasticity of growth is negative. There is, however, reason to doubt the congruency of this relationship. Hineline (2007) has found that estimated coefficients of explanatory variables generally used in growth regression differ substantially between OECD and non-OECD countries. Barro (2000) has also found that the coefficient of inequality in growth regression may differ between the income groups of countries. Sensitivity analysis is thus needed to test the robustness of the results. The sensitivity analysis is conducted using the method suggested in section 3.2.

As explained in section 3.2, in order to study the elasticities of economic growth with respect to explanatory variables separately in different groups of countries, the estimated equation must include group-related dummies and group-related variables, and every group-related variable must have its own group-related instrument.[18] To estimate the elasticity of growth with respect to inequality in OECD and non-OECD countries, the equation (2.1) is transformed into:

$$\begin{aligned} log(growth_{it}) = {} & \beta_1 OECD_i + \beta_2 NOECD_i \\ & + (\beta_3 OECD_i + \beta_4 NOECD_i) log(GDP_{i,t-1}) \\ & + (\beta_5 OECD_i + \beta_6 NOECD_i) log(investment_{i,t-1}) \\ & + (\beta_7 OECD_i + \beta_8 NOECD_i) log(education_{i,t-1}) \\ & + (\beta_9 OECD_i + \beta_{10} NOECD_i) log(inequality_{i,t-1}) + \kappa_{it} \end{aligned} \tag{2.3}$$

where OECD is a dummy variable for OECD economies, NOECD is a dummy variable for non-OECD economies, and κ_{it} is the residual, which includes both the possible country-specific effect, μ_i, and the error term, ϵ_{it} ($\mu_i \sim i.i.d.(0, \sigma_u^2)$, $\epsilon_{it} \sim i.i.d.(0, \sigma^2)$).

To estimate the elasticity of growth with respect to the Gini index in

[18] This means that, for example, if we have a group of OECD countries marked by dummies, this group needs to have its own set of explanatory variables and their instruments in the dataset.

different income groups of countries, equation (2.1) is transformed into:

$$
\begin{aligned}
log(growth_{it}) = {} & \beta_1 dr_i + \beta_2 dm_i + \beta_3 dp_i \\
& + (\beta_4 dr_i + \beta_5 dm_i + \beta_6 dp_i) log(GDP_{i,t-1}) \\
& + (\beta_7 dr_i + \beta_8 dm_i + \beta_9 dp_i) log(investment_{i,t-1}) \\
& + (\beta_{10} dr_i + \beta_{11} dm_i + \beta_{12} dp_i) log(education_{i,t-1}) \\
& + (\beta_{13} dr_i + \beta_{14} dm_i + \beta_{15} dp_i) log(inequality_{i,t-1}) + \kappa_{it}
\end{aligned}
\tag{2.4}
$$

where dr_i is a dummy variable for rich economies, dm_i is a dummy variable for middle-income economies, dp_i is a dummy variable for poor economies, and κ_{it} is the residual, which includes both the possible country-specific effect, μ_i, and the error term, ϵ_{it} ($\mu_i \sim i.i.d.(0, \sigma_u^2)$, $\epsilon_{it} \sim i.i.d.(0, \sigma_\epsilon^2)$).

Table 2.5 shows the results of the non-linear Newey-West GMM estimation of equations (2.3) and (2.4) for inequality. As before, the Newey-West estimator is based on one lag. Group-related first and second lags of first differences are used as instruments for group-related explanatory variables. According to the Hansen's J test, orthogonality conditions cannot be rejected for the chosen set of instruments in all estimations (results not shown).

The magnitude of the effect of inequality is quite different between the two measures in both OECD and non-OECD countries, although none of the parameter estimates of the OECD and the non-OECD countries are statistically significant at the 5% level in either groups of countries. The inequality elasticity of growth varies even more between the two measures in income group estimation. The parameter estimates of the Deininger and Squire (1996) Gini index are positive in the groups of countries whose GDP per capita was under \$1000 and over \$2500 in 1965 and negative in the remaining income groups. However, the parameter estimate of the Gini index is not statistically significant at the 5% level in any of the income groups.

The effect of inequality seems more robust across income groups when the EHII2008 is used as a measure of inequality.[19] The effect is negative in all income groups except in the group of countries whose GDP per capita was

[19]The difference between the measures may be due to sample selection as there are great differences in the number of countries included in estimations between the two measures. This difference could also result from small-sample bias in the GMM estimator or from inconsistency in the Deininger and Squire (1996) dataset.

Table 2.5: Sensitivity analysis: GMM estimation on growth elasticity of inequality measures in selected groups of countries

	Coefficient of ineq. measure	Standard error	Countries	Observations
Whole sample D&S	-0.0368	0.0416	34	103
Whole sample EHII2008	-0.0142*	0.0065	70	263
OECD D&S	-0.0004	0.0033	15	103
non-OECD D&S	-0.0065	0.0102	34	103
OECD EHII2008	-0.0043	0.0073	19	263
non-OECD EHII2008	-0.0156	0.0097	49	263
Income groups:				
D&S:				
<$500	-0.0137	0.0118	8	103
>$500 - <$2000	-0.0014	0.0042	13	103
>$2000	-0.0078	0.0101	13	103
D&S:				
<$1000	0.0015	0.0052	11	103
>$1000 -<$2500	-0.0049	0.0044	14	103
>$2500	0.00001	0.0065	9	103
EHII2008:				
<$500	-0.0230*	0.0098	18	263
>$500 - <$2000	-0.0109	0.0099	37	263
>$2000	-0.0031	0.0065	15	263
EHII2008:				
<$1000	-0.0016	0.0120	33	263
>$1000 -<$2500	-0.0142*	0.0065	14	263
>$2500	0.0108	0.0073	9	263

* = $p<.05$. Countries denote the number of countries marked with dummy variables in the dataset. Observations gives the total number of observatios included in the estimation. D&S denotes the Gini index by Deininger and Squire (1996) and the EHII2008 inequality measure by Galbraith and Kum (2006). Estimation of group-elasticities is done using group-related dummies and instruments in the whole dataset. First and second lags of first difference are used as instruments for explanatory variables in GMM estimation. A Newey-West estimator with lag one is used as the GMM estimator's weight matrix to account for autocorrelation in the variables appearing in the orthogonality conditions.

over \$2500 in 1965. The parameter estimate is also statistically significant in the groups with GDP per capita under \$500 and between \$1000 and \$2500 in 1965, but not in the group with GDP per capita under \$1000 in 1965. Results obtained using the EHII2008 inequality measure do thus indicate that the relationship between income inequality and growth may be non-linear, a finding which is quite well in line with those obtained with non- or semi-parametric methods (Banerjee and Duflo 2003; Lin et al. 2006).

2.6 Conclusions

Our results show that the effect of income inequality on economic growth is statistically significant and negative when using a new measure of income distribution, the EHII2008 measure of inequality. However, group-related estimation revealed that although the negative effect of inequality on growth dominates, there are some non-linearities in the relationship.

Many previous studies have bypassed the problems in the commonly used measure of income distribution, i.e. the Deininger and Squire (1996) Gini index, mostly because there has been no other measure of income distribution available. However, it is likely that Deininger and Squire's dataset contains inconsistencies such that all the results obtained using it are in doubt. The EHII2008 inequality measure used in this study can be assumed to be more consistent. The data coverage is also clearly extended compared to Deininger and Squire's data. Previous studies have usually only been able to use data on 40-50 countries at most while we used information on 70 countries. Because of this, dynamic panel data estimations may have suffered from small-sample bias in previous studies. We also included data on sub-Saharan African economies, on which there was basically no data in Deininger and Squire's dataset.

Results may have been influenced by sample selection bias and measurement error. Since, at its best, the data included only about one-third of all the countries in the world, systematic errors may have influenced the findings. The EHII2008 inequality measure is not an unflawed estimator of income distribution either, because it is only a representation of statistical summaries, like the Gini index. Thus, the level of inequality given by the

EHII2008 inequality measure may not represent the true level of inequality in the countries in question. It should also be noted that the results describe only the short- or medium-term relationship between inequality and growth, and the long-run relationship remains an open question.

In spite of these inevitable reservations, the present findings can be considered more reliable than those of many previous studies. This is mostly due to inaccuracies and inconsistencies in the Gini index by Deininger and Squire (1996). Use of the EHII2008 inequality measure also greatly increased the data coverage thus diminishing the small sample bias and the possibility of systematic errors in estimation. In previous studies, the examination of group-related growth elasticities of inequality by parametric methods was also complicated by statistical obscurities. The use of group-related constants in estimation is statistically dubious, and the asymptotic properties of estimators suffer greatly where several parameters are estimated using only a few dozen observations. However, as was shown here, the problems relating to the use of country constants in panel data can be bypassed in a statistically meaningful way by using a non-linear estimator.

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Appendix B

Country list

Table B.1: Country list

Algeria	Italy
Australia	Jamaica
Austria	Japan
Bangladesh	Jordan
Barbados	Kenya
Belgium	Malawi
Bolivia	Malaysia
Cameroon	Malta
Canada	Mauritius
Central African Republic	Mexico
Chile	Netherlands
Colombia	Nicaragua
Costa Rica	Norway
Cyprus	Pakistan
Denmark	Panama
Dominican Republic	Papua New Guinea
Ecuador	Philippines
Egypt	Poland
El Salvador	Portugal
Fiji	Senegal
Finland	Singapore
France	South Africa
Germany	Spain
Ghana	Sri Lanka
Greece	Sweden
Haiti	Syria
Honduras	Taiwan
Hong Kong	Togo
Hungary	Tunisia
Iceland	Turkey
India	United Kingdom
Indonesia	United States
Iran	Uruguay
Ireland	Venezuela
Israel	Zimbabwe

Chapter 3

Estimating the long-run relationship between income inequality and economic development

Abstract[1]

There are several theories describing the effect of income inequality on economic growth. These theories usually predict that there exists some optimal, steady-state growth path between inequality and development. This study uses a new measure of income distribution and panel data cointegration methods to test for the existence of such a steady-state equilibrium relation. It is shown that there is a long-run equilibrium relationship between the variables, and that this relationship is negative in developed economies.

[1] A paper based on this chapter is forthcoming in the *Empirical Economics*.

3.1 Introduction

The decades long empirical research on the relationship between income inequality and economic development has produced controversial results, with the direction and the statistical significance of the effect of income inequality on economic growth changing between studies (e.g., Banerjee and Duflo 2003, Barro 2000, Chen 2003, Forbes 2000, Li and Zou 1998, Lin et al. 2006). Theories have also generally been divided on the effect of income inequality on growth. The classical approach argues that saving rates are an increasing function of wealth. In this case, inequality will increase incomes of the rich whose marginal propensity to save is the highest. Thus, income inequality will lead to faster capital accumulation (Kaldor 1957; Kuznets 1955; Smith 1776). The political economy approach emphasizes the destabilizing effect that inequality may have on the society (Benhabib and Rustichini 1996). According to this view, equality will increase stability in the society and simulate investments and economic growth. The credit market imperfection approach suggests that equality of incomes diminishes the effect of credit-constraints on human capital accumulation in developed economies (Galor and Moav 2004). Because credit-constraints become less binding in a developed economy where incomes are distributed evenly, equality of incomes will fasten the accumulation of human capital and thus accelerate economic growth.

Despite of several theories describing the relationship between inequality and growth, the dependence between the variables over time remains an open empirical question. Although we have observations on GDP from several consecutive years, values of commonly used Gini indexes (e.g., the Gini index by Deininger and Squire (1996)) have not been consistently measured over time, which has made it virtually impossible to assess the possible time dependence between the two variables. Some studies have tried to bypass this problem by regressing the values of averaged growth rates of 20 years, or more, on the values of the Gini index and other explanatory variables in the first year included in the averaging (Chen 2003; Forbes 2000). The problem with this method is that these multi-decade averages lose a lot of information and there is a risk of spurious parameter estimates. The observed controversy in the relation between inequality and growth has also led some to estimate the relation using non-parametric or semi-parametric methods

(Banerjee and Duflo 2003; Frazer 2006; Lin et al. 2006). The advantages of non-parametric methods are the fact that they can be used to estimate the relation between variables in both short- and long-run and robustness. The drawback of these methods is low statistical power compared to parametric methods, especially in finite samples. Recently, Galbraith and Kum (2006) have gathered a inequality measure dataset that has continuous observations from several countries, which enables the use of panel data time series methods.

From time series analysis we know that, if variables are integrated processes, we can learn about their long-run dependence by testing whether the variables are cointegrated. If variables are found to be cointegrated, there exists a stationary distribution between them, and we can estimate this *steady-state* relationship using standard estimation methods. Unfortunately, these rules do not apply to panel data *per se*. The inference and estimation in panel cointegrated data differs from that in regular time series, because the asymptotic properties of the estimators in panel cointegrated regression models are different from those of time series cointegrated regression models (Baltagi 2008; Phillips and Moon 1999). The time series regression may, for example, be spurious, while the panel regression utilising all cross-sections is not (Phillips and Moon 1999). OLS estimator is also not asymptotically unbiased in cointegrated panel data (Kao and Chiang 2000).

This study uses panel cointegration methods and improved data on income inequality to assess the possible steady-state relationship between income inequality and economic development. According to panel unit root tests, both the logarithmic EHII2.1 inequality measure and the logarithmic GDP series seem to follow an $I(1)$ process in countries in question.[2] They are also found to be cointegrated of order one using panel cointegration tests developed by Pedroni (2004) and Banerjee and Carrion-i-Silvestre (2006), which implies that there is a long-run equilibrium relation between them. The cointegrating coefficient of the EHII2.1 inequality measure is estimated with panel dynamic OLS and panel dynamic SUR estimators and it is found to be negative. According to the income group estimations, this negative

[2]EHII=Estimated Household Income Inequality data set by University of Texas Inequality Project.

relationship is robust in middle-income and rich economies. Results for developing countries are inconclusive.

This paper is organized as follows. Section 2 presents the general theories describing the causal relationship from income inequality to economic growth. Section 3 presents the data and reports the results of panel unit root and cointegration tests. Estimation details and results are given in section 4 and section 5 concludes.

3.2 The main theoretical relationships between inequality and growth

3.2.1 The income approach

In classical economic theory, inequality of incomes was assumed to influence economic growth rates through savings and consumption. According to Smith (1776), an increased division of labor raises productivity, but savings govern capital accumulation, which enables production growth. When the saving function is linear, e.g., $s_i = my_i + b$, where y_i is output per capita, m is the marginal propensity to save, and b is the per capita savings at zero income, aggregate saving behavior in an economy is not affected by the distribution of income (Stiglitz 1969). However, if the saving function is nonlinear, aggregate savings become dependent on the distribution of income.

When the saving function is linear or concave, distribution of income and wealth converge toward equality (Stiglitz 1969). If the saving function is convex, i.e., the marginal propensity to save increases with income,[3] uneqalitarian stationary distributions, or steady-state equilibriums, are Pareto superior to egalitarian stationary distributions. This is because, in the case of a convex saving function, more unequal distribution of income results in higher capital intensity through greater aggregate savings. In these unegalitarian steady-state equilibria, income and consumption for all individuals are greater than in egalitarian steady-state equilibria. In addition, in a steady-state equilibrium, where income is distributed unevenly, the wealth

[3]The hypothesis of convex savings function is supported by empirical findings, see e.g., Dynan *et al.* (2004).

of a nation is greater than in the steady-state equilibrium, where income is distributed evenly. However, these steady-state equilibria exist only when all individuals have positive wealth. Thus, result may not apply, for example, to developing countries.[4]

3.2.2 The credit-market imperfections and combined approach

The income approach emphasizes the effect of income inequality on savings and on physical capital accumulation. Credit market imperfections approach considers the effect of income inequality on the accumulation of human capital (Galor and Zeira 1993). In a model by Galor and Moav (2004), the engine of economic growth changes from physical capital to physical and human capital in the process of economic development. The process of economic development is divided into two regimes, which have their own steady-state growth paths.

Economies in the first regime are underdeveloped, aggregate physical capital is small, and the rate of return to human capital is lower than the rate of return to physical capital (Galor and Moav 2004). There are two types of individuals in the economy: those who own the physical capital (the rich) and those who do not (the poor). The poor consume their entire income (wages) and are not engaged in saving and on capital accumulation. Thus, there is a temporary steady-state equilibrium where the poor are in poverty trap and the rich get richer. Inequality increases aggregate savings by increasing the income of the rich and greater aggregate savings fuel physical capital accumulation.[5]

In the second regime, physical capital accumulation by the rich has in-

[4]According to Keynes (1936), demand is the basis for investments and, because inequality lowers aggregate consumption, inequality of incomes will lead to slower economic growth. This argument that inequality decreases consumption is valid, if the saving function is convex. In this case, aggregate demand diminishes when income becomes more unequally distributed.

[5]In modern less developed economies, it is possible that also human capital drives growth, if the capital and skill-biased technology is imported. In this case, the effect of inequality on growth would be mixed or negative (Galor and Moav 2004).

creased the rate of return to human capital so high that it induces human capital accumulation (Galor and Moav 2004). In this regime, both human and physical capital are engines for economic development. Since individuals' investment in human capital is subjected to diminishing marginal returns, the return to human capital investments is maximized when investment in human capital is widely spread among the population. Because access to credit is constrained, human capital investment is maximized when income in the economy is distributed evenly. However, in a certain phase of economic development income of every individual becomes so high that credit constraints become less binding. In this locally stable steady-state equilibrium, the effect of inequality on growth becomes less significant.

3.2.3 The political economy approach

Political economy models assume that preferences of individuals are aggregated through political process. Therefore, redistribution of incomes and economic growth are driven by the political process. Political process can be driven by a *median* voter or by organized social groups. In the model by Perotti (1993), the equilibrium reached by the economy depends on the initial distribution of income. If the aggregate capital in the economy is very small, redistribution of income through taxes and subsidies will result in a poverty trap where no one is able to acquire education. In this case, more unequal distribution of income will help the economy because in that case at least some individuals can acquire education and increase the level of human capital in the economy. As economy becomes more developed, very unequal income distribution may diminish growth because the accumulation of more human capital would require that middle-income and poor individuals acquire education, as the rich have already educated themselves. In an rich economy, only the poor may increase the level of human capital in the economy and higher steady-state growth path requires that income is distributed evenly.

3.3 Time series analysis of panel data

The theoretical models presented above predict steady-state equilibrium relations, or stationary distributions, that may exist between income inequality and the evolution of output. The estimation of these theoretical stationary distributions requires that we know the time series features of the variables in the model. Many models also assume that income distribution and economic development are determined endogenously, which has to be taken into account in the estimation.[6]

3.3.1 Data

Data for this study consist at 3 variables: real GDP per capita, Estimated Household Income Inequality (EHII) 2.1 measure, and portion of investments on GDP. Gross domestic product is stated in real terms with the base year of 1996. Investments are gross investments as a portion of GDP. The data on GDP and investments are from Penn World Tables (Heston et al. 2006). The EHII2.1 measure of inequality is from the University of Texas Inequality Project (Galbraith and Kum 2006).

Many of the previous studies made on the relationship between income inequality and economic growth have used the Gini index constructed by Deininger and Squire (1996) as a measure on income distribution.[7] The main reason why so many researchers have relied on the Deininger and Squire's Gini index has been its alleged "high quality". However, as pointed out by Atkinson and Brandolini (2001, p. 780), Deininger and Squire's dataset includes so many different datasets that in many cases it would be "highly misleading to regard Deininger and Squire's "high quality" estimates as a continuous series". The different country-related datasets in Deininger and Squire's "high quality" dataset may also not be comparable with each other. These are serious problems for estimation, because the statistical inference requires that observations are from the same parent population. If the obser-

[6] Bénabou (2005) has actually suggested that endogeneity of income inequality in growth regressions is the primary reason for the observed controversy in empirical growth studies.

[7] These include Barro (2000), Banerjee and Duflo (2003), Forbes (2000), and Chen (2003).

vations are not comparable, there is no one coherent parent population and the parameter estimates may be spurious.

Many scholars studying income inequality have already switched to Gini index provided by UNU-Wider.[8] Although UNU-Wider Gini is likely to be more consistent and accurate than Deininger and Squire's Gini index, they share one deficiency. Both Gini indexes are unevenly distributed through time, which restricts their use in time series analysis. However, Galbraith and Kum (2006) have gathered a EHII2.1 inequality measure, which has a consistent, long time series for several countries.

Galbraith and Kum (2006) have build their measure of inequality "on top" of the Gini index by Deininger and Squire (1996), a method that has been suggested by Atkinson and Brandolini (2001). Galbraith and Kum have obtained their inequality measure by regressing Deininger and Squire's Gini coefficients on the values of explanatory variables, which include the different income measures of Deininger and Squire's data set, the set of measures of the dispersion of pay in the manufacturing sector, and the manufacturing share of the population. According to Galbraith and Kum, the EHII2.1 inequality measure has three clear advantages over the Deininger and Squire's Gini index. It has more than 3000 estimates, while Deininger and Squire have only about 700 "high quality" estimates. The EHII2.1 gets its accuracy from the Industrial data published annually by the United Nations Industrial Development Organization (UNIDO). This way changes over time and differences across countries in pay dispersion are reflected in income inequality. All estimates are also adjusted to household gross income, which makes them more congruent. Values of the EHII2.1 also correspond to the estimates of income distributions of other research institutes, such as the OECD and the UNU-Wider, better than those of the Deininger and Squire's Gini index (Föster and Pearson 2003; Galbraith and Kum 2006).

3.3.2 Unit root testing

There are 60 countries in the EHII2.1 dataset where the time series of inequality measure is consistent and at least 20 years long. After individual

[8]World Institute for Development Economics Research of the United Nations University.

Table 3.1: Descriptive statistics

variable	mean	std. deviation	min.	max.
GDP	6624.25	6750.15	145.24	32766.51
GDP growth (%)	6.498	5.692	-27.032	72.860
EHII2.1 inequality	39.713	6.520	23.074	58.975
investments (%)	18.112	8.664	0.191	52.531

unit root tests, 7 countries were discarded from the set because their series of the EHII2.1 inequality measure or GDP did not seem to follow a $I(1)$ process according to the ADF-test.[9] Descriptive statistics of the remaining 53 countries are presented in table 1 and a list of the 53 countries is presented in the appendix.

Most of the time series analysis methods for panel data assume that there is no cross-unit correlation present in the panel. When dealing with economic variables, this restriction is quite uncomfortable, because for example business cycles do transfer to neighboring countries quite easily in modern open economies. To account for the obvious cross-sectional correlation present in the data, the results of panel unit root test allowing for cross-sectional dependence are also reported (Pesaran 2007). Pesaran's test accounts for cross-sectional correlation by introducing common factors. This method captures a linear cross-sectional dependence, where there can be several common factors between the tested series of the panel.

The panel unit root tests used in this study assume two different types of unit root processes. Test by Levin *et al.* (2002) (LLC) assumes a common unit root process, i.e., that all the countries in the dataset have the same unit root. Test by Im *et al.* (2003) (IPS), Fisher type ADF and PP tests, presented by Maddala and Wu (1999), and test by Pesaran (2007) allow for individual unit root processes. That is, they allow the coefficient of unit root

[9] This is a precautionary method. Karlsson and Löfgren (2000) have studied how few stationary series in the panel can alter the results of panel unit root tests. They found that when the time dimension of a dataset is long, small fraction of stationary series in the dataset results to high power and *vice versa*. Therefore, there is a risk that panels with large T would erroneously be modeled as stationary and panels with small T as non-stationary.

to differ across countries. A more detailed discussion about the used panel unit root tests is provided in the appendix.

Summary of the results of the five panel unit root tests are presented in table 3.2.[10] Individual trends and constants are included in the tests for GDP and inequality. For GDP it is natural to allow for both individual time trends and constants, because the time series of GDP usually follows a clear upward trend. The time series of inequality also seems to be trending in many countries,[11] and so it is also allowed to have individual time trends. GDP growth and investments seem not to exhibit a trend, and so only individual constants are included in their tests.[12] All other tests use the unbalanced panel data of 53 countries,[13] except Pesaran's test where a balanced panel of 38 countries with 25 yearly observations is used.[14] Summary tables (years and countries included) of the different datasets can be found in the appendix.

According to all five tests, the logarithmic GDP and inequality seem to follow a $I(1)$ process, and the series of GDP growth and investments seem to be stationary.[15] However, as mentioned above, it is likely that at least some of the tested series are cross-sectionally correlated. This would violate the assumption of uncorrelated residuals among cross-sections. Banerjee *et al.* (2005) have studied the effect of the violation of the assumption of no cross-unit cointegration on rejection frequencies of the null hypothesis. Their results show that in the presence of cross-unit cointegration, the ADF, PP, and IPS tests grossly overreject the null hypothesis of unit root with small time (T) and relatively large cross-sectional (n) dimensions of data. According to all these tests, the null hypothesis of unit root cannot be rejected in series of inequality and GDP. As Pesaran's test also does not reject the null

[10]All tests were performed with Eviews 6, except Pesaran's test which was done with Stata. Lag lengths have been determined using Schwarts information criterion, spectral estimation has been conducted with Bartlett kernel and bandwidth has been selected using Newey-West method.

[11]The time series were inspected visually.

[12]If individual trends are included, the results change only marginally and both series are still stationary according to all five tests.

[13]Panel unit root test were also conducted using the whole dataset of 60 countries. Results were similar to those presented in table 3.2.

[14]Pesaran's test requires that the panel is balanced.

[15]Results were the same when original data of 60 countries are used.

Table 3.2: Panel unit root tests

variable	LLC	IPS	ADF	PP	Pesaran*
log(GDP)	9.068	15.092	15.855	16.072	0.709
	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(0.761)
GDP growth	-45.913	-25.415	572.04	599.36	-12.089
	(<.0001)	(<0.0001)	(<.0001)	(<.0001)	(<.0001)
log(inequality)	0.549	2.702	77.387	70.521	-0.790
	(0.7085)	(0.9966)	(0.9834)	(0.9968)	(0.215)
log(investments)	-6.071	-7.558	244.13	212.80	-4.529
	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)

The p-values of the test statistics are presented in parentheses. All tests include individual effects and trends except the test for GDP growth and investments which include only individual effects. Lag lengths were determined using Schwarts information criterion. All other tests use unbalanced panel of 53 countries except Pesaran's test, where the panel is balanced including 38 countries and 25 yearly observations.

hypothesis for inequality and GDP, they seem very likely to be unit root processes.[16] Because Pesaran's test also finds GDP per capita growth and investments to be stationary, it seems that cross-sectional correlation has not biased the results of traditional unit root tests. Thus, these series are assumed to be stationary.

3.3.3 Cointegration tests

The possible cointegration between inequality and GDP is tested with panel cointegration test developed by Pedroni (2004), which consist of 11 different test statistics.[17] To allow for possible cross-sectional dependence present in the panel, cointegration is also tested with a test developed by Banerjee and

[16] First differenced series are stationary according to all panel unit root tests. GDP and inequality thus seem to be $I(1)$.

[17] There are 7 different test statistics, but Eviews 6 gives also the results of weighted test statistics on the first four tests. Tests statistics include the panel versions of PP and ADF tests, a form of the average of the Phillips and Ouliaris (1990) test statistics (ρ), and panel variance ratio statistics (v).

Carrion-i-Silvestre (2006). A more detailed discussion about these tests is provided in the appendix.

Pedroni's panel cointegration test

The model for testing for cointegration between inequality and GDP is:

$$\log(GDP_{it}) = \alpha_i + \delta_i t + \gamma_i log(inequality_{it}) + \beta_i log(investments_{it}) + \epsilon_{it}, \quad (3.1)$$

where the changes in GDP are explained by the changes in inequality and on the level of investments, and $(1, -\gamma_i)$ is the individual cointegration vector between inequality and GDP. Results of Pedroni's panel cointegration tests on equation (3.1) are presented in table 3.3.[18]

According to all of the 11 test statistics presented in table 3.3, the series of inequality and GDP are cointegrated at the 5% level. The test is also conducted using only the inequality as an explanatory variable for GDP. In this case, 9 of the 11 test statistics find the GDP and inequality to be cointegrated.[19]

If the test is conducted using only investments as an explanatory variable, all of the 11 test statistics find the investments and GDP to be cointegrated. This indicates that there might be cross-sectional cointegration relations in the panel of investments, which may have affected on the results of panel unit root tests. Cross-unit cointegration can bias the results of panel unit root tests towards type I error, i.e., that hypothesis of unit root is rejected far too often (Banerjee *et al.* 2005; Breitung and Pesaran 2008). If series are cross-sectionally cointegrated, the common trends present in the data may be identified as common factors in unit root tests that model the cross-sectional correlation through common factors, like the Pesaran's test, and removed from the analysis (Breitung and Pesaran 2008). In this case, if the remaining idiosyncratic component is stationary, the panel unit root test has a tendency to present the time series as stationary when panel units are actually nonstationary. So, although all panel unit root tests found the investments

[18] The test was conducted with Eviews 6.

[19] If the original data of 60 countries is used, 8 of the 11 tests find the GDP and inequality to be cointegrated.

Table 3.3: Pedroni's panel cointegration test statistics for log(GDP) and log(inequality)

Within-dimension				
	statistic	prob.	weight. statistic	prob.
panel v-statistic	49.309	$<.0001$	44.793	$<.0001$
panel ρ-statistic	7.152	$<.0001$	7.329	$<.0001$
panel PP-statistic	2.888	0.0062	3.494	0.0009
panel ADF-statistic	2.489	0.0180	3.039	0.0039
Between-dimension				
	statistic	prob.		
group ρ-statistic	9.417	$<.0001$		
group PP-statistic	4.555	$<.0001$		
group ADF-statistic	2.313	0.0275		
countries	53			
observations	1961			

The null hypothesis is that there is no cointegration between variables. Within-dimension tests presuppose common AR coefficients among cross sections. Between-dimension tests presuppose individual AR coefficients. Lag lengths were determined with Schwarz information criterion. Spectral estimation was done with Bartlett method and bandwidth was selected with Newey-West method.

to be $I(0)$, the possibility that investments is actually $I(1)$ process that is cointegrated with GDP has to be taken into account in estimation.[20]

Banerjee & Carrion-i-Silvestre's cointegration test

As with panel unit root tests, the presence of cross-sectional dependency may have affected the results of cointegration tests. There may also be structural breaks in the relation between inequality and GDP. To account for possible cross-sectional dependence and structural breaks in the relation between inequality and GDP, cointegration is also tested with the panel cointegration test developed by Banerjee and Carrion-i-Silvestre (2006). Banerjee and Carrion-i-Silvestre's test allows for cross-sectional dependence by introducing common factors in the estimated model.

Table 3.4 reports the results of Banerjee and Carrion-i-Silvestre's panel cointegration test between inequality and GDP using the dataset of 38 countries with 25 yearly observations. The test allows for level and cointegration vector shifs.[21]

According to the basic model allowing just time trend in the tested series, inequality and GDP would be cointegrated. If level and slope trend shift are allowed, only ρ test finds the variables to be cointegrated at the 5% level. If both time trend and cointegration vector shifts are allowed, ρ test finds the variables to be cointegrated at 0.01% level and the t test finds the variables to be cointegrated at the 10%level.

Thus, inequality and GDP seem to be cointegrated even when possible structural breaks in the relation and the possible cross-sectional correlation present in the panel are taken into account. When cointegration relationship includes structural breaks, cointegration tests tend to be biased towards accepting the null hypothesis of no cointegration, whereas cross-sectional correlation tends to bias the results towards rejecting the null (Banerjee and

[20] The cointegration between log(GDP) and log(inequality), and log(GDP) and log(investments) were also tested with Johansen's combined Fisher panel cointegration test developed by Maddala and Wu (1999). According to it, both GDP and inequality and GDP and investments are cointegrated of order one. Detailed results are available upon request.

[21] Estimation done with Gauss. We are grateful to Carrion-i-Silvestre for providing the program code.

Table 3.4: Banerjee & Carrion-i-Silvestre's cointegration test for log(GDP) and log(inequality)

	statistic	p-value
Pedroni model with a time trend		
	statistic	p-value
$Z_{\hat{t}_{NT}}(\hat{\lambda})$	-6.434	<.0001
$Z_{\hat{\rho}_{NT}}(\hat{\lambda})$	-7.122	<.0001
Model with level shift		
	statistic	p-value
$Z_{\hat{t}_{NT}}(\hat{\lambda})$	-1.256	0.1046
$Z_{\hat{\rho}_{NT}}(\hat{\lambda})$	-3.913	<.0001
Model with coint. vector shift		
	statistic	p-value
$Z_{\hat{t}_{NT}}(\hat{\lambda})$	-1.619	0.0527
$Z_{\hat{\rho}_{NT}}(\hat{\lambda})$	-5.992	<.0001
countries	38	
observations	950	

Model with level shift includes time trend and a level and slope trend shift. Model with a cointegrating vector shift includes time trend and cointegration vector shifts.

Carrion-i-Silvestre 2006; Banerjee *et al.* 2004). Results presented in table G.2 imply that cross-sectional correlation and/or structural breaks in the relation between inequality and GDP have not biased the result of Pedroni's panel cointegration tests presented in table 3.3.

3.4 Estimation of the cointegrating coefficient of inequality

3.4.1 Estimation and inference in cointegrated panels

Conventional limit theorems assume one index (n or T) to pass to infinity. The limit theory for panels with large cross-sectional (n) and time (T) dimensions needs to allow both indexes to pass to infinity. This has some profound effects for estimators. For example, the OLS estimator is not asymptotically unbiased, and the standard GMM estimator is inconsistent for panel cointegrated data (Kao and Chiang 2000).

Several estimators for cointegrated panel data have been proposed. Probably the most commonly used estimators have been the fully-modified OLS (FM-OLS) proposed by Phillips and Moon (1999) and Pedroni (2000), and the dynamic OLS (DOLS) proposed by Kao and Chiang (2000). The major problem for estimators in cointegrated panel data has been the modeling of simultaneous cross-sectional and time series dependence (Phillips and Moon 1999). This is a problem in this study, because it is likely that, at least, GDP series are correlated or even cointegrated across the panel. Mark and Sul (2003) have developed a version of DOLS estimator that allows for simultaneous cross-sectional and time series dependence. It uses a common time effect to control for cross-sectional dependency.[22]

[22]Wagner and Hlouskova (2010) have compared the performance of different types of estimators for panel cointegrated data. They found that Mark and Sul's DOLS system estimator (panel DOLS) performs best in the case of cross-unit correlation or cointegration compared to several other estimators developed for panel cointegrated data. The tested estimators included FM-OLS presented by Phillips and Moon (1999), DOLS presented by Kao and Chiang (2000) and Mark and Sul (2003), one-step VAR, and two-step VAR presented by Breitung (2005).

It is, of course, possible that the common time-effect cannot capture all the cross-sectional correlation present in the data. In this case, a panel dynamic seemingly unrelated regression estimator developed by Mark *et al.* (2005) can be used to fully account for the cross-sectional dependence. Panel DSUR estimator can be used when the cross-section is small relative to time series. A more detailed discussion about panel DOLS and DSUR estimators can be found in the appendix.

3.4.2 Estimation results

The estimated model includes a measure of physical capital accumulation (investments) and a measure of income inequality (EHII2.1). Panel DOLS estimation is used to estimate the following equation:

$$\begin{aligned} log(GDP_{it}) = \alpha_i + \gamma_1' log(investments_{it}) + \gamma_2' log(inequality_{it}) + \\ + \lambda_i t + \theta_t + u_{it}, \end{aligned} \tag{3.2}$$

where α_i are individual constant, $\lambda_i t$ are individual trends, θ_t is the common time effect, $(1, -\gamma_1', -\gamma_2')$ is a cointegrating vector between GDP, investments and inequality, and u_{it} is a idiosyncratic error. Table 3.5 presents the results of fixed effects DOLS estimation of equation (3.2).[23]

The cointegrating coefficient of investments is positive and statistically significant at the 5% level in all estimations. The cointegrating coefficient of inequality is negative and statistically significant at the 5% level in all estimations using the dataset with 37 yearly observations. In estimations using the dataset with 25 yearly observations, the cointegrating coefficient of inequality is not statistically significant at the 5% level when two and three leads and lags of the first differences are used as instruments for the explanatory variables.

Thus, the results of panel DOLS estimation using the 15 country dataset with longer time dimension imply that the long-run growth elasticity with respect to income inequality would be negative. However, the results of panel DOLS estimation using the 38 country dataset with shorter time dimension are inconclusive.

[23]Estimation was conducted with Gauss. Author is grateful to Donggyu Sul for providing the program code on his homepage.

Table 3.5: DOLS estimates of the cointegrating coefficient of inequality

Dependent variable: log(GDP)		
Panel DOLS (leads & lags=1)		
log(investments)	0.2199***	0.0954*
	(0.0402)	(0.0455)
log(inequality)	-0.1836***	-0.0678**
	(0.0252)	(0.0217)
Panel DOLS (leads & lags=2)		
log(investments)	0.1851***	0.1852***
	(0.0447)	(0.0433)
log(inequality)	-0.2427***	-0.0632
	(0.0287)	(0.0290)
Panel DOLS (leads & lags=3)		
log(investments)	0.1281***	0.3847***
	(0.0488)	(0.0384)
log(inequality)	-0.3069***	-0.0375
	(0.0297)	(0.0194)
countries	15	38
years	1963-99	1972-96
observations	816	950

* = p<.05, ** = p<.01, *** = p<.001. Standard errors of the parameter estimates are presented in parentheses. Standard errors are estimated using Andrews and Monahan's Pre-whitening method. Inclusion of individual constants means that all estimations are made with fixed effects. Leads & lags=1 means that first lags and leads of first differences of explanatory variables are used as instruments. Leads & lags=2 means that first and second leads and lags of first differences are used as instruments, etc.

3.4.3 Estimation of income group-related elasticities of growth

Recently, Hineline (2008) has found that the estimated coefficients of explanatory variables generally used in growth regressions differ substantially between OECD and non-OECD countries. Panel cointegration tests by Pedroni (2004) and Banerjee and Carrion-i-Silvestre (2006) also allowed for individual cointegrating coefficients between countries. It is therefore possible that the cointegrating coefficient of inequality may differ in different groups of countries. However, none of the theories presented in section 2 imply that there would be differences in the growth elasticity of income inequality between OECD and non-OECD countries. What they do imply is that the growth elasticity of inequality might differ between developing and developed economies.

To estimate the long-run growth elasticities of income inequality and physical capital accumulation in different income groups, countries in the dataset are divided into three income groups. To make the estimation of income groups asymptotically feasible, i.e., to make the groups large enough, countries are divided into three equally sized groups. This is done using all the countries in the 53 country dataset that have observations on GDP in 1972. There are 48 such countries in the dataset of 53 countries and so we have 3 groups of 16 countries. The thresholds for these groups become: GDP per capita under \$1270 in 1972 for less developed countries, GDP per capita between \$1271 and \$3715 in 1972 for middle-income countries, and GDP per capita above \$3715 in 1972 for rich countries. Table 10 presents the results of panel DOLS estimation of equation (3.2) in different income groups of countries.[24]

The cointegrating coefficient of investments is positive and statistically significant in all income groups, when three leads and lags are used as instruments. The cointegrating coefficient of inequality is negative and statistically significant at the 5% level in middle-income and rich economies in all estimations. In less developed economies, the cointegrating coefficient of inequality

[24] Estimation was conducted with Gauss. Author is grateful to Donggyu Sul for providing the program code on his homepage.

Table 3.6: DOLS estimates of the cointegrating coefficients of inequality in different income groups

Dependent variable: log(GDP)			
	less developed	middle-income	rich
Panel DOLS (leads & lags=1)			
log(investments)	0.1766***	0.1000*	-0.0018
	(0.0366)	(0.0496)	(0.0974)
log(inequality)	-0.0069	-0.1317*	-0.1443*
	(0.0190)	(0.0559)	(0.0627)
Panel DOLS (leads & lags=2)			
log(investments)	0.2678***	0.0803	0.0919
	(0.0583)	(0.0543)	(0.0742)
log(inequality)	0.0549*	-0.1520***	-0.2417***
	(0.0238)	(0.0299)	(0.0490)
Panel DOLS (leads & lags=3)			
log(investments)	0.4492***	0.2667***	0.1962**
	(0.0366)	(0.0397)	(0.0596)
log(inequality)	0.1014***	-0.2175***	-0.4558***
	(0.0152)	(0.0397)	(0.0424)
countries	11	12	15
years	1972-96	1972-96	1972-96
observations	275	300	375

* = p<.05, ** = p<.01, *** = p<.001. Standard errors are presented in parentheses. Standard errors are estimated using Andrews and Monahan's Pre-whitening method. All estimations include individual constants, individual trends, and common time effects.

is positive and statistically significant at the 5% level when two and three leads and lags are used as instruments.

The results of table 3.6 have two implications. The elasticity of growth with respect to investments, i.e., physical capital accumulation, diminishes in accordance with the level of economic development and the elasticity of growth with respect to income inequality changes in the process of economic development. In early stages of economic development, the effect of income inequality on growth is positive, but turns negative as the economy becomes more developed. The negative growth elasticity of inequality also increases in accordance with the level of economic development.

However, panel DOLS may be biased if there remains correlation between equilibrium error and leads and lags of instrumental variables of different cross-sections (see appendix C). In this case the panel DOLS exhibits the same form of second order asymptotic bias as pooled OLS (Mark and Sul 2003). To account for this possible cross-equational correlation, the panel DSUR estimator is applied to income group estimation. Because panel DSUR requires that the time series dimension is clearly larger than cross-sectional dimension, a dataset that has 34 yearly observations on 24 countries is used. This dataset spans from 1963 to 1996. Grouping of countries is done in the same way as presented above. There are 44 countries in the dataset of 53 countries that have observations on real GDP per capita in 1963. Thus, 33% of all countries would give 14.6 countries per group. Because of this, 14 countries are included in the groups of less developed and rich countries and 16 countries to the group of middle-income countries. The thresholds for these groups become: GDP per capita under \$637 in 1963 for less developed economies, GDP per capita between \$638 and \$1903 in 1963 for middle-income economies, and GDP per capita over \$1903 in 1963 for rich economies. Table 3.7 gives the results of panel dynamic SUR estimation of equation (3.2) in different income groups.[25]

According to the results presented in table 3.7, the cointegrating coefficient of investments is positive and statistically significant at the 5% level in less developed and middle-income countries.[26] The cointegrating coeffi-

[25] Estimation was conducted with Gauss. Author is grateful to Donggyu Sul for providing the program code on his homepage.

[26] Estimations were also done with three leads and lags, but as there were no major

Table 3.7: DSUR estimates of the cointegrating coefficients of inequality in different income groups

Dependent variable: log(GDP)			
	less developed	middle-income	rich
Panel DSUR (leads & lags=1)			
log(investments)	0.1532***	0.1296***	0.0068
	(0.0309)	(0.0345)	(0.0114)
log(inequality)	-0.1567***	-0.1700***	-0.1187***
	(0.0208)	(0.0282)	(0.0069)
Panel DSUR (leads & lags=2)			
log(investments)	0.1841***	0.0843***	-0.0151
	(0.0132)	(0.0168)	(0.0092)
log(inequality)	-0.1337***	-0.1622***	-0.1216***
	(0.0132)	(0.0168)	(0.0071)
countries	7	6	11
years	1963-96	1963-96	1963-96
observations	238	204	374

* = p<.05, ** = p<.01, *** = p<.001. Standard errors are presented in parentheses. Standard errors are estimated using parametric correction. All estimations include individual constants, individual trends, and common time effects.

cient of investments is not statistically significant at the 5% level in any of the estimations of rich countries. The elasticity of growth with respect to investments also gets smaller as countries get richer. This implies that the influence of investments on per capita growth diminishes as the level of physical capital increases. The cointegrating coefficient of inequality is negative and statistically significant at the 5%level in all income groups.[27]

It is unexpected that the cointegrating coefficient of investments is not positive and statistically significant in rich economies. However, DSUR estimator assumes that the cointegration rank is 1. Because estimated equation includes two explanatory $I(1)$ variables, there may be two cointegrating vectors. If equation (3.2) is estimated with DSUR using only investments as a explanatory variable in rich economies, the cointegrating coefficient of investments is positive (the value of the cointegrating coefficient is about 0.01) and statistically significant at the 5% level.[28] If equation (3.2) is estimated using inequality as the only explanatory variable, the cointegrating coefficients of inequality changes only marginally compared to the results presented in table 3.7.

As such, results presented in table 3.7 contradict the results of panel DOLS estimation, where the cointegrating coefficient of the inequality was positive and statistically significant in less developed economies when two and three leads and lags were used as instruments. This could result from cross-sectional correlation not captured by the common time effect, from correlation between equilibrium error and cross-equations, from efficiency of panel DSUR compared to panel DOLS, or from sample selection bias. To test this, both estimators are used to estimate model (3.2) using the dataset with 34 yearly observations. Results of estimations are presented in table 3.8.

According to the results, the cointegrating coefficient of inequality is not statistically significant in less developed economies, when panel DOLS estimator is used, and negative and statistically significant, when panel DSUR

changes in the results, only results of estimations with one and two leads and lags are presented here.

[27]Equation 3.2) was also estimated using only the data on 6 of the most developed countries. Results were similar to those presented in table 3.7.

[28]The cointegrating coefficient of investments remains more or less the same when estimation in other income groups is done using only investments as a explanatory variable.

Table 3.8: DOLS and DSUR estimates of the cointegrating coefficients of inequality in different income groups

Dependent variable: log(GDP)

	less developed	middle-income	rich
Panel DOLS (leads & lags=1)			
log(investments)	0.263*	0.180***	0.136***
	(0.116)	(0.047)	(0.043)
log(inequality)	-0.101	-0.120***	-0.057
	(0.066)	(0.038)	(0.030)
Panel DOLS (leads & lags=2)			
log(investments)	0.420*	0.162***	0.068
	(0.144)	(0.040)	(0.061)
log(inequality)	-0.106	-0.112***	-0.108***
	(0.070)	(0.032)	(0.035)
Panel DSUR (leads & lags=1)			
log(investments)	0.1532***	0.1296***	0.0068
	(0.0309)	(0.0345)	(0.0114)
log(inequality)	-0.1567***	-0.1700***	-0.1187***
	(0.0208)	(0.0282)	(0.0069)
Panel DSUR (leads & lags=2)			
log(investments)	0.1841***	0.0843***	-0.0151
	(0.0132)	(0.0168)	(0.0092)
log(inequality)	-0.1337***	-0.1622***	-0.1216***
	(0.0132)	(0.0168)	(0.0071)
countries	7	6	11
years	1963-96	1963-96	1963-96
observations	238	204	374

* = p<.05, ** = p<.01, *** = p<.001. Standard errors are presented in parentheses. Standard errors are estimated using parametric correction. All estimations include individual constants, individual trends, and common time effects.

is used. The difference between the estimation results presented in tables 3.6 and 3.8 imply that the estimation results of less developed economies might be driven by the sample selection. However, it is also possible that the difference results from bias in the DOLS estimator caused by correlation in cross-equations. Unfortunately, due to the limited extent of the data this issue cannot be solved here and this question needs to be addressed further in future research.

There are no major differences in results of middle-income and rich economies compared to results presented in table 3.6. Thus, the results obtained for middle-income and rich countries seem to be robust across samples.

3.5 Conclusions

The results show that the distribution of income and economic development seem to have a steady-state equilibrium relation, or relations, as commonly predicted by theoretical models. According to estimations, this long-run growth elasticity of income inequality is negative in middle-income and rich economics. Estimation results also indicate that the long-run growth elasticity of inequality may differ between less developed economies.

There are (at least) three reservations that have to be attached to the results: the highly simplified production function, the time dimension, and the extent of the data used in estimation. The production function used in estimation included only two inputs, namely physical capital and income inequality. It was assumed that the coefficient of inequality reflects the effect of human capital on production growth. However, it is likely that the observed effect of income inequality reflects the economic effects of several other variables as well. It has been shown that income inequality may, in addition to human capital, have an effect on several variables, e.g., social capital, aggregate savings, and social stability. Controlling for all these variables could result in biased coefficient of inequality, because the coefficient would not represent the aggregate effect of income inequality but only a partial effect. Thus, it may be feasible not to try to control the different channels through which income inequality may affect growth.

Panel cointegration methods have made it possible to test for cointegration using only a handful of time series observations. This has brought about a dilemma. If only a few dozen time series observations are needed for cointegration testing, what is the time dimension after which the relationship can be described as a long-run relation? It was assumed here that a "lower bound" for long-run relationship is one generation (25 to 30 yearly observations). Some may argue that, economically, this does not constitute long-run. However, theories describing the effect of inequality on growth predict that there may be temporary steady-state equilibria between them at different stages of economic development. As results presented here indicate that countries in question seem to be, at least, in their temporary steady-state equilibria within this period, it seems that one generation could be considered long-run in this setting.

The dataset used in estimation was fairly small including only 38 countries at maximum. There were also only few less developed countries included in group-related estimations. Due to this, the results on poor countries remain inconclusive, but the data on developed economies was far more comprehensive. In rich economies, estimation results validated the general finding of the theories describing the relationship between income inequality and growth. That is, income inequality is associated with lower long-run economic growth in rich economies.

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Appendix C

Panel unit root tests

The traditional panel unit root tests used in this study are based on the following regression:

$$\triangle y_{it} = \rho_i y_{i,t-1} + \delta_i + \eta_i t + \theta_t + \epsilon_{it}, \tag{C.1}$$

where δ_i are the individual constants, $\eta_i t$ are the individual time trends, and θ_t is the common time effect. All tests rely on the assumption that $E[\epsilon_{it}\epsilon_{js}] = 0$ $\forall\ t, s$ and $i \neq j$, which is required for the calculation of common time effects. The inclusion of individual constants and time trends is also optional.

The null hypothesis in all tests is $H_0 : \rho_i = 0 \ \forall\ i$, but the tests have different assumptions about the heterogeneity of ρ and on the alternative hypothesis. Im *et al.* (2003), Fisher type ADF and PP tests, and Pesaran (2007) tests introduced below allow for individual processes. Their alternative hypothesis is that some but not all of the individual series may have unit roots. Levin *et al.* (2002) test, on the other hand, assumes a common unit root process, i.e., $\rho_i = \rho \ \forall\ i$.

The test by Pesaran (2007) is based on a regression

$$\triangle y_{it} = \rho y_{i,t-1} + \eta_i t + \alpha_i + \delta_i \theta_t + \epsilon_{it}, \tag{C.2}$$

where α_i are the individual constants, $\eta_i t$ are the individual time trends, θ_t is the common time effect, whose coefficients, δ_i, are assumed to be non-stochastic and they measure the impact of the common time effect on series i, $\epsilon_{it} \sim i.i.d.N(0, \sigma^2)$ over t, and ϵ_{it} is independent of ϵ_{js} and θ_s for all $i \neq j$ and s, t. Cross-sectional dependence is allowed through the common time effects which are proxied by the cross-section mean of y_{it} ($\bar{y}_t = n^{-1}\Sigma_{j=1}^{n} y_{jt}$) and its lagged values, $\bar{y}_{t-1}$, $\bar{y}_{t-2}$, etc. The null hypothesis is that $H_0 : \rho_i = 0 \ \forall \ i$ and alternative hypothesis allows for some of the tested series to be nonstationary.

Appendix D

Pedroni's and Banerjee & Carrion-i-Silvestre's panel cointegration tests

Panel cointegration test developed by Pedroni (2004) is based on the model:

$$y_{it} = \alpha_i + \delta_i t + \beta_i X_{it} + \epsilon_{it}, \tag{D.1}$$

where α_i:s and δ_i:s allow for member specific fixed effects and deterministic trends, X_{it} is a m-dimensional column vector of explanatory variables for each member i, and β_i is an m-dimensional row vector for each member i.

The data generating process is described as a partitioned vector $z'_{it} \equiv (y_{it}, X_{it})$ where the true process is generated as $z_{it} = z_{i,t-1} + \zeta_{it}$, $\zeta'_{it} = (\zeta^y_{it} \zeta^X_{it})$ (Pedroni 2004). $\frac{1}{\sqrt{T}} \sum_{t=1}^{[Tr]} \zeta_{it}$ is assumed to converge to a vector Brownian motion with asymptotic covariance of Ω_i as $T \longrightarrow \infty$. The individual process is assumed to be $i.i.d.$ so that $E[\zeta_{it}\zeta'_{js}] = 0 \ \forall s, t, i \neq j$.

Let $\hat{e}_{it}$ denote the estimated residuals of (D.1) and $\hat{\Omega}_i$ the consistent estimator of Ω_i. The 7 test statistics can now be defined as :

$$
\begin{aligned}
Z_{\hat{v}_{NT}} &\equiv \left(\Sigma_{i=1}^{N}\Sigma_{t=1}^{T}\hat{L}_{11i}^{-2}\hat{e}_{i,t-1}^{2}\right)^{-1},\\
Z_{\hat{\rho}_{NT}-1} &\equiv \left(\Sigma_{i=1}^{N}\Sigma_{t=1}^{T}\hat{L}_{11i}^{-2}\hat{e}_{i,t-1}^{2}\right)^{1}\Sigma_{i=1}^{N}\Sigma_{t=1}^{T}\hat{L}_{11i}^{-2}(\hat{e}_{i,t-1}\Delta\hat{e}_{it}-\hat{\lambda}_i,\\
Z_{\hat{t}_{NT}} &\equiv \left(\tilde{\sigma}_{NT}^{2}\Sigma_{i=1}^{N}\Sigma_{t=1}^{T}\hat{L}_{11i}^{-2}\hat{e}_{i,t-1}^{2}\right)^{-1}\Sigma_{i=1}^{N}\Sigma_{t=1}^{T}\hat{L}_{11i}^{-2}(\hat{e}_{i,t-1}\Delta\hat{e}_{it}-\hat{\lambda}_i),\\
Z_{\hat{t}_{NT}} &\equiv \left(\tilde{s}_{NT}^{*2}\Sigma_{i=1}^{N}\Sigma_{t=1}^{T}\hat{L}_{11i}^{-2}\hat{e}_{i,t-1}^{*2}\right)^{-1}\Sigma_{i=1}^{N}\Sigma_{t=1}^{T}\hat{L}_{11i}^{-2}(\hat{e}_{i,t-1}^{*}\Delta\hat{e}_{it}^{*}-\hat{\lambda}_i),\\
\tilde{Z}_{\hat{\rho}_{NT}-1} &\equiv \Sigma_{i=1}^{N}\left(\Sigma_{t=1}^{T}\hat{e}_{i,t-1}^{2}\right)^{-1}\Sigma_{t=1}^{T}(\hat{e}_{i,t-1}\Delta\hat{e}_{it}-\hat{\lambda}_i),\\
\tilde{Z}_{\hat{t}_{NT}} &\equiv \Sigma_{i=1}^{N}\left(\hat{\sigma}_i^{2}\Sigma_{t=1}^{T}\hat{e}_{i,t-1}^{2}\right)^{-1/2}\Sigma_{t=1}^{T}(\hat{e}_{i,t-1}\Delta\hat{e}_{it}-\hat{\lambda}_i),\\
\tilde{Z}_{\hat{t}_{NT}}^{*} &\equiv \Sigma_{i=1}^{N}\left(\Sigma_{t=1}^{T}\hat{s}_i^{*2}\hat{e}_{i,t-1}^{*2}\right)^{-1/2}\Sigma_{t=1}^{T}(\hat{e}_{i,t-1}^{*}\Delta\hat{e}_{it}^{*}),
\end{aligned}
$$

where $L_{11i}^{-2} = \hat{\Omega}_{11i} - \hat{\Omega}_{21i}'\hat{\Omega}_{22i}^{-1}\hat{\Omega}_{21i}$, $\hat{\lambda}_i = 1/T\Sigma_{s=1}^{k_i}(1-s/(k_i+1))\Sigma_{t=s+1}^{T}\hat{\mu}_{it}\hat{\mu}_{i,t-s}$, $\hat{s}_i^2 \equiv 1/T\Sigma_{t=1}^{T}\hat{\mu}_{it}^2$, $\hat{\sigma}_i = \hat{s}_i^2 + 2\hat{\lambda}_i$, $\tilde{\sigma}_{NT}^2 \equiv 1/N\Sigma_{i=1}^{N}\hat{L}_{11i}^{-2}\hat{\sigma}_i^2$, $\hat{s}_i^{*2} \equiv 1/t\Sigma_{t=1}^{T}\hat{\mu}_{it}^{*2}$, $\tilde{s}_{NT}^{*2} \equiv 1/N\Sigma_{i=1}^{N}\hat{s}_i^{*2}$, $\hat{L}_{11i}^2 = 1/T\Sigma_{t=1}^{T}\hat{\vartheta}_{it}^2 + 2/T\Sigma_{s=1}^{k_i}(1-s/(k-i+1))\Sigma_{t=s+1}^{T}\hat{\vartheta}_i, \hat{\vartheta}_{i,t-s}$. The residuals $\hat{\mu}_{it}, \hat{\mu}_{it}^*$ and $\hat{\vartheta}_{it}$ are attained from regressions: $\hat{e}_{it} = \hat{\gamma}\hat{e}_{i,t-1} + \hat{\mu}_{it}$, $\hat{e}_{it} = \hat{\gamma}_i\hat{e}_{i,t-1} + \Sigma_{k=1}^{K-i}\hat{\gamma}_{ik}\Delta\hat{e}_{i,t-k} + \hat{\mu}_{it}^*$, $\Delta y_{it} = \Sigma_{m=1}^{M}\hat{b}_{mi}\Delta x_{mi,t} = \hat{\vartheta}_{it}$. (Pedroni 1999, 2004)

The first 4 statistics are constructed by pooling the data by its within dimension (Pedroni 2004). Here the numerator and denominator terms are summed separately for the analogous conventional time series statistics. The last 3 statistics pool the between dimension of the panel. These statistics are constructed by computing the ratio of the corresponding conventional time series statistics and then by computing the standardized sum of the N time series of the panel. In the weighted statistics presented in table 3, the numerator and denominator of the panel statistics are weighted by the member specific long-run conditional variances. Pedroni (1999, 2004) shows that under the null of no cointegration the asymptotic distributions of the 7 statistics presented above and the weighted statistics converge to normal distributions with zero mean and variance of one as N and T sequentially converge to infinity.

Panel cointegration test developed by Banerjee and Carrion-i-Silvestre (2006) is based on a model:

$$\begin{aligned} y_{i,t} &= f_i(t) + x'_{i,t} + u_{i,t}, \\ \triangle x_{i,t} &= v_{i,t}, \\ f_i(t) &= \mu_i + \beta_i t + \theta DU_{i,t} + \gamma_i DT^*_{i,t}, \\ u_{it} &= F'_t \pi_i + e_{it} \end{aligned} \tag{D.2}$$

where $e_{i,t} = \rho_i e_{i,t} + \epsilon_{i,t}$,

$$DU_{i,t} = \begin{cases} 0 & t \leq T_{bi} \\ 1 & t > t_{bi} \end{cases}, \tag{D.3}$$

$$DT^*_{i,t} = \begin{cases} 0 & t \leq T_{bi} \\ (t - t_{bi}) & t > t_{bi} \end{cases}, \tag{D.4}$$

where $T_{bi} = \lambda_i T$, $\lambda_i \in \Lambda$, denotes the time of the break for the i-th unit in a closed subset of (0,1), and F'_t:s are the common factors which are used to account for the possible cross-sectional dependence. The cointegrating vector is specified as a function of time:

$$\delta_{i,t} = \begin{cases} \delta_{i,1} & t \leq T_{bi} \\ \delta_{i,2} & t > t_{bi} \end{cases}. \tag{D.5}$$

Banerjee & Carrion-i-Silvestre's test computes a $Z^e_{\bar{t}_{NT}}(\lambda) = N^{-1} \sum_{i=1}^{N} t_{\hat{p}_i}(\lambda)$ statistic for each break point using the idiosyncratic disturbance terms (e_{it}). The break point is estimated as the argument that minimizes the sequence of standardized statistics. Thus, the estimated break date is given by

$$\hat{T}_b = arg \min_{\lambda \in \Lambda} \left(\frac{N^{-1/2} Z^e_{\bar{t}_{NT}}(\lambda) - \Theta^e_2(\lambda)\sqrt{N}}{\sqrt{\psi^e_2(\lambda)}} \right).$$

Appendix E

Panel DOLS and panel DSUR estimators

E.1 Panel DOLS

Mark and Sul (2003) consider a DOLS estimator with fixed effects, fixed effects and heterogenous trends, and with fixed effects, heterogenous trends, and common time effects. The last model accounts for cross-sectional dependence by introducing a common time effect. Mark and Sul's model assumes that observations on each individual i obey the following triangular representation:

$$y_{it} = \alpha_i + \lambda_i t + \theta_t + \gamma' x_{it} + u_{it}, \tag{E.1}$$

where $(1, -\gamma')$ is a cointegrating vector between y_{it} and x_{it}, which is identical across individuals, α_i is a individual-specific effect, $\lambda_i t$ is a individual-specific linear trend, θ_t is a common time-specific factor, and u_{it} is a idionsyncratic error that is independent across i, but possibly dependent across t. Model (E.1) allows for a limited form of cross-sectional correlation, where the equilibrium error for each individual is driven in part by θ_t.

Panel DOLS eliminates the possible endogeneity between explanatory variables and the dependent variable by assuming that u_{it} is correlated at most with p_i leads and lags of $\triangle x_{it}$ (Mark and Sul 2003). The possible endogeneity can be controlled by projecting u_{it} onto these p_i leads and lags:

$$u_{it} = \Sigma_{s=-p_i}^{p_i} \delta'_{i,s} \triangle x_{i,t-s} + u_{it}* = \delta'_i z_{it} + u^*_{it}. \tag{E.2}$$

The projection error u_{it}^{*} is orthogonal to all leads and lags of $\triangle x_{it}$ and the estimated equation becomes:

$$y_{it} = \alpha_i + \lambda_{it} + \theta_t + \gamma' x_{it} + \delta_i z_{it} + u_{it}^{*}, \tag{E.3}$$

where $\delta_i' z_{it}$ is a vector of projection dimensions. The consistent estimation of (I.4) is based on sequential limits, i.e., as $T \to \infty$ then $n \to \infty$. Equation (I.4) can be feasible estimated in panels with small to moderate n.

E.2 Panel DSUR

However, if there remains correlation between equilibrium error, u_{it}, and leads and lags of other cross-sections $\triangle x_{jt}$, $j \neq i$, the panel DOLS exhibits the same form of second order asymptotic bias as pooled OLS (Mark and Sul 2003). Panel DSUR estimator can be used to account for this correlation.

The data generation process in Mark *et al.* (2005) DSUR estimator is of the form

$$y_{it} = \beta_i x_{it}' + u_{it}, \tag{E.4}$$

$$\triangle x_{it} = e_{it} \tag{E.5}$$

where there are n cointegrating regression each with T observations, and x_{it} and e_{it} are $k \times 1$ dimensional vectors. Endogeneity is controlled for by including leads and lags of (I.2) into the regression, as in panel DOLS estimator presented above. Panel DSUR estimates a long-run covariance matrix that is used in estimation of equation (I.1). This makes panel DSUR more efficient than panel DOLS when cross-sections are dependent. The efficiency of panel DSUR actually improves as the correlation between cross-sections increases.

Appendix F

Country lists

Table F.1: Country list I

Country	observations	country	observations
Australia	35	Malaysia	32
Austria	37	Malta	27
Bangladesh	21	Mauritius	32
Barbados	28	Mexico	30
Belgium	30	Netherlands	37
Bolivia	30	New Zealand	34
Canada	37	Nicaragua	21
Chile	37	Norway	36
Colombia	37	Panama	32
Cyprus	37	Papua New Guinea	20
Denmark	36	Philippines	35
Ecuador	37	Portugal	27
Egypt	36	Senegal	24
El Salvador	28	Singapore	37
Fiji	23	Spain	37
Finland	36	Sweden	37
Germany	25	Syrian Arab Republic	36
Greece	37	Taiwan	25
Hong Kong	27	Turkey	36
Hungary	30	UK	32
India	37	USA	37
Indonesia	29	Uruguay	23
Ireland	36	Venezuela	29
Israel	34		
Italy	32		
Japan	37		
Korea, Republic of	37		
Kuwait	38		
Macao	20		
Madagascar	22		
N=53			

Observations give the maximum number of simultaneous observations in the series of EHII2.1 inequality measure and real GDP per capita.

Table F.2: Country list II

Countries (25 years) 1973-1996	Countries (34 years) 1963-1996	Countries (37 years) 1963-1999
Australia	Australia	Austria
Austria	Austria	Canada
Barbados	Canada	Chile
Bolivia	Chile	Colombia
Canada	Colombia	Ecuador
Chile	Denmark	Finland
Colombia	Ecuador	Greece
Cyprus	Finland	India
Denmark	Greece	Japan
Ecuador	India	Korea, Republic of
Egypt	Ireland	Netherlands
Finland	Israel	Singapore
Greece	Japan	Spain
Hungary	Korea, Republic of	Sweden
India	Netherlands	United States
Indonesia	New Zealand	
Ireland	Norway	
Israel	Philippines	
Italy	Singapore	
Japan	Spain	
Korea, Republic of	Sweden	
Kuwait	Syria	
Malaysia	Turkey	
Malta	United States	
Mauritius		
Mexico		
Netherlands		
New Zealand		
Norway		
Philippines		
Singapore		
Spain		
Sweden		
Syria		
Turkey		
United Kingdom		
United States		
Venezuela		
N=38	N=24	N=15

Years give the number of simultaneous yearly observations in the series of EHII2.1 inequality measure and real GDP per capita.

Chapter 4

Income inequality and savings: a reassessment of the relationship in cointegrated panels

Abstract[1]

The effect of income inequality on savings and consumption has remained an open empirical issue despite several decades of research. Results obtained in this study indicate that income inequality and private consumption are both $I(1)$ nonstationary variables that are cointegrated, and inequality has had a negative effect on private consumption in Central-European and Nordic countries. Results for Anglo-Saxon countries are inconclusive. These findings suggest that previous empirical research may have produced biased results on the effect of inequality on savings by assuming that inequality would be a stationary variable.

[1]An earlier version of this chapter has been published in Helsinki Center of Economic Research Discussion Papers, No. 337

4.1 Introduction

The effect of savings on capital accumulation and growth has always been one of the fundamental research topics in economics. According to Smith (1776), increased division of labor raises productivity, but savings govern capital accumulation, which enables production growth. In the 18th century, only rich people saved. Therefore, economic growth was possible only when there were enough rich people in the society. However, according to Keynes (1936), inequality of income would slow down economic growth. Keynes argued that marginal consumption decreases as the income of an individual increases, and thus, aggregate consumption depends on changes in aggregate income. Because demand is the basis of investments, and because inequality lowers aggregate consumption, inequality of income would diminish economic growth. In neo-classical growth models, income distribution determines the level savings and thus the level of capital accumulation (Solow 1956; Kaldor 1957).

In addition to the approach of classical economics, there exist several theories describing the effect of income inequality on savings and consumption. These include the permanent income hypothesis by Friedman (1957), life-cycle hypothesis by Ando and Modigliani (1963), which was augmented with intergenerational transfers by Kotlikoff and Summers (1981), savings under liquidity constraints by Deaton (1991), and political-economy models (e.g. Alesina and Perotti (1994)).

Although theoretical research spans several decades, the effect of income inequality on savings remains an open empirical question. This is due to the fact that empirical cross-country studies have produced controversial results on the effect of income inequality on savings. In one of the most recent panel econometric studies, Leigh and Posso (2009) estimate the effect of the income share of the top 1% on the percentage value of gross savings of the GDP and find no statistically significant effect of inequality on national savings. Similarly, Schmidt-Hebbel and Servén (2000) find no statistically significant effect of the percentage value of savings of the GDP using several different measures of income inequality. However, Smith (2001) finds that inequality, measured with Deininger and Squire's (1996) Gini index, has a statistically robust positive effect on the percentage value of savings of the GDP. Cook

(1995) finds the same effect in less developed economies. Li and Zou (2004) find that inequality has a negative effect on private savings using Deininger and Squire's (1996) Gini index and the ratio of private savings of GDP.

All the empirical studies summarized above have assumed that income inequality, measured either by the Gini index or by the share of income earned by different income classes, is a stationary variable. However, in the early theoretical literature on income inequality, the income variation was assumed to be driven by a stochastic process (Chambernowne 1953; Mandelbrot 1961). Moreover, Mandelbrot (1961) argued that time-independent, i.e. stationary, income variations are unlikely, and it is possible that the distribution of income will never reach a steady state implying a nonstationary process of income variation. In recent studies with cross-country panel data, Malinen (2012) and Herzer and Vollmer (2012) have obtained results according to which the data generating process of income inequality would be driven by a stochastic trend, indicating that inequality would be an $I(1)$ nonstationary variable. Previously, for example, Mocan (1999) has obtained similar results.[2] If this assumption of the early theoretical models held in general, it would offer an explanation to the controversy in the previous empirical studies. This is because regressing a stationary variable on an $I(1)$ variable(s) can lead to a spurious regression (Stewart 2011). In empirical studies, savings is usually measured as a percentage of the GDP. If both logarithmic savings and the logarithmic GDP are $I(1)$ variables and cointegrated, their difference results, by construction, in a stationary variable, namely savings as a percentage of the GDP. Thus, if inequality were an $I(1)$ variable and savings as a ratio of the GDP a stationary $I(0)$ variable, regressing savings on inequality would give spurious results.

This study uses panel cointegration methods to test the time series properties of the included variables and to estimate the (possible) long-run relation between income inequality and savings. We use data on nine developed economies, and spanning four decades starting from the year 1960. The income share of the top 1%, used to proxy the distribution of income, has been found to track broader measures of income inequality, like the Gini index, very well (Leigh 2007). According to panel unit root tests, the logarithmic in-

[2] See also Jäntti and Jenkins (2010).

come share of the top 1%, logarithmic gross national savings and logarithmic private consumption are all $I(1)$ nonstationary variables. Income share of the top 1% is also found to be cointegrated with private consumption, which implies that there is a long-run dependency relation between them. The effect of inequality on private consumption is found to be negative in the Nordic and Central-European countries, but for the Anglo-Saxon countries the direction of the effect (positive vs. negative) remains somewhat ambiguous. The results of the panel cointegration tests are inconclusive on possible cointegration between gross savings and the top 1% income share. The real GDP per capita and gross savings as well as the real GDP per capita and private consumption are also found to be cointegrated. This implies that the ratios of savings and private consumption to GDP would be stationary variables and hence previous research is likely to have produced biased results on the effect of inequality on savings and consumption.

The rest of the paper is organized as follows. Section 2 gives the theoretical and empirical background of the study. Section 3 describes the data and presents the results of unit root tests. Section 4 reports the results of cointegration tests and section 5 gives the estimation results. Section 6 concludes.

4.2 Theoretical and empirical considerations

Several theories have been constructed to explain the effect of inequality on savings. In classical economic theory, the form of the individual saving function determines the effect of income inequality on savings. When the saving function is linear or concave, the distribution of income and wealth converge toward equality as the economy grows (Stiglitz 1969). If the saving function is convex, the marginal propensity to save increases with income. According to the permanent income hypothesis, individuals with low income have higher propensity to consume, and small changes in income, or its distribution, do not affect the consumption decisions of households (Friedman 1957). The life-cycle hypothesis argues that, if bequests are luxury, the saving rate should be higher among wealthier individuals (Kotlikoff and Summers 1981). In political-economy models, more unequal income distribution may create demand for more redistribution through taxation and income transfers, and if the saving function of individuals in the economy is convex, i.e. the rich save more, this will diminish aggregate savings through diminished incomes of the rich (Alesina and Perotti 1994).

What is common to all of the theories introduced above is that they generally assume that the individual income process is non-stochastic. However, as pointed out by Stiglitz (1969), the very first (formal) models of income inequality by Chambernowne (1953) and Mandelbrot (1961) were based on stochastic processes. Chambernowne (1953) developed a model assuming that the evolution of income of an individual is determined by his/her income in the previous year and by a stochastic (chance) process. In modern terms, this process would be said to be $I(1)$ non-stationary.

$I(1)$ non-stationary processes have a infinite memory, i.e., they are highly persistent. Assuming some degree of persistence in the evolution of the income series of an individual is quite intuitive as shocks (e.g., wage raise) to the income process of an individual are likely to have permanent effects on the future incomes of the individual. Microeconomic literature on household income and consumption behavior adopted the idea of permanent effects affecting the income series of an individual. For instance, Hall and Mishkin (1982) considered a stochastic model of consumption proposed by Muth (1960), where the effect of individual income on consumption was divided into permanent and transitory components. In a recent study on the evolution of consumption and income inequality, Blundell *et al.* (2008) use the same kind of formulation where the income of households varies according to the following function:

$$logY_{it} = Z_{it}\vartheta_t + P_{it} + v_{it}, \tag{4.1}$$

where Z_{it} is a set of income characteristics of household i that are observable and known by consumers at time t,[3] v_{it} follows an $MA(q)$ process, and $P_{i,t} = P_{i,t-1} + \epsilon_{it}$ with ϵ_{it} serially uncorrelated, indicating that the process $\{P\}$ is $I(1)$ non-stationary. Several studies in the micro literature tend to find that also empirically the permanent component P_{it} is a random walk, and hence it can be modeled as an $I(1)$ nonstationary process (Meghir and Pistaferri 2004; Hall and Mishkin 1982; Blundell *et al.* 2008).

[3] These include demographic, education, employment status, ethnic, etc. factors (Blundell *et al.* 2008)

Deaton (1991) studied how liquidity constraints affect national savings, when incomes are driven by a random walk with drift.[4] He argued that the assumption of optimal intertemporal consumption behavior of consumers being restricted by borrowing constraints would help to create a model that could explain the observed patterns of household wealth and the dependency of consumption on income during the life cycle of an individual. According to Deaton, the problem with stochastic life cycle - permanent income models, like the model by Hall and Mishkin (1982), is that they assume substantial wealth accumulation at some point of the life cycle of an individual, which was not supported by the data. Deaton assumed that the labor income of an individual follows an $AR(1)$ process of the form:

$$log(y_{t+1}) = log(y_t) + log(z_{t+1}) + \delta, \tag{4.2}$$

where y_t is labor income, z_{t+1} is stochastic random variable, and $\delta > 0$ is a constant. When z_{t+1} is assumed to be identically and independently distributed, the labor income process, $\log(y_t)$, is $I(1)$ non-stationary and, specifically, it follows a random walk with drift. Deaton found that, when income is a random walk and borrowing constraints are binding, it is undesirable for households to undertake any smoothing of consumption, i.e., they have no incentives to save. This implies that consumption equals income on all income levels. However, he assumed that the interest rate is higher than the consumer's discount rate. If the interest rate equals the consumer's discount rate, the stochastic income process and borrowing constraints lead to the result that the propensity to consume is lower at higher income levels (Seater 1997; Travaglini 2008). In this day and age, the debate on the validity of the life cycle - permanent income hypothesis is still very much ongoing. In a recent paper, Attanasio and Weber (2010) review the literature on intertemporal allocation models and present some modifications to the standard life cycle hypothesis framework to make the model fit the micro data better.

When individual income series are affected by a random walk component, the aggregated time series is likely to be characterized by a random walk (Rossanan and Seater 1995). This applies to the *aggregate* income, but the

[4] Assuming a drift in income relation is intuitive and necessary, because income tends to grow over time. Thus, just variations around that trend are assumed to be stochastic.

distribution of income is often measured using some bounded measure, like the Gini index or share of total income. This changes things a bit as any measure that varies within some boundaries like the income share, cannot, by definition, be an $I(1)$ nonstationary process. This is because the variance of such an series cannot grow to infinity with time, which is what happens with random walk series. However, it is possible that the distribution can have a stochastic trend in its other moments, like the mean, skewness, and kurtosis, than variance (White and Granger 2010). Thus, when individual income series that are affected by a random walk component are aggregated to a bounded distribution, it is likely that this distribution has a stochastic trend in its kurtosis and/or in its skewness. This way the measure of income inequality, being a functional of some income distribution, may exhibit such high levels of persistence that it is better approximated by an $I(1)$ process than a stationary process.

Figure 1 presents the detrended and demeaned time series of the top 1% income share series for 5 developed countries. Time series of the shares seem to "wander" randomly through time in all countries, which is a distinctive feature of a series that is driven by a stochastic trend. The series are also clearly not mean- or trend-reverting in the observed period, which is one condition of stationarity.

Thus, the possibility that income inequality is driven by a stochastic trend needs to be taken into account in the analysis of the relationship between inequality and savings. Especially in empirical analysis, this is quite crucial, as the possible $I(1)$ non-stationarity of the included variables determines the way this relationship can be consistently estimated (see the Introduction). That is why we next turn to testing the time series properties of relevant variables.

4.3 Data and unit root tests

4.3.1 Data

In this study we use the the top 1% income share of population to proxy the income distribution in different countries. Since the work of Piketty (2003),

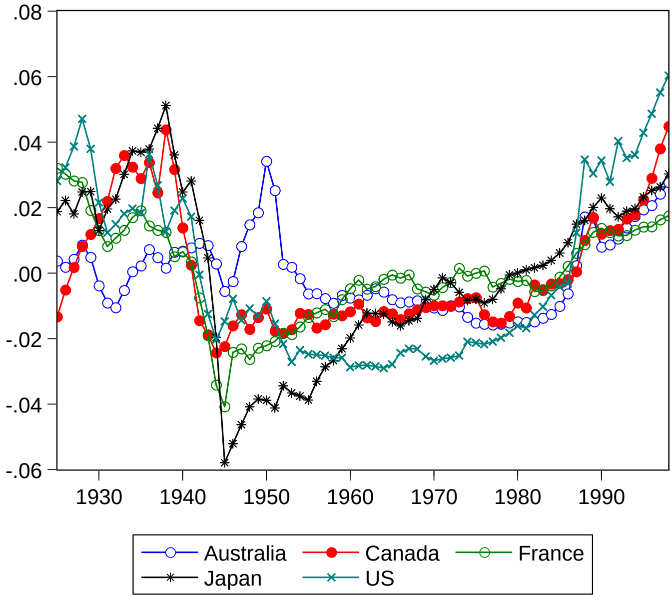

Figure 1. The detrended and demeaned shares of income of the top 1% of population in 5 developed countries 1925-1998 Source: Leigh (2007)

there has been a growing interest towards building long time series of the evolution of top income shares of the population. Measuring the developments in top income shares makes it possible to construct substantially longer time series from the evolution of the distribution of income than would be possible using the Gini index or similar aggregate measures. Top income series are built using national tax data and applying the same method across countries to make the series comparable (Atkinson and Piketty 2007). Leigh (2007) has also demonstrated that the top 1% income share series have a high correlation with other measures of income inequality, like the Gini index. The dataset on the top 1% income shares gathered by Leigh is a primary source of data in this study.

However, after Leigh (2007) there have been additions to the pool of countries for which a historical dataset of the evolution of top incomes is available.

Roine and Waldenström (2011) have used data collected from several different sources in their analysis of common trends and shocks in top income series. Their dataset is extensive, but it, like the dataset by Leigh (2007), has one caveat. Due to the length of some series (starting from the beginning of the 20 century) the observations from all countries are not continuous, and thus they are forced to extrapolate over some observations. This is problematic, because extrapolation of over just one observation may alter the time series properties of the observed variable. From the dataset of Leigh we know that the series of New Zealand has observations missing in 1961, 1974, and 1976. Thus, New Zealand is not included in the datasets that consists of those periods. For the other countries neither Leigh nor Roine and Waldenström explicitly list the observations over which they are extrapolating, and thus we have to check the original data sources to find out about the location of the missing observations. After observing the individual sources of data, we include nine countries in our baseline dataset. These countries are: Australia, Canada, Finland, France, the Netherlands, Norway, Sweden, Switzerland, the United Kingdom and the United States.[5] All these countries have continuous observations from the year 1960 onwards, except Switzerland from which we have only bi-annual average observations (Dell *et al.* 2010). That is, for example, in 1995 and in 1996 the value corresponds to the average share of the top 1% income during 1995-1996. Thus, we do not include Switzerland on any of the unit root tests, but observations from Switzerland are included in the cointegration testing and estimations. Because of the restrictions imposed by some of our testing methods explained later, the nine countries are divided into three groups of countries according to their (assumed) economic models. The groups are: Nordic, Central-European, and Anglo-Saxon countries.[6] In

[5]The problematic countries in this dataset are Finland and the Netherlands. In Finland's case the original data, allegedly spanning from 1920 to 2005, could not be checked, but we could check that the data is continuous at least from 1966 onwards. For the Netherlands there are direct observations only from the year 1977 onward and significant part of the previous observations are a result of interpolation and pure estimation. However, panel unit root tests are done also without Nordic countries and the Netherlands, and because extrapolation would have the biggest impact on those tests, the bias created by possible extrapolation over some values of top 1% series in Finland and the Netherlands is diminished.

[6]Canada, United Kingdom and Unites States are included in the Anglo-Saxon group.

addition, Japan and New Zealand are included in the testing for the time series properties of the top 1% income share data.

The endogenous variables used in this study are the gross savings and the private consumption expenditures. The data on these is obtained from the AMECO database compiled and published by the Directorate-General for Economic and Financial Affairs of the European Comission. AMECO is used, because it has more extensive time series coverage on the variables in question than, for example, the dataset of World Bank. AMECO does not include data on private savings, but because private consumption is the mirror image of private savings, it should not make any difference which of these two variables is used. Both variables are measured in aggregate terms to minimize the effects that a third variable might have on the relation between inequality and savings. Changes, for example, in fertility may have an effect on variables that are measured in per capita terms without affecting the income share of the top 1%. Thus, expressing gross savings and private consumption in per capita terms could add stochastic elements to the time series of those variables unrelated to their relation with income inequality.

The other variables included in the estimation are the real gross domestic product per capita, the dependency rate, and the interest rate. The real GDP per capita is historically thought to proxy the expected lifetime wealth of the residents in a country (Cook 1995). The level of national income may also have a direct effect on gross savings and consumption. The dependency rate is used to control for possible changes in the saving patterns across the life cycle of individuals, and it measures the ratio of the population under 15 to that over 64 years of age. Interest rates may affect the individual propensity to save by affecting the profitability of saving. The year 1960 is the first year included in the dataset but the last year varies from one country to another. The data on dependency is obtained from the World Development Indicators of the World Bank and the data on interest rates is from the database of the International Monetary Fund.

The data on interest rates varies a little across countries in the dataset. The baseline rate is the discount or the bank rate, i.e. the rate at which cen-

France, Netherlands, and Switzerland are included in the Central-European group, and Finland, Norway, and Sweden are included in the group of Nordic countries.

tral banks lend to deposit banks. However, for some countries, observations of this variable are not available for the whole time period. That is why there are some differences in the indicators of interest rates between the groups of countries. For Finland, Sweden, Norway, and Switzerland, the central bank rate is used. For Canada, the United Kingdom, and the USA, the treasury bill rate is used, which gives the rate at which short-term securities are issued or traded in the market. For France and the Netherlands, the money market rate is used, which gives the rate on short term lending between financial institutions. Although using different indicators of interest rates is not optimal, all these indicators should reflect changes in the interest rate at which consumers borrow from and deposit money to banks.

4.3.2 Unit root tests

To test for possible unit roots, four different panel unit root tests are used. The first two are the so called traditional and the last two the so called second generation panel unit root tests. Traditional panel unit root tests do not allow for cross-sectional dependency while the second generation tests allow for cross-sectional correlation.

The traditional panel unit root tests, by Im *et al.* (2003) and the panel version of the ADF test by Maddala and Wu (1999), are based on the following regression:

$$\triangle y_{it} = \rho_i y_{i,t-1} + \eta_i t + \alpha_t + \theta_t + \epsilon_{it}, \tag{4.3}$$

where α_i are individual constants, $\eta_i t$ are individual time trends, and θ_t are the common time effects. The tests rely on the assumption that $E[\epsilon_{it}\epsilon_{js}] = 0$ $\forall\ t, s$ and $i \neq j$, which is required for calculating common time effects. Thus, if the different series are correlated, the last assumption is violated.

The second generation tests by Pesaran (2007) and Phillips and Sul (2003) are based on the regression

$$\triangle y_{it} = \rho y_{i,t-1} + \eta_i t + \alpha_i + \delta_i \theta_t + \epsilon_{it}, \tag{4.4}$$

where α_is are the individual constants, $\eta_i t$ are the individual time trends, and θ_t is the common time effect, whose coefficients, δ_i, are assumed to be non-stochastic, measure the impact of the common time effects of series i, and ϵ_{it} is assumed to be normally distributed with mean zero and covariance of σ^2 and independent of ϵ_{js} and θ_s for all $i \neq j$ and s, t. Cross-sectional dependence is allowed through the common time effect, which generates the correlation between cross-sectional units. The matrix δ_i gives the non-random factor loading coefficients that determine the extent of the cross-sectional correlation. The null hypothesis in all tests is that $\rho_i = 0 \ \forall \ i$. The alternative hypotheses are:

$$H_1 : \rho_i < 0, \quad i = 1, 2, ..., N_1, \quad \rho_i = 0, \quad i = N_1 + 1, N_1 + 2, ..., N. \tag{4.5}$$

For consistency of panel unit root tests it is also required that, under the alternative, the fraction of the individual processes that are stationary is non-zero, formally $lim_{N \to \infty}(N_1/N) = \gamma$, $0 < \gamma \leq 1$ (Im *et al.* 2003).

Table 4.1 presents the results of the four panel unit root tests for the top 1% income share. The tests have been applied to three different datasets. The first includes the data on five countries with the longest continuous time series in the dataset by Leigh (2007).[7] The second dataset includes the eight countries on which we have data for all the included variables excluding Switzerland. The third dataset includes observations from seven countries excluding the Nordic countries. This dataset spans from 1983 to 2002.[8] The third dataset is used, because, according to Roine and Waldenström (2011), there is a trend break in the series of the top 1% income share in 1991 in the Nordic countries. According to Roine and Waldenström (2011), there are similar trend breaks in the top 1% income share series in the Anglo-Saxon countries, including Australia, Canada, UK and USA (in 1982), in Central European countries, including France, Switzerland, and Netherlands (in 1976), and in Asian countries, including Japan (in 1983). So, to make sure that the results of the panel unit root tests are not driven by structural breaks, the tests are run using only those countries that should not have breaks in their top 1% income share series in the test period. According to all tests in all datasets, the logarithmic top 1% income share is a $I(1)$

[7]Countries included in the test are: Australia, Canada, France, Japan, and the USA. All these countries should have continuous observations throughout the period.

[8]Countries included in the test are: Australia, France, Japan, New Zealand, the United Kingdom, and the USA.

Table 4.1: Panel unit root tests of the top 1% income share

variable	period	IPS	ADF	Pesaran	PS
top 1%	1925-1998	3.449	2.270	-0.103	4.200
		(0.998)	(0.994)	(0.459)	(0.838)
top 1%	1960-1996	5.256	1.282	-0.348	3.212
		(0.999)	(0.998)	(0.364)	(0.976)
top 1%	1983-2002	-0.302	16.670	-0.198	16.636
		(0.381)	(0.273)	(0.421)	(0.187)

The tested equation is: $\triangle y_{it} = \rho_i y_{i,t-1} + \delta_i + \eta_i t + \theta_t + \epsilon_{it}$. All variables are tested in logarithms. P-values of the test statistics appear in parentheses. With the exception of the PS test, lag length was determined using Schwarts information criterion (SIC). In PS test the lag length is selected with top-down method. The dataset of 1925-1998 includes 6 countries and 444 observations, the dataset of 1960-1996 includes 9 countries and 333 observations, and the dataset of 1983-2002 includes 6 countries and 121 observations.

nonstationary process. This holds even in the last test, where the Nordic countries are excluded from the test to control for the possible structural breaks present in their top 1% income share series.

Table 4.2 presents the results of panel unit root tests of the other variables. Because gross savings is expressed in constant Euros and private consumption in purchasing power parities (ppp), two different series of real GDP per capita series are included in the dataset. According to all tests, gross savings, private consumption, the interest rates, and both versions of the real GDP per capita are $I(1)$ processes. With the exception of the test by Pesaran (2007), all tests clearly reject the null hypothesis of the nonstationarity of the dependency rate, indicating that it is a trend-stationary variable.

4.4 Cointegration tests

4.4.1 Testing with the whole data

The methods for testing for cointegration in panel data have developed very rapidly during the first decade of the 21st century. One of the most com-

Table 4.2: Panel unit root tests of the other included variables, 1960-1996

variable	IPS	ADF	Pesaran	PS
gross savings	2.207	2.144	-0.186	4.79
	(0.986)	(0.999)	(0.426)	(1.000)
private consumption	12.532	0.0645	0.221	7.53
	(1.000)	(1.000)	(0.587)	(0.960)
GDP, ppp	11.006	14.039	0.347	5.331
	(1.000)	(1.000)	(0.636)	(0.994)
GDP, eur	3.912	19.453	2.420	11.210
	(1.000)	(0.364)	(0.992)	(0.796)
dependency	-5.077	82.382	1.005	50.92
	(<.001)	(<.001)	(0.843)	(<.001)
interest rate	0.717	13.937	-1.144	19.97
	(0.764)	(0.731)	(0.126)	(0.220)

The tested equation is: $\triangle y_{it} = \rho_i y_{i,t-1} + \delta_i + \eta_i t + \theta_t + \epsilon_{it}$. All variables are in logarithms. Probabilities of the test statistics appear in parentheses. In all other tests, except in the PS test, lag lengths were determined using Schwarts information criterion (SIC). Testing includes 9 countries and 333 observations.

monly used cointegration testing methods has been the residual based panel cointegration test by Pedroni (2004). The limitation of Pedroni's test is that it assumes independence of cross-sections, an assumption, which is likely to be violated in econometric cross-country studies.[9] Cross-sectional correlation may bias the results towards rejecting the null of no cointegration (Banerjee *et al.* 2004). To account for this bias, we use a panel cointegration test developed by Banerjee and Carrion-i-Silvestre (2006) that controls for cross-sectional dependency by introducing common factors. The test also controls for possible endogeneity of regressors by including leads and lags of differenced explanatory variables in estimation (this method is explained more thoroughly in the appendix I describing the panel DSUR estimator). A more thorough explanation of the test by Banerjee and Carrion-i-Silvestre (2006)

[9]There are, for example, only few countries that avoided the downturn of 2008 that started from the U.S.

can also be found in the appendix G. The test is based on two different test statistics, namely $Z_{\hat{\rho}_{NT}}(\hat{\lambda})$ and $Z_{\hat{t}_{NT}}(\hat{\lambda})$ to test for the possible cointegration between two variables. Both statistics are based on the ADF regression, from where the former uses the estimated coefficients of $\hat{\rho}$ and the latter the associated t-ratio to compute the test statistic.

Table 4.3 presents the results of the panel cointegration test by Banerjee and Carrion-i-Silvestre (2006). It reports the results of the cointegration tests between gross savings and the top 1% income share and gross savings and the GDP per capita.[10] In addition, we test for cointegration between private consumption and the top 1% income share and private consumption and GDP per capita. [11] According to the results of the $Z_{\hat{t}_{NT}}(\hat{\lambda})$ test presented in table 4.3, gross savings and the income share of top 1% as well as private consumption and top 1% income share are cointegrated at the 5% level. According to the $Z_{\hat{\rho}_{NT}}(\hat{\lambda})$ test, only gross savings and the top 1% income share are cointegrated. However, Banerjee and Carrion-i-Silvestre (2006) note that the $Z_{\hat{t}_{NT}}(\hat{\lambda})$ statistic should be preferred over the $Z_{\hat{\rho}_{NT}}(\hat{\lambda})$ statistic, because the former has considerably better size and power properties especially in small samples. Thus, we rely more on the results of the $Z_{\hat{t}_{NT}}(\hat{\lambda})$, and conclude that both gross savings and private consumption seem to be cointegrated with the top 1% income share. The GDP per capita and gross savings as well as GDP per capita and private consumption seem to be cointegrated of order 1.

Table 4.3 only presents the results of the test without breaks. However, we also conducted tests with breaks, but if trend breaks are allowed for, the results do not change dramatically. This is expected as structural breaks tend to bias the results towards the acceptance of the null (Banerjee and Carrion-i-Silvestre 2006). The results of the tests including structural breaks are available upon request.

[10] GDP per capita in euros is used in the for gross savings as the gross savings series is also presented in euros. GDP per capita in ppp is used in the test for private savings for the same reason.

[11] Estimation is done with Gauss. We are grateful to Carrion-i-Silvestre for providing the program code.

Table 4.3: Banerjee & Carrion-i-Silvestre's cointegration test for gross savings, final consumption and the income share of top 1%

	gross savings	private consumption
Top 1% income share		
$Z_{\hat{t}_{NT}}(\hat{\lambda})$	-3.952	-2.255
	(<.0001)	(0.0121)
$Z_{\hat{\rho}_{NT}}(\hat{\lambda})$	-3.084	-0.548
	(0.0010)	(0.292)
GDP per capita		
$Z_{\hat{t}_{NT}}(\hat{\lambda})$	-5.683	-5.494
	(<.0001)	(<.0001)
$Z_{\hat{\rho}_{NT}}(\hat{\lambda})$	-3.090	-6.399
	(0.0010)	(<.0001)
countries	9	9
years	1960-1996	1960-1996
observations	333	333

The tested model includes individual deterministic constants and trends.

4.4.2 Testing for the cointegration rank

One of the obvious drawbacks of the residual tests, like the ones presented above, is that they cannot identify the number of cointegrating vectors between the variables. If we have just two variables, this is not a problem, because then there cannot be more than one cointegrating vector. However, with three variables, there can be two cointegrating vectors, with four variables three cointegrating vectors, etc. The cointegration rank affects estimators, because some estimators, like the panel DSUR estimator, are based on the single equation approach meaning that a single cointegration relationship is assumed. If there are two or more cointegration relationships between the variables, the asymptotic properties of the estimators derived under the assumption of one cointegration relation are no longer valid. In addition, estimators allowing for multiple cointegrating vectors, like the estimator by Breitung (2005) used in this study, usually assume that the cointegration rank is homogenous across the countries included in the panel.

To allow for multiple cointegrating vectors, we use the panel trace cointegration test developed by Larsson and Lyhagen (2007) to test for the cointegration rank in models involving several explanatory variables. Their test is based on the likelihood ratio test of Johansen (1995). The general model on which Larsson ja Lyhagen's test is based can be written as

$$\triangle Y_t = \mu + \Pi Y_{t-1} + \Sigma_{k=1}^{m-1} \Gamma_k \Delta Y_{t-k} + \epsilon_t, \tag{4.6}$$

where $\Pi = \alpha_{ik}\beta'_{kj}$, Π and Γ_k are of order $Np \times Np$ and $\mu = (\mu'_1, \mu'_2, ..., \mu'_n)$ and $\epsilon_t = (\epsilon'_{1t}, \epsilon'_{2t}, ..., \epsilon'_{nt})$ are of order $Np \times 1$, and $\epsilon_t = (\epsilon'_{1t}, \epsilon'_{2t}, ..., \epsilon'_{nt})$ is assumed to be multivariate normally distributed with mean zero and covariance matrix Ω.

It is assumed that matrix Π has a reduced rank of Nr, $0 \leq r \leq p$, and can be decomposed as $\Pi = \alpha_{ik}\beta'_{kj}$. The matrix α_{ik} is assumed to be unrestricted, but $\beta_{kj} = 0 \; \forall i \neq j$. The fact that unrestricted α_{ik} means that different panel units can be dependent, but because of the restriction on β_{kj}, these dependency relations can only appear in the short run. In other words, cointegrating relations are only allowed *within* the units of the panel. The cointegration rank is estimated by sequentially testing

$$H(r) : rank(\Pi) \leq Nr \tag{4.7}$$

against the alternative

$$H(p) : rank(\Pi) \leq Np \tag{4.8}$$

as in Johansen (1995). A more detailed explanation of the test is provided in Appendix B.

A limitation in the panel cointegration test by Larsson and Lyhagen (2007) is that the number of estimated parameters increases rapidly with the number of cross sections. This means that there need to be enough time series observations compared to cross-sectional units or the parameters of the model cannot be estimated. In our baseline dataset, there are nine countries and 37 time series observations per country, a relation which is far too small for the test. That is why countries are divided into three groups as explained in the section 3.1. Because countries in these groups tend to have similar economic and social structures, it is more likely that they also have homogenous cointegration relations.

Tables 4.4 and 4.5 present the results of the test for the cointegration rank by Larsson and Lyhagen (2007) for the three groups of countries for gross savings and private consumption as the dependent variable.[12] All variables are detrended and demeaned before testing. The VAR lag length was determined using the Schwartz information criterion (SIC).

According to the results presented in table 4.4, the top 1% income share and gross savings appear to be difference stationary variables in the Central European and Anglo-Saxon countries. That is, both are $I(1)$ variables that are *not* cointegrated. This result contradicts the results presented in Table 4.3, where gross savings and the top 1% income share were found to be cointegrated. The results of Nordic countries indicate that there would be, at least, two cointegration vectors between top 1% income share and gross savings. When the GDP per capita and the interest rate are added test finds a cointegration rank of two in the Nordic countries.

According to results of table 4.5, private consumption and the top 1% income share are cointegrated in the Central European and Anglo-Saxon countries. When the GDP per capita and the interest rate are added, the test finds a cointegration rank of two in the Anglo-Saxon countries and coin-

[12] All testing is done by Gauss. We are grateful to Johan Lyhagen for providing the Gauss code on his homepage.

Table 4.4: Panel trace cointegration test for savings and the top 1% income share for the 3 country groups

	Nordic	Central-Europe*	Anglo-Saxon**
top 1%			
r=0	211.12	292.15	72.32
	(197.64)	(307.22)	(92.86)
r≤ 1	57.52	-	-
	(50.71)		
top 1%, GDP & interest			
r=0	469.50	-	-
	(381.22)		
r≤1	301.53	-	-
	(283.40)		
r≤2	186.47	-	-
	(175.66)		
r≤3	113.70	-	-
	(83.32)		
countries	3	3	3
years	1960-03	1960-96	1960-00
observations	132	111	123

All series are detrended and demeaned before testing. * In the group of Central European countries, only GDP per capita and top 1% income share were included in the test, because there were too few time series observations per country to include a 4 variable. ** for Anglo-Saxon countries, GDP per capita in constant Euros was used instead of GDP per capita in purchasing power parities in the test with private consumption. All variables are tested in logarithms. Bartlett corrected critical values are presented in parentheses. Lag lengths were selected using Schwarz information criterion.

Table 4.5: Panel trace cointegration test for consumption and the top 1% income share for the 3 country groups

	Nordic	Central-Europe*	Anglo-Saxon**
top 1%			
r=0	295.33	294.36	194.75
	(167.08)	(270.17)	(171.47)
r≤1	68.33	72.97	38.86
	(51.49)	(83.63)	(59.64)
top 1%, GDP & interest			
r=0	410.85	516.43	1137.26
	(381.27)	(470.88)	(992.44)
r≤1	281.61	194.42	586.90
	(267.77)	(214.56)	(523.78)
r≤2	172.84	-	300.25
	(166.60)		(336.24)
r≤3	58.99	-	-
	(89.81)		
countries	3	3	3
years	1960-03	1960-96	1960-00
observations	132	111	123

All series are detrended and demeaned before testing. * In the group of Central European countries, only GDP per capita and top 1% income share were included in the test, because there were too few time series observations per country to include a 4 variable. ** for Anglo-Saxon countries, GDP per capita in constant Euros was used instead of GDP per capita in purchasing power parities in the test with private consumption. All variables are tested in logarithms. Bartlett corrected critical values are presented in parentheses. Lag lengths were selected using Schwarz information criterion.

tegration rank of three in the Nordic countries. In the Central European countries only private consumption, the top 1% income share and the GDP per capita were included in the testing, because there were not enough time series observations for including four variables. In Central-European countries the cointegration rank among these three variables is found to be one.

The results of Nordic countries presented above thus indicate that there are two stationary cointegration relations between gross savings and the top 1% income share as well as between private consumption and the top 1% income share. In the time series case this would imply that, in both of these tests, the two variables are $I(0)$ trend-stationary. However, it does not seem likely that some of these series would be trend-stationary in Nordic countries, as all of the panel unit root tests found gross savings, private consumption and the top 1% income share to be $I(1)$ non-stationary (see section 3.2). If the time series of a variable in three out of nine countries would be trend-stationary, it would be highly unlikely for the tests to present the series as $I(1)$ non-stationary.

With panel data, the implications of the cointegration rank test are not so straightforward as they are in the case of time series. In model (4.7), the block matrix elements of Π are given by $\Pi_{ij} = \Sigma_{k=1}^{N}\alpha_{ik}\beta'_{jk}$, which equal $\alpha_{ij}\beta'_j$ when $\beta_{ij} = 0$ for all $i \neq j$. However, if $\beta_{ij} \neq 0$ for $i \neq j$, then the block matrix elements of Π are given $\alpha_{ij}\beta'_{jk}$ and the rank of Π can be larger than the number of variables. That is, because the dimension of Π is $Np \times Np$, the number of cross-sectional cointegration relations may increase the rank of the matrix. One likely source of cross-sectional cointegration would be a stationary linear combination of $I(1)$ non-stationary common factor(s) driving the GDP per capita series in the Nordic countries. As Nordic countries have very similar social structures, and because they are small countries within close proximity to each other, it would be quite natural if a common stochastic trend would affect their GDP series. As GDP per capita and consumption were found to be cointegrated, common stochastic trend driving the GDP series would also affect on the series of savings and private consumption. So, the results of the Nordic countries presented in table 4.5 are likely to be explained by cross-sectional cointegration relations affecting the GDP per capita and consumption series.

In conclusion, results of cointegration tests indicate that income inequality, measured with the top 1% income share, and private consumption are cointegrated, but the results of the cointegration tests for gross savings are somewhat inconclusive. It is not quite clear why this is or why the results deviate from the results of the unit root tests. It should be noted, however, that in the case of the test of Banerjee and Carrion-i-Silvestre (2006) we had more than double the number of observations compared to the test of Larsson and Lyhagen (2007). So, even with the Bartlett correction, it is possible that the power of Larsson and Lyhagen's test was not sufficient to reject the null hypothesis of zero rank of the Π matrix.

4.5 Estimation

According to the results presented in the previous section, the cointegration rank among the included variables varies between the groups of countries. Because of this, two different estimation methods are applied to estimate the long-run effect of the income share of the top 1% on the gross savings and private consumption. Panel dynamic seemingly unrelated regressors (DSUR) estimator of Mark *et al.* (2005) is used when there seems to be only one cointegrating vector between the variables, while the two-step maximum-likelihood panel VAR estimator by Breitung (2005) is used when there seem to be two or more cointegrating relations between the variables. The reason for using panel DSUR estimator is that Wagner and Hlouskova (2010) have found that single-equation estimators, like panel DSUR, perform better than the VAR estimator of Breitung (2005), when cross-sections are cross-sectionally correlated and/or cointegrated.[13] Both estimators control for possible endogeneity of the regressors. The panel DSUR estimator controls for endogeneity by including lags and leads of first differences of the explanatory variables in the estimated equation. Panel VAR controls for endogeneity by imposing

[13]Results of Wagner and Hlouskova (2010) imply that panel DOLS would perform better than panel VAR by Breitung (2005) in cross-sectionally cointegrated panels. Panel DSUR was not included in testing. However, as panel DSUR is more efficient than panel DOLS when cross-sections are correlated, it is also likely to be more efficient than panel DOLS when cross-sections are cointegrated.

block-diagonality of the Fisher information matrix with respect to short- and long-run parameters. A more detailed explanation of the estimators used can be found in the Appendix. The possible long-run cross-unit dependency relations in income and consumption series between the Nordic countries found in previous section cannot be controlled with estimators allowing for short-run dependencies and/or cross-sectional correlation. Fortunately, Wagner and Hlouskova (2010) have found that, if there is only a cross-sectionally identical unit-specific cointegrating relationship(s) between the cross-sections, it creates only a small bias in the results of cointegration estimators used here.

The estimated model is:

$$\begin{aligned} log(Y_{it}) = \alpha_i + \gamma_1' log(GDP_{it}) + \gamma_2' log(top1_{it}) + \\ + \gamma_3'(interest_{it}) + \lambda_i t + u_{it}, \end{aligned} \tag{4.9}$$

where where α_i's are individual constant, $\lambda_i t$'s are individual trends, and u_{it} is a white noise error vector with $E(u_{it}) = 0$. Table 4.6 presents the results of estimation of equation (4.9) using the panel DSUR and panel VAR estimators.[14] According to the results, the relation between the top 1% income share and gross savings somewhat depends on the included variables. The initial estimate of the cointegrating coefficient of inequality measured with the top 1% income share is negative,[15] but the panel VAR estimate from the model including also the GDP per capita and the interest rate is positive in all country groups. However, the parameter estimate of the top 1% income share is statistically significant only in Nordic countries and on the last estimation of the Anglo-Saxon countries.

Theories describing the relation between income inequality and savings usually concentrate on household savings behavior, which makes private savings or consumption a more valid measure to assess the effect of inequality on consumption or savings than gross savings that includes also the government. Table 4.7 presents the results of panel DSUR and panel VAR estimations where the dependent variable is private consumption.[16] According

[14]Estimation was conducted with Gauss. Author is grateful to Donggyu Sul and Joerg Breitung for providing the program codes on their homepages.

[15]If first equation is estimated with panel VAR, results are similar to those presented in table 4.6.

[16]Estimation was conducted with Gauss. Author is grateful to Donggyu Sul and Joerg Breitung for providing the program codes on their homepages.

Table 4.6: Estimates of the long-run elasticity of gross savings with respect to top 1% income share in 3 groups of countries

Dependent variable: log(gross savings)			
	Nordics	Central-Europe	Anglo-Saxon
Panel DSUR (l&l =2)			
log(top 1%)	-0.0846**	-0.127***	-0.4462
	(0.0288)	(0.0405)	(0.3706)
Panel VAR (lags=2;1;1)			
log(top 1%)	0.0799***	0.3794	0.2499
	(0.0251)	(0.2751)	(0.1769)
log(GDP)	0.0118***	0.0946***	0.0903***
	(0.0015)	(0.0100)	(0.0108)
Panel VAR (lags=2;1;2)			
log(top 1%)	0.5654*	0.1866	0.5385*
	(0.2512)	(0.2583)	(0.1990)
log(GDP)	0.1374***	0.0894***	0.0983***
	(0.0169)	(0.0097)	(0.0105)
log(interest)	-0.3655**	-0.0213	0.0990
	(0.1237)	(0.0477)	(0.0803)
countries	3	3	3
years	1960-03	1960-96	1960-00
observations	132	111	123

* = p<.05, ** = p<.01, *** = p<.001. Standard errors of the parameter estimates are presented in parentheses. Standard errors are estimated using Andrews and Monahan's Pre-whitening method. Inclusion of individual constants means that all estimations are made with fixed effects. Lags gives the lag order of the VAR model. L&l =2 means that first and second leads and lags of first differences of the explanatory variables are used as instruments.

Table 4.7: Estimates of the long-run elasticity of private consumption with respect to top 1% income share in 3 groups of countries

Dependent variable: log(private consumption)			
	Nordic	Central-Europe	Anglo-Saxon
Panel DSUR (l&l=2)			
log(top 1%)	-0.1107***	-0.1219***	-0.1260***
	(0.0097)	(0.0342)	(0.0325)
Panel VAR (lags=2;1;2)			
log(top 1%)	-0.1409**	-0.2101***	0.1130***
	(0.0490)	(0.0530)	(0.0290)
log(GDP)	0.0905***	0.1002***	0.0982***
	(0.0039)	(0.0026)	(0.0021)
Panel VAR (lags=1;1;2)			
log(top 1%)	-0.1349*	-0.1748***	0.0826***
	(0.0512)	(0.0451)	(0.0262)
log(GDP)	0.0919***	0.0996***	0.1007***
	(0.0042)	(0.0024)	(0.0021)
log(interest)	-0.0132	0.0203	-0.0383***
	(0.0262)	(0.0120)	(0.0108)
countries	3	3	3
years	1960-03	1960-96	1960-00
observations	132	111	123

* = p<.05, ** = p<.01, *** = p<.001. Standard errors of the parameter estimates are presented in parentheses. Standard errors are estimated using Andrews and Monahan's Pre-whitening method. Lags gives the lag order of the VAR model. Individual constants and trends are included in the regressions. L&l =2 means that first and second lags and leads of first differences of explanatory variables are used as instruments.

to the results, the cointegrating coefficient of the GDP per capita has the expected positive sign in all groups of countries, but the interest rate has a statistically significant negative effect only in the group of the Anglo-Saxon countries. The "blurry" estimate of interest rates in Central-European countries is not a surprise as these countries had differing indicators of interest rates. Among the Anglo-Saxon and Nordic countries, individual countries had the same indicator of interest rate within each group, but the indicators differed between the groups. In the Anglo-Saxon countries, the treasury bill rate was used, whereas in the Nordic countries, the central bank rate was used. Although it is surprising that the interest rate has no statistically significant effect on the level of private consumption in the Nordic countries, the result may also be explained by different consumption profiles. Bacchetta and Gerlach (1997) found that in the United States and Canada, the changes in credit conditions had a larger impact on consumption than in France or the UK. Humphrey (2004) also shows that credit cards are used more often as a means of payment in Canada and the US than in Europe. Thus, it is likely that changes in the interest rates have a greater effect on private consumption in the Anglo-Saxon than in the European countries.

According to the results of Table 4.7, the cointegrating coefficient of inequality is negative in all three country groups when the top 1% income share is the only explanatory variable. However, when the GDP per capita is added as an explanatory variable, the cointegrating coefficient of inequality changes to positive in the Anglo-Saxon countries. In the Nordic and Central-European countries the coefficient remains negative and statistically significant, thus indicating that these results are robust.

As such, the results imply that the long-run elasticity of private consumption with respect to inequality would be negative in the Nordic and Central-European countries, but positive in the Anglo-Saxon countries. Although this result is somewhat counterintuitive, it is, of course, always possible that the individual saving function is convex in the European countries and concave in the Anglo-Saxon countries. However, this contradicts the results of most theories and also some quite recent micro-econometric evidence from the US stating that propensity to save raises with income (Dynan *et al.* 2004). From these reasons some reservations need to be attached to the estimation results of the Anglo-Saxon countries.[17] It is, for example, possible that the cointegration rank differs among the Anglo-Saxon countries in estimations including the GDP per capita. In this case, the asymptotic properties of the panel VAR estimator derived under the assumption of homogenuous cointegration rank are no longer valid. Unfortunately, the time series dimension of individual countries is too small for meaningful country-specific testing of the cointegration rank. Thus, the ambiguity concerning the estimation results of the Anglo-Saxon countries has to be left to be addressed in future studies.

4.6 Conclusions

In this study we assessed the relationship between income inequality and savings using a panel of developed economies. We also tested the assumption presented in early theoretical literature on income variation that the size distribution of income could follow a random walk. According to the results, income inequality, measured with the logarithmic top 1% income share, logarithmic aggregate savings and logarithmic private consumption are driven by stochastic trends. The non-stationarity of the logarithmic top 1% income share implies that the current macroeconomic literature may have taken an erroneous stand by assuming a stationary process of income variation.

The results concerning cointegration between the top 1% income share and gross savings were contradictory as the series were found to be cointegrated by both of the used tests only in the Nordic countries. All tests found the top 1% income share and private consumption to be cointegrated, which indicates that there is a long-run *steady-state* relation between them. The long-run elasticity of private consumption with respect to inequality was found to be negative in the Central-European and Nordic countries, but positive in the Anglo-Saxon countries. This result implies that, in the

[17]To check that this result does not relate to the expansion of credit in the wake of growing inequality, we added the domestic credit claims on the private sector as an explanatory variable for Anglo-Saxon countries. The variable was found to be $I(1)$ according to all panel unit root tests mentioned in section three. The variable was obtained from IMF database. Adding a measure of credit did not change the main results for Anglo-Saxon countries and it has the expected statistically significant positive effect on private consumption.

Anglo-Saxon countries, the marginal propensity to save would decrease with income, while in the rest of the countries it would increase. However, estimation results for the Anglo-Saxon countries crucially depend on the inclusion of the GDP per capita series. When the GDP per capita was not included in the estimation, the parameter estimate of the top 1% income share was negative and statistically significant. Thus, it is possible that the inclusion of the GDP per capita series may introduce some form of bias in the estimation of Anglo-Saxon countries which cannot be controlled with current panel estimation methods.

One assumption that needs to be tested in the future is the assumption of homogenous cointegration rank among the Anglo-Saxon countries. If the cointegration rank has differed among the Anglo-Saxon countries in estimations including the GDP per capita, the estimates will have been biased. In this study, the individual country cointegration relations could not be tested, because testing would have required considerably more time series observations than were available in our dataset. For the Nordic and Central-European countries the observed positive effect of inequality on private savings seems robust. Estimation results were unchanged when either only the top 1% income share or the interest rate and the GDP per capita were also included as explanatory variables. This implies that even if the cointegration rank has differed within the groups of Nordic and Central-European countries in estimations with additional explanatory variables, this has not changed the basic results.

So, although the results for the Anglo-Saxon countries are somewhat inconclusive, the results for the Nordic and Central-European countries clearly indicate that income inequality leads to higher level of private savings. This result is well in-line with the theoretical and micro-econometric evidence. It also implies that the controversy surrounding the results of the previous empirical macroeconomic studies has been likely to result from miss-specification of the estimated models by assuming stationary income inequality.

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Appendix G

Panel cointegration test by Banerjee and Carrion-i-Silvestre (2006)

Panel cointegration test developed by Banerjee and Carrion-i-Silvestre (2006) is based on the normalized bias and the pseudo t-ratio test statistics by Pedroni (2004). The data generating process behind Pedroni's test statistics is given by:

$$\begin{aligned} y_{it} &= f_i(t) + x'_{it} + e_{it}, \\ \triangle x_{it} &= v_{it}, \\ e_{it} = \rho_i e_{i,t-1} + \epsilon_{it} \zeta_{it} &= (\epsilon_{it}, v_{it})', \end{aligned} \tag{G.1}$$

where $f_i(t)$ includes member specific fixed effects and deterministic trends.

The data generating process is described as a partitioned vector $z'_{it} \equiv (y_{it}, x_{it})$ where the true process is generated as $z_{it} = z_{i,t-1} + \zeta_{it}$, $\zeta'_{it} = (\zeta^y_{it} \zeta^X_{it})$ (Pedroni 2004). $\frac{1}{\sqrt{T}} \sum_{t=1}^{[Tr]} \zeta_{it}$ is assumed to converge to a vector Brownian motion with asymptotic covariance of Ω_i as $T \longrightarrow \infty$. The individual process is assumed to be $i.i.d.$ so that $E[\zeta_{it} \zeta'_{js}] = 0 \ \forall s, t, i \neq j$.

Let $\hat{e}_{it}$ denote the estimated residuals of obtained from (G.1) and $\hat{\Omega}_i$ the consistent estimator of Ω_i. The two test statistics can now be defined as :

$$\tilde{Z}_{\hat{\rho}_{NT}-1} \equiv \sum_{i=1}^{N}\left(\sum_{t=1}^{T}\hat{e}_{i,t-1}^{2}\right)^{-1}\sum_{t=1}^{T}(\hat{e}_{i,t-1}\Delta\hat{e}_{it}-\hat{\lambda}_i),$$
$$\tilde{Z}^{*}_{\hat{t}_{NT}} \equiv \sum_{i=1}^{N}\left(\sum_{t=1}^{T}\hat{s}_i^{*2}\hat{e}_{i,t-1}^{*2}\right)^{-1/2}\sum_{t=1}^{T}(\hat{e}^{*}_{i,t-1}\Delta\hat{e}^{*}_{it}),$$

where $\hat{\lambda}_i = 1/T\sum_{s=1}^{k_i}(1-s/(k_i+1))\sum_{t=s+1}^{T}\hat{\mu}_{it}\hat{\mu}_{i,t-s}$, $\tilde{\sigma}^2_{NT} \equiv 1/N\sum_{i=1}^{N}\hat{L}_{11i}^{-2}\hat{\sigma}_i^2$, $\hat{s}_i^{*2} \equiv 1/t\sum_{t=1}^{T}\hat{\mu}_{it}^{*2}$, $\tilde{s}_{NT}^{*2} \equiv 1/N\sum_{i=1}^{N}\hat{s}_i^{*2}$, $\hat{L}_{11i}^2 = 1/T\sum_{t=1}^{T}\hat{\vartheta}_{it}^2$
$+\,2/T\sum_{s=1}^{k_i}(1-s/(k-i+1))\sum_{t=s+1}^{T}\hat{\vartheta}_i,\hat{\vartheta}_{i,t-s}$. The residuals $\hat{\mu}_{it},\hat{\mu}_{it}^{*}$ and $\hat{\vartheta}_{it}$ are attained from regressions: $\hat{e}_{it} = \hat{\gamma}\hat{e}_{i,t-1}+\hat{\mu}_{it}$, $\hat{e}_{it} = \hat{\gamma}_i\hat{e}_{i,t-1}+\sum_{k=1}^{K-i}\hat{\gamma}_{ik}\Delta\hat{e}_{i,t-k}+\hat{\mu}_{it}^{*}$, $\Delta y_{it} = \sum_{m=1}^{M}\hat{b}_{mi}\Delta x_{mi,t} = \hat{\vartheta}_{it}$. (Pedroni 1999, 2004)

The statistics pool the between dimension of the panel and they are constructed by computing the ratio of the corresponding conventional time series statistics and then by computing the standardized sum of the N time series of the panel. Pedroni (1999, 2004) shows that under the null of no cointegration the asymptotic distributions of the two statistics presented above converge to normal distributions with zero mean and variance of one as N and T sequentially converge to infinity.

Banerjee and Carrion-I-Silvestre (2006) extend the model by Pedroni (2004) to include common factors:

$$\begin{aligned} y_{i,t} &= f_i(t) + x'_{i,t} + u_{i,t}, \\ \triangle x_{i,t} &= v_{i,t}, \\ f_i(t) &= \mu_i + \beta_i t \\ u_{it} &= F'_t\pi_i + e_{it} \end{aligned} \tag{G.2}$$

where $e_{i,t} = \rho_i e_{i,t} + \epsilon_{i,t}$ and F'_t:s are the common factors which are used to account for the possible cross-sectional dependence.

Appendix H

Panel trace cointegration test statistic by Larsson and Lyhagen (2007)

The trace cointegration test by Larsson and Lyhagen (2007) is based on the following model:

$$\triangle Y_t = \mu + \Pi Y_{t-1} + \Sigma_{k=1}^{m-1} \Gamma_k \Delta Y_{t-k} + \epsilon_t, \tag{H.1}$$

where $\mu = (\mu_1', \mu_2', ..., \mu_N')'$, $\epsilon_t = (\epsilon_{1t}', \epsilon_{2t}', ..., \epsilon_{nt}')$, Y_{t-1} and ΔY_{t-k} are of order $Np \times 1$, Π and Γ_k are $Np \times Np$, and ϵ_t is assumed to be multivariate normally distributed with mean zero and covariance matrix Ω_{ij}.

It is assumed that matrix Π has a reduced rank of Nr, $0 \leq r \leq p$, which is specified as $\Pi = \alpha_{ik}\beta_{kj}'$ (Larsson and Lyhagen 2007). Matrices α and β are both order of $Np \times Nr$ and the former contains the short-run coefficient and the latter the long-run coefficient. In β, $\beta_{ii} \equiv \beta_i$ for each rank of r. Because of the restriction, $\beta_{kj} = 0 \ \forall i \neq j$, the block matrix elements of Π are given by $\Sigma_{k=1}^{N} \alpha_{ik}\beta_{kj}' = \alpha_{ij}\beta_j'$.

The cointegration rank is estimated by sequentially testing

$$H(r) : rank(\Pi) \leq Nr \tag{H.2}$$

against the alternative

$$H(p) : rank(\Pi) \leq Np, \tag{H.3}$$

which is the same method as in Johansen (1995).

Define Q_T as the maximum likelihood ratio test statistic for the test of $H(r)$ against $H(p)$, and assume that the matrix $\alpha' \perp \Gamma\beta \perp$ has a full rank and that the roots of the characteristic polynomial

$$A(z) = (1 - z)I_{Np} - \alpha\beta' z - \Sigma_{i=1}^{m-1}\Gamma_k(1 - z)zi \tag{H.4}$$

lie outside the complex unit circle. Now, if $r > 0$,

$$\text{-2 } \log Q_t \xrightarrow{w} U + V, \tag{H.5}$$

as $T \longrightarrow \infty$, where V is χ^2 with $N(N-1)r(p-r)$ degrees of freedom independent of U, and

$$U = tr\left\{\int dBF'\left(\int FF'\right)^{-1}\int F\mathrm{d}B'\right\}. \tag{H.6}$$

Larsson and Lyhagen (2007) show that the limit distribution of the test statistic (H.5) equals the convolution of Dickey-Fuller distribution (B) and an independent χ^2 variate (F). The distribution can be simulated by approximating the Wiener process of B by a random walk.

Appendix I

Panel DSUR and Panel VAR estimators

I.1 Panel DSUR estimator by Mark *et al.* (2005)

The data generation process in Mark *et al.* (2005) DSUR estimator is of the form

$$y_{it} = \alpha_i + \lambda_i t + \theta_t + \beta' x_{it} + u_{it}, \tag{I.1}$$

$$\triangle x_{it} = e_{it} \tag{I.2}$$

where there are n cointegrating regression each with T observations, $(1 - \beta')$ is the cointegration vector between y_{it} and x_{it}, and x_{it} and e_{it} are $k \times 1$ dimensional vectors. Panel DSUR eliminates the possible endogeneity between explanatory variables and the dependent variable by assuming that u_{it} is correlated at most with p_i leads and lags of $\triangle x_{it}$ (Mark *et al.* 2005). The possible endogeneity can be controlled by projecting u_{it} onto these p_i leads and lags:

$$u_{it} = \sum_{s=-p_i}^{p_i} \delta'_{i,s} \triangle x_{i,t-s} + u_{it}* = \delta'_i z_{it} + u^*_{it}. \tag{I.3}$$

The projection error u^*_{it} is orthogonal to all leads and lags of $\triangle x_{it}$ and the estimated equation becomes:

$$y_{it} = \alpha_i + \lambda_{it} + \theta_t + \beta' x_{it} + \delta_i z_{it} + u^*_{it}, \tag{I.4}$$

where $\delta'_i z_{it}$ is a vector of projection dimensions. Panel DSUR estimates a long-run covariance matrix that is used in estimation of equation (I.1). This makes panel DSUR more efficient when cross-sections are dependent. The efficiency of panel DSUR actually improves as the correlation between cross-sections increases. Asymptotics properties of the estimator are based on $T \longrightarrow \infty$ with N fixed.

I.2 Panel VAR estimator by Breitung (2005)

Breitung (2005) proposes a panel VAR(p) model which can be presented as a panel vector error-correction model (VECM) as

$$\triangle y_{it} = \psi_i d_t + \alpha_i \beta'_{y,t-1} + \Sigma_{j=1}^{p-1} \Gamma_{ij} \triangle y_{i,t-j} + \epsilon_{it}, \tag{I.5}$$

where d_t is a vector of deterministic variables and ψ_i a $k \times k$ matrix of unknown coefficients, Γ_{ij} is unrestricted matrix, and ϵ_{it} is a white noise error vector with $E(\epsilon_{it}) = 0$ and positive definite covariance matrix $\Sigma_i = E(\epsilon_{it}\epsilon'_{it})$. The model is estimated in two stages. First, the models are estimated separately across N cross-section units. Then cointegration vectors are normalized so that they do not depend on individual specific parameters. Second, the system is transformed to a pooled regression of the form:

$$\hat{z}_{it} = \beta' y_{i,t-1} + \hat{v}_{it}, \tag{I.6}$$

where $\hat{z}_{it} = (\hat{\alpha}'_i \hat{\Sigma}_i^{-1} \hat{\alpha}_i)^{-1} \hat{\alpha}'_i \hat{\Sigma}_i^{-1} \triangle y_{it}$ and $\hat{v}_{it}$ is defined in similar fashion. The cointegration matrix, β, can now be estimated from (I.6) using the OLS estimator. It is assumed that the statistical units included in the panel have the same cointegration rank. Consistent estimation is based on sequential limits. Cross-sectional correlation is accounted by using an estimated asymptotic covariance matrix.

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