JYU DISSERTATIONS 403

Toni Juuti

Essays on the Relationship Between Income Inequality and Economic Growth

JYVÄSKYLÄ UNIVERSITY
SCHOOL OF BUSINESS
AND ECONOMICS

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ABSTRACT

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This doctoral dissertation studies the relationship between income inequality and economic growth. It adds to the literature by incorporating the division of income between capital and labor into the analysis, by evaluating the role of financial conditions, by acknowledging country-specificity, by closely examining popular estimation techniques, and by adopting multiple measures of inequality. The dissertation comprises an introductory chapter and five studies. The first four are empirical, while the fifth contains both empirical and theoretical analyses.

The first essay documents how results on the association between income inequality and subsequent per capita GDP growth depend on estimation technique. Specifically, accounting for country-specific unobservable characteristics explains many of the negative associations obtained using techniques that ignore them. It is also found that GMM techniques are not effective in disentangling causation from correlation.

The second essay tests the prevalence of financial development as a determinant of the inequality-growth relationship. A multi-dimensional measure of financial development is adopted, and the results imply that promoting the development of financial markets may alleviate the adverse effects of income inequality on economic growth in under-developed countries.

Unlike the first two essays, which rely on cross-country panel data, the third focuses on individual countries. Clear differences between countries are documented, and evidence is found for the proposition that economic growth responds asymmetrically to fluctuations in inequality.

The fourth essay introduces data on capital shares and shows that shares are integrated between countries. In all sample countries, changes in capital shares are mainly driven by a single latent factor. In most of the countries, the factor is correlated with both trade openness and total factor productivity.

The fifth essay shows that, as a matter of both empirics and theory, the association between top income shares and growth is positive when the capital share of income is low and negative when the capital share of income is high. The empirical regularity emerges from historical data. The theoretical analysis stresses the importance of precautionary saving motives and consumption smoothing.

Keywords: Income inequality, top income shares, economic growth, panel data, GMM estimators, financial development, cross-country integration, functional income distribution, capital share

TIIVISTELMÄ

Juuti, Toni
Taloustieteellisiä tutkimuksia tuloerojen ja talouskasvun välisestä yhteydestä
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Väitöskirjassa tutkitaan tuloerojen ja talouskasvun välistä suhdetta. Aiempaa kirjallisuutta täydennetään sisällyttämällä tarkasteluun tulojen jakautuminen työ- ja pääomatulojen kesken, arvioimalla rahoitusolosuhteiden merkitystä, huomioimalla maakohtaiset tekijät, tutkimalla suosittujen tilastollisten menetelmien ominaisuuksia ja käyttämällä useita tuloeromittareita. Väitöskirja koostuu johdantoluvusta ja viidestä tutkimuksesta, joista neljä ensimmäistä ovat empiirisiä ja viides sisältää sekä empiiristä että teoreettista analyysia.

Ensimmäinen tutkimus osoittaa, kuinka tuloerojen ja talouskasvun välinen yhteys riippuu käytetyistä tilastollisista menetelmistä. Maakohtaisten havaitsemattomien tekijöiden huomioiminen selittää pitkälti nämä tekijät sivuuttavien menetelmien tuottaman negatiivisen estimoidun yhteyden. Syy-seuraussuhteen erotteleminen tilastollisesta yhteydestä osoitetaan vaikeaksi.

Toinen tutkimus arvioi rahoitusmarkkinoiden ja -instituutioiden roolia tuloerojen ja talouskasvun välistä suhdetta mahdollisesti määrittävänä tekijänä. Tutkimuksen tulosten mukaan rahoitusmarkkinoiden kehittyneisyys näyttää heikentävän tuloerojen talouskasvua haittaavaa vaikutusta matalan tulotason maissa.

Toisin kuin kaksi ensimmäistä tutkimusta, jotka nojaavat useita maita kattaviin paneeliaineistoihin, kolmas tutkimus keskittyy yksittäisiin maihin. Sen lisäksi, että maakohtaiset erot osoittautuvat merkittäväksi, talouskasvun havaitaan olevan eri tavalla yhteydessä laskeviin ja nouseviin tuloeroihin.

Neljäs tutkimus esittelee aineiston pääoman tulo-osuuksista, ja osoittaa, että tulo-osuudet ovat integroituneita maiden kesken. Muutokset tulo-osuuksissa ovat pääosin yhden yhteisen latentin tekijän ajamia kaikissa otoksen maissa. Tekijä on korreloitunut kansainvälisen kaupan määrän ja kokonaistuottavuuden kanssa useimmissa maissa.

Viides tutkimus osoittaa sekä teoreettisesti että empiirisesti, että tuloerojen ja talouskasvun välinen suhde on positiivinen pääoman tulo-osuuden ollessa matala. Pääoman tulo-osuuden ollessa korkea suhde on negatiivinen. Empiirinen tulos nojaa historialliseen aineistoon, kun taas teoreettinen analyysi korostaa varautumissäästämisen ja kulutuksen tasoittamisen merkitystä.

Asiasanat: Tuloerot, ylimpien tuloluokkien tulo-osuudet, talouskasvu, paneeliaineisto, GMM-estimaattorit, rahoitusinstituutioiden ja -markkinoiden kehittyneisyys, maiden välinen integraatio, funktionaalinen tulonjako, pääoman tulo-osuus

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I want to thank my pre-examiners Professor Jukka Pirttilä and Professor Daniel Waldenström for helpful comments. Granted, the received praise was heart-warming, but more importantly, your insightful ideas helped me to clarify the message I wished to deliver in several crucial sections below. I also owe gratitude to Professor Vance Martin for helping me to visit the IMF, for guidance on research and for showing that doing high-quality research does not have to be deadly serious. The latter also applies to my current collaborators Jarkko Harju, Tuomas Matikka and Tuomas Kosonen. Moreover, although our ongoing projects share little resemblance with this dissertation, working with you has helped me to identify the strengths and weaknesses of the essays below and to integrate them with the relevant economic literature.

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Thanks also go to my parents, Tiina and Jouko, and sister, Mari. Thank you for trusting me and letting me make my own decisions, and being there for me if I needed support. I also want to thank my parents-in-law, Juha and Hannele, for your support during the past few years.

In a way, the roots of this dissertation can be traced back to September 2016 when I started to work on my Master's thesis. This is by far the most important month of my life. Certainly not because of the first uncertain steps in the realm of economic research, but because I met you, Susanna. These past years have been the best ones of my life. And I think it's getting better day by day.

Espoo, June 2021
Toni Juuti

CONTENTS

1 INTRODUCTION

This doctoral dissertation comprises five empirical essays. In broad terms, I investigate the association between income inequality and economic growth. The two essays that follow the introductory chapter deploy common panel regression techniques. The focus of the first essay is on revealing patterns that are associated with different estimators and inequality measures. In the second essay, financial development is introduced as a mechanism that potentially affects the inequality-growth relationship. The third essay takes a different route by focusing on individual countries. It examines positive and negative changes in inequality separately. The fourth essay introduces data on functional income distribution, that is, the division of income between labor and capital, and it analyzes cross-country integration on this dimension of income distribution. The last essay inquires whether functional income distribution influences the inequality-growth relationship.

Although the essays are empirical, the results are interpreted in terms of theoretical mechanisms. The last essay goes further and provides a macroeconomic model to complement the empirical findings. The title of the dissertation refers to a relationship between inequality and growth rather than an effect to avoid the appearance of false claims about causality. The first four essays are single-authored. The last is co-authored with my supervisors, Professor Kari Heimonen and Professor Juha Junttila, and PhD candidate Teemu Pekkarinen (University of Helsinki, Helsinki Graduate School of Economics).

1.1 Background

Economic inequality lies at the core of sociopolitical discourse and public debate. In the first two decades of the new millennium, much was written about the richest percentile and top earners to adduce of the rise of inequality. As I am writing this dissertation, the economic impacts of the COVID-19 pandemic and the best policy responses are the subject of a heated debate alongside the imme-

diate health concerns. Much of the economic discussion rightly focuses on means to support those who suffer the most from travel restrictions, restaurant closures, mass event cancellations and other measures that aim to contain the virus. Fundamentally, these debates are closely related to what we see as just. Is it fair that the top percentile of the population earns a fifth of the total income? What should the state do when a restaurant manager loses their livelihood because people are told to stay at home while a PhD candidate can continue working from home?

Although inequality is debated intensily, the concept of economic inequality is ambiguous. The first important distinction is between equality of opportunity and inequality of outcome. Anthony Atkinson (2015) aptly pointed out that the two are intimately connected. Inequality of outcome should matter even for those who start from the premise of a level of playing field. First, chance plays a significant role in outcomes for individuals. Unequal outcomes would not be determined solely by individual effort even if there was complete equality of opportunity. Second, inequality of outcome affects equality of opportunity for the next generation directly. Third, our social and economic arrangements determine the income structure, which tends to be associated with high-income positions at the top. Atkinson argues that the unequal distribution of income leads us to attach considerable weight to equality of opportunity.

Inequality of outcome is not a clear-cut concept, either. Typically, economists are interested in wealth, income, wages and consumption. Theoretical work usually emphasizes wealth inequality, while data that are gathered from either household surveys or tax records predominantly concern income. Consequently, empirical studies of economic inequality are often studies of income inequality. By now, it must have become clear to the reader that income inequality is also a multi-dimensional concept. Many measures of inequality exist. Income can be calculated for individuals, households, or some other population category, and the data can cover income before or after taxes and transfers. Moreover, inequality may be defined in terms of either absolute or relative differences in income, consumption and wealth: if the incomes of all individuals or households are doubled, relative income inequality would remain unchanged and absolute differences in income would increase.

Inequality of income can also be examined globally, within countries, or between countries. The adoption of a global scale involves comparing all individuals in the world and thus accounts for within-country and between-country income differences. Measuring within-country inequality requires well-off Finns or Americans to be compared to low-income individuals in Finland and in the United States, respectively. Finally, if the average incomes of different countries are compared to each other, the results capture inequality between countries. In this dissertation, inequality refers to relative inequality within countries unless stated otherwise.

As mentioned above, economic inequality is often interpreted in terms of justice. In other words, equality has intrinsic value. One of the fundamental elaborations on the theme is by John Rawls (1971). In his view, society should emphasize the position of the worst off and only permit inequalities if the least

fortunate are better off than they would be under equal distribution.

Instead of approaching social justice from the perspective of political philosophy, this dissertation studies the consequences of inequality empirically. Namely, I analyze the relationship between income inequality and economic growth. That relationship has fascinated economists since the birth of the discipline. As early as the 18th century, Adam Smith recognized that inequality may affect overall economic activity through various mechanisms. He identified a trickle-down channel: wealth at the top of the distribution can benefit the rest of the society. He also argued that a certain level of inequality supports productivity. However, as documented by Dennis Rasmussen (2016), Smith's views are not as one-sided as his reputation as the father of capitalism might suggest. For example, he also saw that extreme inequality leads people to sympathize with the rich at the expense of the poor, which harms both morality and happiness.

The formal study of the transmission channels of the effect of inequality on economic growth was launched when the notion of a convex savings function emerged. Described in brief, it denotes the idea that because rich save more, inequality is positively associated with aggregate savings and the accumulation of capital, which eventually enhances economic growth (Kaldor, 1957; Bourguignon, 1981). Starting in the 1990s, a new wave of studies introduced many mechanisms ranging from sociopolitical instability to human capital accumulation and fertility (Alesina and Perotti (1996), Galor and Zeira (1993), Galor and Moav (2004) and De La Croix and Doepke (2003), to name but a few.). In the main, these models posited that economic inequality dampens growth. Following the resurgence of theoretical interest and advances in data availability and estimation techniques, a large body of empirical studies has accumulated. In this dissertation, I build on these studies, and I aim to complement the literature on three fronts: the methods that were used previously, introducing new empirical techniques, and proposing new mechanisms and new methods for evaluating them.

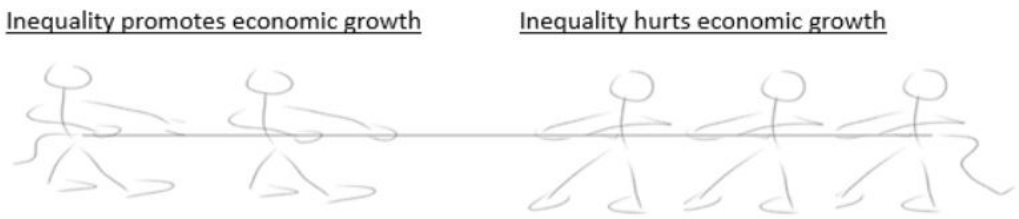

FIGURE 1.1 Underlying mechanisms of the inequality-growth relationship

Figure 1.1 depicts the literature on the inequality-growth relationship (often labeled the equity-efficiency relationship) as a tug-of-war. In this illustration, theoretical studies are agents that recruit individual contestants. The empirical literature can be divided into two branches. Some studies have emphasized the result of the contest and sought to obtain parameter estimates typically using panel growth regressions. Others have focused on the strength of individual contestants by aiming to validate suggested mechanisms empirically. The former try to identify a winner, while the latter inquire into the contribution of each contestant. In this dissertation, I am primarily interested in the "who won?" question.

The answer depends on the circumstances of the contest. At the same time, I interpret the results in terms of the underlying mechanisms, and test for their relevance.

The opposite direction of causality in the inequality-growth relationship is also widely studied. The hypothesis raised by Simon Kuznets (1955) has had a lasting impact on economics. According to Kuznets, economic inequality increases as a country develops and then declines after a certain level of economic development is reached. More recently, Thomas Piketty (2014) has suggested that the long-run evolution of inequality depends on the relationship between the rate of economic growth and return on capital. Both contributions have excited tremendous interest. However, these studies, as well as other notable works on the topic, are not presented in detail. Rather, in this dissertation, I seek to improve the academic understanding of the question whether income inequality matters for overall economic activity.

The empirical studies of the inequality-growth nexus have yielded divergent results over the years. In their meta-analysis, Pedro Cunha Neves, Óscar Afonso, and Sandra Tavares Silva (2016) reviewed 28 studies that were published between 1994 and 2014. The first wave of studies relied on a cross-sectional data structure. More recently, researchers have predominantly used panel data and started to apply techniques (variants of generalized method of moments, GMM) that aim to separate causation from correlation. Perhaps the most interesting finding of the meta-analysis is evidence of publication bias. Statistically significant results are reported and published more frequently. In addition, positive and negative estimates tend to be reported cyclically. The findings suggest that estimation techniques, data quality and specification choices for the growth regression are not significant drivers of the varying estimates. Instead, cross-sectional analyses tend to find stronger negative associations than panel studies. The negative association is stronger in less developed countries, the inclusion of regional dummies soaks up most the previous findings, and the concept of inequality affects the results significantly.

Without belittling the numerous empirical studies on the topic, few have made a particularly strong impact. The cross-sectional studies by Alberto Alesina and Dani Rodrik (1994) and Roberto Perotti (1996) found evidence that inequality hurts growth. Robert Barro's (2000) findings suggested that the association between inequality and growth is negative for low levels of economic development and positive for high ones. Abhijit Banerjee and Esther Duflo (2003) showed that changes in inequality, whatever their direction, are associated with lower subsequent growth rates. Sarah Voitchovsky (2005) found that inequality at the top end of the income distribution supports economic activity, while inequality at the bottom dampens growth. Daniel Halter, Manuel Oechslin and Josef Zweimüller (2014) focused on the time dimension and found that inequality supports growth in the short-run but is harmful for longer-term economic performance. Jonathan Ostry, Andrew Berg and Charalambo Tsangarides (2014) studied both inequality and redistribution. Their results suggest that inequality has an adverse impact on growth when redistribution is controlled for. At the same time, redistribu-

tion does not appear to hinder growth. It is safe to say that no clear consensus emerges.

The Gini coefficient is by far the most common measure of inequality in the empirical literature. However, the most extensively discussed inequality patterns are based on the top income shares (Piketty, 2014) rather than broader measures, such as the Gini. Few studies have analyzed the relationship between top income shares and growth. Barro (2000) investigated whether his results held between different measures. The findings of Dan Andrews, Christopher Jencks and Andrew Leigh (2011) suggested that during the latter half of the 20th century, the top 10 % income share was positively associated with subsequent growth. Dierk Herzer and Sebastian Vollmer (2013) focused on the level of per capita GDP and found that rising top income shares have negative repercussions for economic development. The findings of Stefan Thewissen (2014) are similar to those of Andrews, Jencks and Leigh. In Finland, Tuomas Malinen (2011) and Elina Tuominen (2015) analyzed the theme in their doctoral dissertations.

The dominance of the panel studies over some papers that have focused on specific countries (Gobbin and Rayp, 2008; Risso et al., 2013) is natural: the data on inequality are scarce, and pooling data from many countries is understandable. However, for a small group of countries, tax-record data permit country-specific patterns to be analyzed over more than just a few decades. My verdict is that these sources have not been fully utilized yet.

1.1.1 Theoretical mechanisms

Numerous mechanisms have been suggested to explain why economic inequality may affect overall economic activity. The conventional view is that inequality is good for incentives and, consequently, for economic growth. Another traditional argument is that because the savings rate of the rich is higher than that of the poor, more unequal economies tend to save more and experience faster economic growth (Kaldor, 1957; Bourguignon, 1981). Hereafter, I will use the term convex savings function argument to refer to this notion. In the absence of sufficiently developed financial markets and institutions, some level of inequality is needed for entrepreneurial individuals to cover the set-up costs for a new firm. Thus, according to this argument, inequality may be good for growth.

As pointed out by Philippe Aghion, Eve Caroli and Cecilia Garcia-Penalosa (1999), development economists have long presented informal counterarguments to the views that inequality enhances growth. Starting in the 1990s, numerous authors developed these arguments into theoretical models. One of the most influential models is that constructed by Oded Galor and Joseph Zeira (1993): under credit frictions, individual-level investment in human capital is determined by inherited wealth. Consequently, inequality dampens aggregate-level human capital accumulation and economic growth. Together with Omer Moav (2004), Galor developed a model whereby human capital replaces physical capital as a primary growth engine. In the early stages of development, when the accumulation of physical capital drives growth, the convex savings function argument

dominates, and inequality is growth-enhancing. Later, the Galor-Zeira channel assumes a dominant role, and inequality is bound to decelerate growth.

Leaky buckets and sociopolitical instability denote two additional channels through which inequality may hurt growth. In brief, the leaky bucket metaphor posits that due to the necessity of redistribution, higher inequality leads to higher taxation and lower economic growth. The idea of a leaky bucket was introduced by Arthur Okun (1975): "The money must be carried from the rich to the poor in a leaky bucket. Some of it will simply disappear in transit, so the poor will not receive all the money that is taken from the rich." The concept was developed further by Alberto Alesina and Dani Rodrik (1994) and by Torsten Persson and Guido Tabellini (1994). The role of sociopolitical instability was formalized by Alesina and Roberto Perotti (1996), who argued that by fueling social discontent, inequality induces instability, which is harmful for investments and overall economic activity. Many other mechanisms have been suggested. In my judgement, the ones presented here are the most influential. They thus suffice to provide a simple yet illustrative conceptual setting for this dissertation.

1.1.2 Data

In the essays that follow, I make use of several data sources and various measures of income inequality. Their use is not limited to the analyses that are developed in the essays. Instead, whenever it is possible, I provide a set of measures to ensure that the results are not driven by the chosen statistical concept.

Social scientists use household surveys and tax records as data sources in empirical studies of income inequality. The main advantage of surveys over tax records is that while tax data include only those who pay income tax, surveys capture the left tail of the income distribution. This distinction is particularly important in poor countries, where the coverage of the tax system is incomplete. However, there is evidence that surveys may not capture the top incomes adequately. This may be due to under-reporting and refusal to take part in surveys[1]. Another distinction between the two sources is that the surveys typically cover a larger number of countries than tax data, whereas the measures that build on tax records are superior to surveys if one wishes to track long-run patterns in inequality. Moreover, tax data typically corresponds to income before taxes and transfers, while surveys often incorporate data on pre-tax and pre-transfer income, disposable income and consumption. Finally, surveys can often be used to calculate statistical measures that correspond to the full income distribution, whereas the tax data with the best coverage provide information on the income shares of the top earners.

The main survey source used in this dissertation is the fourth version of the World Income Inequality Database (WIID), which is maintained by the United Nations University World Institute for Development Economics Research (UNU-WIDER, 2018). It is a secondary database that combines information from several

[1] See Burkhauser et al. (2012) for the US and Burkhauser et al. (2018) for the UK.

sources[2]. The data that are estimated from national tax records and cover long time spans originate from the World Inequality Database (World Inequality Lab, 2020, WID).

The measures of inequality covered in this dissertation are the Gini coefficient and various income shares. The latter are also used as ratios. Following the conceptualization of Amartya Sen (1973), these measures are objective. However, distilling the income distribution into a single number necessarily entails normative choices as well. Other measures – such as the Atkinson index or the Theil index, which are not covered in this dissertation – take an explicit normative stand that is rooted firmly in a particular position on welfare.

The Gini coefficient, named after the Italian statistician Corrado Gini, is probably the most widely-used measure of income inequality. It measures inequality from 0 to 1 (or 0 to 100). A value of 0 denotes perfect equality and 1 indicates that a single individual has all the income. It is well-known that two income distributions that are quite different from another can yield the same Gini coefficient. This property is largely due to the fact that the Gini places a heavy weight on the middle of the distribution, where the incomes tend to be stable relative to the tails of the distribution.

The top income shares – popularized by Thomas Piketty (2014) – emphasize the relative incomes of the top earners. These measures not only highlight evolutions in the right tail but also portray patterns in income inequality over a very long-run for some countries because the shares are estimated from historical tax records. The Palma ratio makes use of data on income shares in a different way. It is based on the observations of Gabriel Palma (2006, 2011), who noticed that the middle-income groups from the fifth decile to the ninth tend to capture roughly half of total national income in a large, heterogeneous group of countries. Meanwhile, the division of the other half of the total income varies substantially between countries. Thus, the Palma ratio (top 10 % income share / bottom 40 % income share) may be a more relevant measure of income inequality than the Gini coefficient as argued by a group of researchers (Cobham et al., 2013), who ask whether "the Gini should be put back in the bottle". Other ratios, similar to the Palma, are used in the first essay.

In the two last essays, I use a historical data set on the division of income between labor and capital compiled by Erik Bengtsson and Daniel Waldenström (2018). The data set contains capital shares, both gross and net of capital depreciation, and the top income shares for the highest-earning 10 %, 1% and 0.1 %. The top income shares can be traced back to the WID.

The data on GDP are taken either from the Penn World Table database (Feenstra et al., 2015, PWT) or from the Maddison project (Bolt et al., 2018) if data prior to 1950 are needed. Other variables that are used to complement the analysis are not covered here. The essays provide information about these variables

[2] The Organisation for Economic Co-operation and Development (OECD), The EU-Statistics on Income and Living Conditions (EU-SILC), The Luxembourg Income Study (LIS), The World Bank, The Socio-Economic Database for Latin America and the Caribbean (SEDLAC), national statistical offices and independent research papers.

and the data sources.

1.1.3 Methods

The bulk of the empirical literature on the relationship between inequality and economic growth has relied on panel data, and thus, on panel regression techniques. In this dissertation, all essays except the fourth use at least some of these techniques. The simplest estimator builds on ordinary least squares (OLS), and as the data is pooled from many countries, it is labeled as pooled OLS (POLS). This involves ignoring the panel structure and leaving unobservable country-specific characteristics unaddressed, which necessitates the introduction of a serially correlated error term.

The random effects (RE) estimator can be used to secure efficiency gains on the POLS. However, both the POLS and the RE assume that the unobservable country-specific effects are not correlated with the explanatory variables. If inequality is largely driven by unobservable institutional traits, the assumption is quite restrictive. An alternative approach is to rely on a technique that makes no such assumption by removing the unobserved characteristics. This estimator is known as the fixed effects (FE) estimator. Using the FE also comes at a cost: it sweeps away all the variables that are constant in time, which may pose concerns even with variables that evolve slowly, such as income inequality.

The econometric specifications in this dissertation are dynamic, that is, I include per capita GDP in the growth regressions as an explanatory variable. This introduces additional bias to the POLS, RE and FE estimates, although for the FE, consistency depends on the number of observations in the time dimension (Nickell, 1981). For panels that consist of few time periods and many countries, variants of generalized method of moments (GMM) estimators can be used to address dynamic panel bias, reverse causality and omitted variables. These estimators use suitably lagged variables as instrument variables. The estimator that is commonly labeled as the difference GMM utilizes only variation in time, similarly to the FE, while the so-called system GMM uses both within-country and between-country variation, like the POLS and the RE.

As demonstrated in the first essay, and previously by Bazzi and Clemens (2013) and Kraay (2015), the GMM estimators should not be viewed as a remedy to the enmeshment of causation and correlation. Consequently, the empirical results on the inequality-growth nexus should not be over-interpreted. Discussions should center on associations rather than effects, whatever the stylistic implications.

In the third essay, I focus on individual countries instead of a panel data set. I adopt an approach where the relationship between the top income shares and the growth of per capita GDP is augmented by the lagged first-differences of both variables to capture the data generating process. Models of this type are called autoregressive distributed lag models. Furthermore, I make a distinction between positive and negative changes in inequality. In the fourth essay, where I introduce the data on functional income distribution, the objective is not to investigate the

consequences of inequality for growth. Instead, I employ principal component analysis to inquire whether capital shares of total national income are integrated in a sample of developed countries.

1.1.4 Research questions

The objectives of the essays in this dissertation span from analyzing the properties of popular panel estimation techniques and various measures of inequality to revealing country-specific patterns and novel drivers of the inequality-growth relationship. The emphasis of the dissertation is empirical. Here, only the research questions for each essay are listed. Section 1.2 below offers overviews of the five essays.

In the first essay, I evaluate how the results of reduced-form panel growth regressions depend on the various choices that an empirical researcher must face. Is the relationship between inequality and growth sensitive to the measure of income inequality? Do the results vary if imputed values that allow for larger number of observations are used instead of actual surveys? Does the relationship depend on the level of inequality or the level of economic development? Is the relationship different in developed economies and in poor countries? Do the results vary between different estimation techniques, and more specifically, are the results conditional on the choice between using variation in time alone and combining with between-country variation? What should we think about the widely-used system GMM estimator? Is it an improvement to the simple standard techniques or should we take the results with a pinch (or two) of salt? How do the mechanisms suggested by earlier theoretical work contribute to the results?

Much of theoretical literature on the relationship between inequality and growth emphasizes the role of credit frictions. In the second essay, I adopt a multi-dimensional measure of financial development to bridge the gap between theory and empirical work. Is the inequality-growth relationship conditional on the level of financial development? Should a distinction be drawn between financial institutions and markets, or does it suffice to focus on aggregate development? Proceeding even further, should we disentangle the sub-components, labeled as access, depth and efficiency, from one another? Is the relationship different in developed economies and in poor countries? Like in the entire dissertation, are the results robust to different inequality measures and different estimation techniques?

The third essay takes a different route by focusing on individual countries. The empirical strategy allows for the growth of per capita GDP to have asymmetric responses to rising and falling inequality. Is there evidence that growth responds asymmetrically to positive and negative changes? What is the magnitude of the responses, and how does adjustment to the new equilibrium unfold? How quick is the adjustment process? What are the potential transmission channels? Do different countries show uniform patterns, or rather, is the relationship characterized by cross-country heterogeneity? What do previously used panel

techniques suggest when up-to-date data are used?

In the fourth essay, I introduce the concept of functional income distribution, that is, the division of income between capital labor, and analyze the macroeconomic inter-dependencies between the capital shares of total national income in a group of developed countries. Is it sufficient to examine simple correlations and plotted time series? Specifically, are the country-specific capital shares driven by the same underlying factors in the absence of limited correlational and graphical evidence?

In the last essay, my co-authors and I introduce functional income distribution as a potential determinant of the relationship between inequality and growth. Does the association between inequality and growth depend on the capital share of total national income when historical data is analyzed? How can we use theory to build a bridge between empirically observed regularities and underlying mechanisms? Does accounting for financial frictions affect the results?

1.2 Overview of the essays

The first four essays of this dissertation are single-authored – I am responsible for the formulation of the research problem, contextualizing the research to previous literature, the chosen econometric framework, data retrieval, data analysis, interpretation of the findings and writing in each of the four essays. I acknowledge the help I received in the title page of each chapter below. In the fifth essay, which is jointly written with Kari Heimonen, Juha Junttila and Teemu Pekkarinen, I am the main author. More precisely, I am the main liaison in the following elements: previous literature, the chosen econometric framework (research design), data retrieval, data analysis and writing. I am one of the main liaisons in the formulation of the research problem and interpretation of our findings. My role is auxiliary, but not negligible, in the theoretical analysis of the study.

1.2.1 Essay 1: Inequality and Economic Growth: Different Panel Estimators and Various Measures of Income Inequality

This essay lays the foundation for the dissertation by illustrating the choices that an empirical researcher faces in studying the interplay between inequality and growth. The sensitivity of the results to these choices is investigated in detail. What remains fixed is the data source: the fourth version of the survey-based World Income Inequality Database (WIID) is used (UNU-WIDER, 2018). These data enable me to compare results between various measures of income inequality. I pool data from 103 countries, of which 34 are OECD members.

First, different estimation techniques yield different results. After controlling for unobserved time-invariant country-specific characteristics, and bias stemming from model dynamics and the endogeneity of the explanatory variables (sGMM), the estimated association between income inequality and subsequent

economic growth is predominantly negative but statistically insignificant across the different specifications. Moreover, the technique is found to suffer from identification issues. Therefore, it is unclear whether it is an improvement on a simpler class of estimators. The lack of statistical significance equally holds for simpler techniques that also account for country-specific unobservable characteristics (FE and dGMM). Conversely, assuming that these characteristics are not correlated with the explanatory variables (POLS and RE) – meaning that inequality is not assumed to be driven by unobserved country-specific traits – yields statistically significant negative estimates. Thus, a cursory analysis suggests that a rise in inequality seems to be associated with lower subsequent growth, whereas accounting for country-specificity changes the conclusion and the association seems negligible.

Second, the patterns that are related to the different estimators do not depend critically on the measure of income inequality. The considered measures are the Gini coefficient, the Palma ratio, various other ratios, and top income shares. However, if a data source that uses imputation methods to improve the coverage of the WIID is adopted, the estimates are typically much higher than the ones that rely on raw data.

Third, there are no clear differences between the FE, dGMM and sGMM results for OECD and non-OECD countries. However, the POLS and RE results are driven by the non-OECD subsample. Allowing for the relationship to vary conditionally on the level of inequality does not change these findings.

Fourth, to understand the roots of the results better, the estimated association is evaluated in terms of potential transmission channels. The findings suggest that inequality promotes growth through physical investments and that it hurts growth via lower accumulation of human capital. These two mechanisms seem to balance each other out.

1.2.2 Essay 2: The Role of Financial Development in the Relationship Between Income Inequality and Economic Growth

Many seminal studies on the inequality-growth nexus have emphasized the role of financial frictions (see e.g. Galor and Zeira (1993), Aghion et al. (1999) and Galor and Moav (2004)). This essay evaluates the significance of financial development for the relationship between income inequality and growth. It employs standard panel regression analysis. Data compiled by Svirydzenka (2016) is used to allow the association between income inequality and the subsequent growth of per capita GDP to depend on multi-dimensional financial development. Financial conditions are evaluated at the aggregate level, and institutions and markets are analyzed separately. Inequality data come from the survey-based World Income Inequality Database maintained by UNU-WIDER (2018).

The findings highlight a difference between OECD and non-OECD countries. When financial markets are sufficiently developed, the association between income inequality and growth is positive in non-OECD countries. If the financial markets are poorly developed, the association is statistically insignificant.

The finding is robust to different measures of inequality and different estimation techniques. Such a dependency is not present when institutional development is considered or when the OECD member countries are analyzed.

1.2.3 Essay 3: Income Inequality and Economic Growth: Difference Between Rising and Falling Top Income Shares

In this essay, the interplay between the income shares of the highest-earning 1 % and economic growth is analyzed on a country level. Data that rely on tax records originate from the World Inequality Database (World Inequality Lab, 2020), and the analysis covers Australia, Canada, France, India, Japan and the United States over the period between 1950 and 2010. The empirical results are based on a novel technique (Schorderet et al., 2003; Shin et al., 2014): the growth of per capita GDP is allowed to respond asymmetrically to rising and falling income shares.

The results suggest that the relationship between inequality and growth was characterized by cross-country heterogeneity and asymmetries between 1950 and 2010. First, in France and the United States, a decrease in the income share of the highest-earning percentile was associated with lower subsequent growth of per capita GDP while the growth-response to rising inequality was small and statistically insignificant. Second, in India, growth responded positively to rising inequality but showed no significant response to falling inequality. Third, changes in the top income shares seemed not to significantly translate into the growth process in Australia, Canada and Japan. Though, in Japan, the statistically insignificant point estimates for both positive and negative changes are negative, and as a result, there is evidence for asymmetry. In all countries, the short-run responses are larger than the long-run ones. Moreover, the adjustments took place in two to seven years depending on the country, which suggests that the empirical approach captures mechanisms that are related to relatively direct economic mechanisms rather than factors that change slowly.

Moreover, the essay also revisits two previously used panel estimation approaches. Herzer and Vollmer (2013) conducted a panel cointegration analysis and found that the concentration of income is bad for economic development. Their finding does not generalize beyond their sample. First, there is only weak evidence for cointegration between economic development and the top income shares as opposed to the original study. Second, the estimates that I obtain for the top income shares on economic development are positive. When standard panel growth regressions are considered, the evidence is in line with previous studies that have used similar data (Andrews et al., 2011; Thewissen, 2014): a small positive association between top income shares and growth emerges.

1.2.4 Essay 4: Integrated Capital Shares

This essay deviates from the other four, in that it does not include any analysis of the links between income distribution and economic growth. Instead, functional income distribution, that is, the division of income between capital and labor,

is introduced. Although many drivers of the documented decline in the share of national income paid to workers have been suggested (see e.g. Karabarbounis and Neiman (2013), Piketty (2014), Acemoglu and Restrepo (2018), Stansbury and Summers (2020), and Autor et al. (2020)), the cross-country inter-dependencies of functional income distributions have not been analyzed previously. To investigate whether the same latent factors drive fluctuations in capital shares of total national income in different countries, historical data (Bengtsson and Waldenström, 2018) and a technique previously used to measure financial integration (Pukthuanthong and Roll, 2009) are employed.

Identifying common unobservable factors from cross-country correlations reveal that the changes in capital shares are mainly driven by a single factor in all sample countries. This primary factor is strongly correlated with both trade openness and total factor productivity (variables that have been documented to contribute to the observed changes in capital shares) in the majority of the countries. Such cross-country integration is not visible to the naked eye in correlation matrices or in time series graphs. The results are robust across samples, where both the country and year coverage change, and to the way capital depreciation is taken into account.

1.2.5 Essay 5: When Aiyagari meets Piketty: Growth, Inequality and Capital Shares

While the first four essays of this doctoral dissertation are single-authored, the final one is the result of a collaboration with Kari Heimonen, Juha Junttila and Teemu Pekkarinen. We incorporate the division of income between capital and labor into our analysis on the relationship between inequality and growth. Using historical, "Pikettyan" (2014), data (Bengtsson and Waldenström, 2018) and standard panel estimation techniques, we show that an increase in the top 1 % income share is associated with higher subsequent growth of per capita GDP when capital share is low. Alternatively, under a high capital share, the association between inequality and growth is negative. These findings are robust to several tests, and compatible with the predictions of our theoretical analysis, which builds on the seminal study by Aiyagari (1994).

Theoretically, we stress the importance of the interplay between precautionary saving motives and consumption smoothing. Crucially, this interplay depends on the share of capital income in total national income, which in turn translates into changes in capital accumulation and economic growth. We demonstrate the theoretical predictions in a simple capital market equilibrium and using computational methods. The main findings hold when financial frictions are sufficiently low – a property that is also present in the data.

1.3 Discussion

The first two essays of this dissertation rely on survey-based panel data and standard panel regression techniques. The first essay contributes to the previous literature on inequality and growth by providing further evidence on the properties of the widely-used estimation techniques. Furthermore, it summarizes the choices an empirical researcher studying the topic necessarily faces, and documents how these choices affect the conclusions. The second essay tests the significance of financial development as a potential determinant of the inequality-growth relationship. The results imply that promoting the development of financial markets may alleviate the adverse effects of income inequality on economic growth in under-developed countries.

The findings of the first essay also suggest that the relationship between inequality and growth is characterized by cross-country heterogeneity – the results depend on whether unobservable country-specific traits are considered. The third essay addresses country-specificity explicitly by focusing on individual countries. Evidence of differences between countries is found. Moreover, positive and negative changes in income inequality are disentangled, and economic growth is found to respond asymmetrically to changes in inequality in France, India and the United States.

The contribution of the fourth essay lies in showing that the changes in the division of income between capital and labor, that is, the functional income distribution, are driven by the same underlying factors in different countries. The finding helps to put together country-specific evidence on the drivers of the changes in functional income distributions. More broadly, it shows how macroeconomic inter-dependencies can be examined beyond cross-country correlations and time series graphs by borrowing statistical methods from the financial literature.

To my interpretation, the main academic contribution of this dissertation is the central finding of the fifth essay. My co-authors and I show how accounting for functional income distribution determines whether changes in income inequality are associated positively or negatively with subsequent economic growth. Our explanation (precautionary saving motives, consumption smoothing and setting our focus on the accumulation of capital) of the observed empirical regularity is potentially one of many, and we hope that our study will spark an active discussion on the empirical finding, which is both novel and robust. We believe that potential complementary mechanisms may be discovered by focusing on the composition of income in different income brackets, the accumulation of human capital, the potential role that new innovations play, and the labor supply decisions of households, to name some of the ones that we have thought but not yet formally analyzed.

Even though the question of whether inequality boosts or dampens growth is intriguing politically, clear recommendations stemming from either theoretical or empirical economic literature cannot be given. Theoretically, there are valid arguments on both sides. As far as the empirical evidence is concerned, there

are at least three fundamental issues. First, it has proven to be extremely difficult – perhaps impossible – to establish a causal interpretation to the empirical findings. Second, constrained by data availability, the results typically rely on information from multiple years and from multiple countries. It is problematic to interpret findings associated with such structure of the data in terms of an individual country, where policy-makers operate. Third, bypassing the two previous notions, inequality can be affected through specific policies. Thus, it is perhaps more fruitful to focus on the evaluation of feasible reforms when county-specific policies are discussed. Moreover, the efficiency-equity trade-off is a second order issue in the political process, whose chief concern should be with individuals' views about justice.

Studies on inequality and growth can still be of use, beyond satisfying the hunger of the academics dedicated to the topic, despite them being ill-suited for country-specific policy discussions. Complemented with other evidence on how our societies fare, carefully documented statistical associations interpreted in terms of applicable conceptual frameworks can help us to get "the big picture right". To me, problems arise if evidence on such large-scale patterns are taken to argue for specific issues.

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2 INEQUALITY AND ECONOMIC GROWTH: DIFFERENT PANEL ESTIMATORS AND VARIOUS MEASURES OF INCOME INEQUALITY

Abstract*

This study re-examines the much-studied inequality-growth relationship. An empirical analysis that covers over a hundred countries finds no clear evidence that inequality boosts or dampens the growth of per capita GDP. Furthermore, evidence is found that inequality promotes growth through physical investments and that it hurts economic development via lower accumulation of human capital. These two mechanisms seem to balance each other out. The conclusions are based on a thorough investigation using the World Income Inequality Database maintained by UNU-WIDER and considering different measures of inequality, various estimation techniques, different specifications of the growth regression, allowing for non-linearities in the relationship and separating the OECD members from the non-OECD countries. The properties of the much-used system GMM estimator are investigated in detail. Even though its use is motivated by a desire to disentangle causality from correlation, the technique is found to suffer from weak instrument variables and sensitivity to small changes in the econometric specification. The results from simpler panel techniques follow a predictable pattern, where the use of cross-country (time) variation is associated with negative (positive) estimates. More profoundly, a strong result that stems from a data set that combines information from several countries would be of limited use for policy purposes because the actions to curb or promote income inequality are within the purview of national policy-makers.

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Keywords: Economic growth, Income inequality, Panel data, GMM

2.1 Introduction

The interplay between inequality and economic activity has fascinated economists since the early days of the discipline and the topic is widely studied. The empirical research on the topic has predominantly focused on the disposable income (net) Gini coefficient as the broad measure of income inequality since it captures the full income distribution into a single number and addresses the income that people consume and save. In the public debate however, the income shares of the top earners are frequently used as narrower measures to illustrate the evolutions of income inequality. This has been particularly prevalent in the US. Moreover, the Gini is by construction especially sensitive to changes in the middle of the income distribution and thus inherently incorporates values regarding how to measure inequality by giving a smaller weight for the tails of the distribution. As the middle class incomes tend to be more stable than the incomes in the tails of the income distribution, the Gini coefficient undervalues the part of the distribution that typically has the most variation. Thus, it does not paint the full picture. Therefore, complementing the analysis with top income shares and for example decile ratios (e.g. the Palma ratio) to track income inequality more broadly seems essential. The seminal studies using both the Gini and alternative measures for income inequality are by Barro (2000) and Voitchovsky (2005).

In this study, I aim to complement the existing empirical panel data literature and meta-analytical approach (Neves et al., 2016) by considering the Gini coefficient together with decile and quintile shares of different income brackets (and various ratios) as measures of disposable income inequality. The empirical investigation relies on the World Income Inequality Database (WIID)[1], which builds on several data sources and household surveys. The analysis covers several estimation techniques. This approach enables me to evaluate how the reduced-form results depend on, among other factors, the measure of income inequality, the estimation technique, the specification of the growth regression, the sample of countries and potential forms of non-linearity while fixing the data source. This allows for comparison between different choices, other than data issues, that an empirical researcher necessarily faces. Furthermore, the properties and limitations of panel data estimation methods are investigated in detail.

I will also demonstrate how the results differ if data that rely on imputed values (Solt, 2016)[2] are used instead. Based on the evaluative work by Atkin-

[1] The fourth major update of the database maintained by the United Nations University World Institute for Development Economics Research (UNU-WIDER) was released in December 2018. The open access data is available at https://www.wider.unu.edu/database/world-income-inequality-database-wiid4.

[2] The analysis of this study uses the seventh version of the Standardized World Income Inequality Database (SWIID). The newest version can be accessed at https://fsolt.org/swiid/.

son and Brandolini (2001) and Jenkins (2015) together with the well-documented choices of the team behind the WIID, I conclude that the WIID is an apt and transparent data source when a study focuses on a large panel of countries[3]. However, it is far from a remedy for the quality and comparability issues surrounding empirical studies on inequality. The full nature of this coverage-quality trade-off is discussed in Section 2.3.

Ever since the late 1980s through advances in estimation techniques, combining a panel structure with a generalized method of moments (GMM) estimator has gained popularity when analysing the determinants of economic growth in a cross-country setting. In particular, the use of an estimator often labelled as system GMM or sGMM (Arellano and Bover, 1995; Blundell and Bond, 1998) has skyrocketed in popularity as it can, under certain conditions highlighted below in Section 2.3, mitigate the identification issues caused by omitted variables and reverse causality. In this study, the main focus of the empirical analysis is on the reduced-form sGMM estimates, which are accompanied by the results of simpler estimation techniques.

Throughout the analysis, the interplay between income inequality and the growth of per capita GDP is labeled as a conditional correlation, a partial correlation or an association rather than as an effect. The reason for this choice is blunt: the adoption of the sGMM estimator does not enable a researcher to state that cross-country or time series variation in income inequality causes changes in economic growth. Furthermore, empirical results relying on country panels are problematic in terms of policy recommendations even if the findings could be interpreted as causal. Both predistributive and redistributive actions are controlled by national policy-makers, whereas the results of a country panel analysis correspond to a set of countries as a whole.

The results of this study suggest that no clear relationship between income inequality and economic growth can be established. Distinctive patterns specific to different estimation techniques emerge. The preferred sGMM estimator delivers a message that inequality does not enhance or suppress the growth of per capita GDP. Moreover, the technique seems to suffer from "weak instruments"[4]. Subsample analysis or allowing for non-linearities to either the level of inequality or the level of economic development do not change the conclusion. A brief analysis on the potential transmission channels suggests that there are different factors at play either boosting or hurting growth. Namely, investments seem to be a channel through which inequality supports growth, whereas the education and fertility channels pull in the different direction. These forces deliver the net result.

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3 For subsamples of countries, such as the OECD members, alternatives with higher quality arguably exist. Yet, it is not clear how to combine information from these several alternative sources. As the team behind the WIID has devoted its resources to the task of gathering information from various places, it is a suitable data source when a large group of countries is analyzed.

4 Testing for instrument strength has only recently been under explicit investigation when the growth-consequences of inequality have been studied (Kraay, 2015; Bartak and Jabłoński, 2019).

The structure of the study is the following. The next section briefly summarizes the vast earlier literature on the topic while Section 2.3 introduces the data and empirical approach. 2.A.1 complements the section on data. The fourth section together with the detailed regression tables in 2.A.2 and 2.A.3 present the results. Section 2.5 and 2.A.4 contain the analysis on the potential transmission channels behind the inequality-growth relationship. Finally, the last section concludes the findings.

2.2 Earlier literature

The existing literature on the consequences of income inequality on economic growth can be separated into three branches (Neves et al., 2016). First, theoretical papers have aimed to model the channels through which inequality affects growth. Second, empirical studies have focused on testing the validity of the theoretical mechanisms while the third branch has focused on estimating the reduced-form relationship between inequality and growth. This study falls into the last category while also briefly addressing the second branch.

The first main channel according to which inequality is harmful for economic growth is growth-dampening taxation caused by redistributional policies, which in turn are affected by economic inequality (Alesina and Rodrik, 1994; Persson and Tabellini, 1994). Other suggested channels span from socially unoptimal accumulation of human capital due to the lack of resources to educate one selves at low levels of income under credit constraints (Galor and Zeira, 1993) to the growth-hurting effects of socio-political instability induced by inequality (Alesina and Perotti, 1996). Galor and Moav (2004) suggest that inequality promotes economic growth during the early stages of development by channelling resources towards people who have a higher propensity to save. The effect is reversed during the process of economic development when the accumulation of human capital as an engine for growth gains strength and inequality, under credit constraints, suppresses human capital accumulation.

Others have claimed that inequality may promote growth by for example inducing higher investment through a higher savings rate (Kaldor, 1957; Bourguignon, 1981) and by facilitating the business-minded individuals to accumulate sufficient resources to start their businesses under set-up costs for investments (Barro, 2000). Furthermore, a straightforward story on economic incentives is appealing when the growth-supporting impact of inequality is discussed. A high level of income inequality is associated with high-income positions and if people see these positions attainable, they are likely to increase their work input, which in turn may boost economic activity. The significance of these transmission channels, and numerous other potential mechanisms, is likely to depend on the level of inequality and economic development. The tug-of-war described above is summarized in Chapter 1 (Figure 1.1).

Following the newly discovered interest in the mechanisms that may drive

the relationship between equity and efficiency, numerous empirical studies aiming to find reduced-form estimates for the effect of inequality on economic growth have emerged since the 1990s. The bulk of the first studies relied on cross-sectional data structure and estimated the growth regression using least squares (Alesina and Rodrik, 1994; Perotti, 1996). The findings supported the dominance of the growth-dampening mechanisms over the growth-supporting ones. The quality of data in these first papers were criticized by Deininger and Squire (1996), whose data set was heavily used during the following years.

In the 2000s, cross-sectional data sets have been superseded by country panels. One of the most influential study of this class is by Barro (2000), who studied the relationship between income inequality and economic growth using both the Gini coefficient and quintile share data. The income distribution is divided into the richest quintile, the three middle quintiles and the poorest quintile. His results on the consequences of inequality on growth are similar between the net income Gini coefficient and the net income share of the richest quintile[5]. In the linear form, inequality seems not to matter for growth but the association is statistically significant when it is allowed to depend on the level of per capita income. The association between inequality and growth is negative for low levels of economic development and positive for high ones.

Instead of specifying a growth regression with controls and a single inequality measure as regressors, Voitchovsky (2005) includes measures for top and bottom end inequality and finds that inequality at the top end of the income distribution supports economic activity while inequality at the bottom dampens growth. Her preferred measures are the ratio of the equivalised individual median income to the first decile equivalised individual income and the ninth decile income to the 75th percentile income for bottom and top end inequality, respectively.

Recently, for example Berg et al. (2018) have documented how panel estimators relying on time series variation tend to find a positive association between inequality and growth, whereas estimators that utilize either cross-sectional variation or both the time series and cross-sectional variation find a negative correlation. Since within-country inequality is typically persistent, the first class of estimators, such as the fixed effects and the so-called difference GMM estimator (Arellano and Bond, 1991), is likely to ignore relevant variation in data. The cross-country panel analysis on the topic has also been extended to cover the sustainability of economic growth by using duration analysis (Berg et al., 2012), to include measures of redistribution (Ostry et al., 2014; Berg et al., 2018) and to address the role of inequality of opportunity (Aiyar and Ebeke, 2019).

The above review is by no means comprehensive but rather aims to offer a glimpse on the previous research[6]. Clearly though, the reduced-form analyses on the association between income inequality and economic growth have generated divergent results over the years. As summarized for example in the meta-analysis

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5 The simple cross-country correlations between the Gini and the top income share are 0.89 in 1960, 0.92 in 1970, 0.95 in 1980 in 0.98 for 1990.

6 Other widely-cited empirical studies include Banerjee and Duflo (2003), Knowles (2005), Castelló-Climent (2010) and Halter et al. (2014)

by Neves et al. (2016), the numerous empirical studies differ in structure of the data (cross-section or panel), the sample of countries, the concept of inequality (disposable income, pre-tax & pre-transfer income or wealth) and the estimation technique. The main finding of Neves et al. (2016) is evidence for publication bias: statistically significant results are more willingly reported and published following a predictable time pattern with cyclically alternating positive and negative reduced-form estimates. The results also suggest that the estimation technique, data quality and the specification choice for the growth regression are not significant drivers of the varying estimates. Rather, cross-sectional analyses tend to find a stronger negative association than panel studies, the negative association is stronger in less developed countries, the inclusion of regional dummies soak up much of the previous finding and the concept of inequality significantly affects the results.

2.3 Data and methodology

The primary data source for income inequality in this study is the fourth version of the World Income Inequality Database (WIID) maintained by the United Nations University World Institute for Development Economics Research (UNU-WIDER, 2018). It is a secondary database combining information from several sources[7] and builds on the work by Deininger and Squire (1996). Each update has aimed at improving data comparability, both within countries over time and across countries, by taking seriously the issues raised in the evaluative studies by for example Atkinson and Brandolini (2001) and Jenkins (2015). Even though the data issues cannot be fully removed, I believe that the newest version of the WIID is the best available data source for income inequality in a cross-country setting if the analysis focuses on both developed and developing countries. This conclusion is founded on the well-documented choices – both by the WIID staff and this study – that account for the influential critique directed to the construction and use of secondary databases.

As informatively summarized by Jenkins (2015), Atkinson and Brandolini (2001) state that non-comparability in secondary data sets may arise because of differences in the definitions of income, in the data sources or in the processing of the income data in the original source. Differences both within countries over time and across countries may emerge. Many of the differences are associated with predictable patterns on inequality if their nature is not drastically heterogeneous over time and across countries. Unfortunately, the assumption of homogeneity is unlikely to hold for the WIID despite major improvements over the earlier databases, and thus, the practical implications need to be assessed by

[7] The Organisation for Economic Co-operation and Development (OECD), The EU-Statistics on Income and Living Conditions (EU-SILC), The Luxembourg Income Study (LIS), The World Bank, The Socio-Economic Database for Latin America and the Caribbean (SEDLAC), national statistical offices and independent research papers.

comparing the WIID series with other sources of at least as good a quality. This is presented together with the data selection algorithm in 2.A.1. The comparative exercise focuses on the OECD member countries due to data availability. Better quality data sets on income inequality may exist for the OECD countries but if a researcher is willing to analyze a large group of countries – over 100 countries in this study – and compare the OECD and non-OECD subsamples, the WIID is the best available data set to my judgement. As emphasized below, the use of the WIID is conditional on being transparent on the treatment of the data.

The empirical studies on the linkage between income inequality and economic growth have predominantly focused on disposable income, also referred to as net or post-tax & post-transfer income. Since I aim to shed light on the divergent results obtained by previous studies, I follow this approach: all measures of income inequality discussed below are based on disposable income. Although many of the suggested mechanisms in the theoretical literature emphasize wealth inequality rather than the dispersion of income, the focus on disposable income is well-founded as our consumption, saving and investing decisions are based on income after taxes and transfers. The listed economic decisions in turn are relevant for aggregate economic activity. As a practical matter, the data on wealth inequality are difficult to come by.

In the WIID, each observation is labeled as one of possible income, consumption or expenditure concepts as strongly recommended by the seminal evaluative studies. Following the assertive conclusion of Jenkins (2015), I explicitly report the data selection algorithm inspired by Jäntti et al. (2018) in 2.A.1. After separating the net income observations from the rest, two issues remain for empirical work: the observations are of varying quality and there are often multiple observations for each country-year pair. Some of the multiple observations are due to multiple surveys but predominantly the measurements come from the same survey and it is just the computation (and the statisticians in charge) that change. Helpfully, the WIID team has introduced a variable called a quality score, which ranks the observations from 3 to 13. By ranking the observations based on this score, presented in 2.A.1, and picking the highest, I can use the observations of best possible quality to form the final country panel and get rid of many of the duplicate observations. In case of observations tied on the quality score for a given country-year pair, a simple average is taken to obtain unique observations. I believe that this data selection procedure may be helpful for future researchers who need to merge the WIID into some other cross-country panel.

The resulting series for the net income Gini coefficient, the decile shares and the quintile shares are annual and characterized by varying lengths and coverage depending on the country. In short, the series are filled with gaps. To account for this imbalance and variation in time caused by noise associated with heterogeneity of different observations, I rely on five-year non-overlapping windows for which the inequality observations are calculated as averages inside the window. After dropping the countries that are short on data (fewer than three five-year windows) for at least one of the inequality measures or relevant control variables specified below, the panel covers 103 countries. Obviously, this

selection procedure tilts the composition of the panel towards more developed countries by effectively dropping out the countries that are simultaneously associated with low level of economic development and more severe data issues. Of the 103 countries, 34 are members of the Organisation for Economic Co-operation and Development (OECD) with Japan and New Zealand being the two OECD nations excluded from the sample due to poor coverage in the WIID. For the full list of countries, see 2.A.1.

Table 2.1 documents the extent of the cross-country variation for the variables in the WIID. Especially the spreads for the Gini coefficient, whose values by construction lie between zero and one, and the top income shares (1 % - 100 %) are very wide. The sample means also provide interesting broad-scale evidence of income distribution. On average in the sample, the top decile has earned roughly 30 % of the total income, which is clearly more than what the bottom half has made. In turn, the income share of the richest quintile has on average been larger than the share of the seven bottom deciles. As depicted by the large standard deviations and the ranges given by the minimum and maximum sample values, the proportions show substantial differences across countries.

TABLE 2.1 The WIID, descriptive statistics

Variable	Mean	Std. Dev.	Min	Max	Observations
The Gini	0.37	0.10	0.18	0.74	749
The income shares					
Quintile 1	6.73 %	2.16 %	1.07 %	12.05 %	696
Quintile 2	11.24 %	2.51 %	2.03 %	15.55 %	692
Quintile 3	15.50 %	2.38 %	5.46 %	18.95 %	692
Quintile 4	21.66 %	1.70 %	11.08 %	27.75 %	693
Quintile 5	44.86 %	8.25 %	30.80 %	78.25 %	697
Decile 1	2.62 %	1.00 %	0.41 %	5.45 %	663
Decile 2	4.11 %	1.21 %	0.57 %	6.61 %	663
Decile 3	5.13 %	1.27 %	0.81 %	7.40 %	663
Decile 4	6.10 %	1.28 %	1.22 %	8.20 %	663
Decile 5	7.14 %	1.24 %	2.27 %	9.10 %	663
Decile 6	8.33 %	1.15 %	3.19 %	10.10 %	663
Decile 7	9.80 %	0.99 %	4.67 %	11.53 %	664
Decile 8	11.82 %	0.73 %	6.41 %	13.92 %	664
Decile 9	15.21 %	0.97 %	8.78 %	19.89 %	665
Decile 10	29.72 %	7.81 %	17.48 %	67.44 %	665

Notes: The data correspond to a structure of five-year non-overlapping windows. The treatment of the raw data is discussed in the text and in detail in 2.A.1. The Gini coefficient is scaled to take values between zero and one, whereas the income shares are expressed in percentages. All measures of inequality correspond to disposable income as specified in the WIID and in the data selection algorithm (2.A.1).

In addition to the Gini coefficient and the income shares, I use the decile data to construct measures of bottom-end and top-end inequality as in Voitchovsky (2005). The former is defined as the income share of the fifth decile divided by the share of the first one (p50/p10), whereas the latter is the ratio of the ninth decile share to the seventh one (p90/p70). Moreover, I also construct the Palma ratio that proportions the income share of the highest-earning decile to the income

share of the bottom 40 %. As it is argued to circumvent the over-sensitivity of the Gini to the middle parts of the income distribution, and thus, it is claimed to be a more policy-relevant measure of inequality (Cobham et al., 2013), it is insightful to compare the results between the Gini and the Palma ratio below.

Many recent studies, of which some have received much attention (Ostry et al., 2014), have used the Standardized World Income Inequality Database (Solt, 2016, SWIID) as their source for data on the Gini coefficients. The SWIID is based on the WIID, supplemented by other sources and all observations come from its imputation model. In his conclusions, Jenkins (2015) states that costs associated with the use of the WIID are present for the SWIID too. Additionally, he urges to set questions about the imputation model against the benefits of coverage and draws a conclusion that the WIID should be used instead of the SWIID given that the use of the WIID is accompanied by a tractable data selection algorithm. Since the two are connected and the SWIID is largely used, I believe that it is informative to examine whether the forthcoming results differ between data that rely on actual surveys and data that build on imputations.

TABLE 2.2 Pairwise Pearson correlation coefficients between some inequality measures

	Gini WIID4	Gini SWIID7	Palma WIID4	Top 20 % WIID4	Top 10 % WIID4
Gini, WIID4	1.00				
Gini, SWIID7	0.89	1.00			
Palma ratio, WIID4	0.88	0.74	1.00		
Top 20 % income share, WIID4	0.99	0.90	0.89	1.00	
Top 10 % income share, WIID4	0.97	0.89	0.90	0.99	1.00

The panel level correlations between the survey-based Gini coefficient, the Gini that relies on imputations, the Palma ratio and two alternative top income shares are shown in Table 2.2. The observations are averages over five-year non-overlapping windows. Clearly, the different measures are strongly correlated. However, positive correlation does not guarantee that different measures give similar estimates for income inequality on economic growth. Naturally, these panel level coefficients disguise cross-country heterogeneity, i.e. in some countries the correlation over time is even stronger than depicted by the table while in some other countries, the correlations are smaller.

For the second focal variable of interest, economic growth, I rely on the Penn World Table (Feenstra et al., 2015, PWT), which is a standard data source for empirical cross-country studies offering annual data on numerous variables for nearly 200 countries. Economic activity is defined as expenditure-side per capita gross domestic product (GDP) and the rate of growth corresponds to logarithmic differences.

Taking a simple dynamic perspective as in Atkinson (2015, Figure 9.3, page 259) by going back half a century and examining the average annual growth of per capita GDP between 1990 and 2015 against the 1990 level of the Gini coefficient, reveals no clear pattern (Figure 2.1)[8]. The countries experiencing fastest

[8] 14 countries from the panel are excluded due to missing data around 1990.

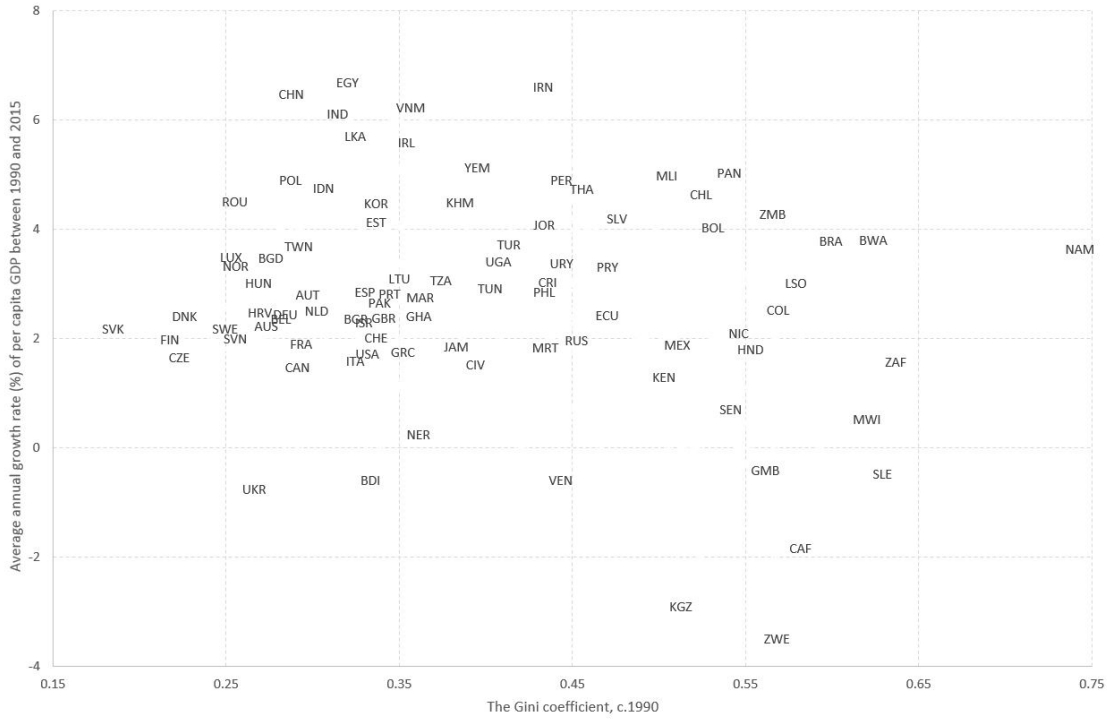

FIGURE 2.1 Inequality (the Gini, WIID) and economic growth (PWT) in 89 countries

per capita growth are the ones that are catching up, the top five being China, Egypt, India, Iran and Vietnam. The large majority of the countries have seen growth rates between 1.5 % and 5 % with no apparent dependency on the initial level of inequality. The picture is very similar if the Gini coefficient is replaced by alternative measures of inequality.

The most popular approach in empirical studies on the interplay between inequality and growth has been to adopt a reduced-form growth regression, where economic growth is explained by a measure of inequality and a set of other growth determinants as control variables. Holding the other factors constant is a well-recognized issue as the number of potential determinants of growth is enormous. In this study, I restrict the set of control variables in the preferred statistical models to cover the initial level of per capita GDP, investments relative to GDP and schooling as a measure of human capital for three reasons[9]. First, controlling for growth convergence and the accumulation of physical and human capital has a solid foundation on growth theory. Second, the data for these three growth determinants are easily available from standard sources. Third, the preferred estimation technique, specified below, together with the scarcity of inequality data tends to run into numerical issues under a large set of control variables. Moreover, the technique can under certain conditions address the problems caused by reverse causality and omitted variables that often plague any cross-country growth analysis. The data on investments are gathered from the PWT, whereas schooling is

9 In robustness analysis, the quality of political institutions (Marshall et al., 2002, Polity IV), debt to GDP ratios (Lane and Milesi-Ferretti, 2007) and the sum of imports and exports relative to GDP (PWT) are also included as regressors.

defined as the sum of average years of primary and secondary education and the data come from a broadly-used data set by Barro and Lee (2013), which contains observations for every five years.

A standard convention in the literature is to focus on growth inside five-year non-overlapping windows. I can identify three reasons for this approach in the context of this study. First, by adopting five-year intervals, the growth analysis moves away from a short-run scope influenced by business cycles towards medium-run analysis. Second, the WIID series for income inequality measures are characterized by missing observations and noise stemming from measurement error. Taking averages over five year periods mitigates the issues. Third, the estimation techniques often used in the panel studies are designed for data sets that cover many individuals (e.g. countries) over a relatively low number of time periods and focusing on five-year windows reduces the time dimension. Consequently, the generic statistical specification taken for this study is the following:

$$\begin{aligned}\frac{1}{4}(lnY_{i,t+4} - lnY_{i,t}) = \beta(\frac{1}{5}\sum_{j=0}^{4} Inequality_{i,t-5+j}) + \gamma_0 lnY_{i,t-1} \\ +\gamma_1(\frac{1}{5}\sum_{j=0}^{4} ln\frac{GCF_{i,t+j}}{Y_{i,t+j}}) + \gamma_2 lnEdu_{i,t-5} + \alpha_i + \eta_t + \varepsilon_{i,t},\end{aligned} \tag{2.1}$$

where $Y_{i,t}$ is expenditure-side real per capita GDP in country i in year t, the accumulation of physical capital is measured as gross capital formation (GCF) to GDP, the sum of average primary and secondary education in years (Edu) measures human capital, α_i and η_t are the vectors of fixed country and year effects and $\varepsilon_{i,t}$ is the overall error term. The country and year fixed effects are introduced to capture time-invariant unobserved country-specific characteristics and changes common to all countries (e.g. productivity), respectively.

If the model is estimated by using standard panel techniques, such as pooled least squares, fixed effects or random effects, the β-coefficient only captures a partial correlation. In the spirit of for example Acemoglu et al. (2001), both low levels of inequality and high economic performance may be driven by inclusive political institutions and thus a potential finding of a statistically significant negative reduced-form estimate would in fact provide little information on the equity-efficiency question[10]. Moreover, controlling for growth convergence, $lnY_{i,t-1}$, introduces dynamism into the model, which adds an additional source of inconsistency to the estimates.

To address the identification issues caused by both omitted variables and reverse causality and the dynamic nature of the growth regression, researchers have

[10] I am skeptical towards the attempts that aim to augment the growth regression with a measure of the quality of political institutions (Marshall et al., 2002, Polity IV) as such measurements are probably even more demanding to construct than the concepts of inequality. Moreover, the number of suspects that may affect the β-coefficient is vast and thus controlling for all of the potential underlying causes in empirical work is impossible.

increasingly started to apply generalized method of moments (GMM) estimators. The so-called system GMM or sGMM (Arellano and Bover, 1995; Blundell and Bond, 1998)[11] has been particularly popular. In short, the sGMM estimates equation (2.1) and its first-difference as a system using suitably lagged values of the regressors as instrument variables for the first-differenced equation and lagged variables of first-differences as instruments for the level equation. The estimator can therefore exploit both variation in time and across individuals since the individual-specific characteristics are not removed from the equation in levels. In this study, first, all regressors are treated as endogenous to economic growth. Second, not instrumenting the control variables is examined. As summarized by Roodman (2009), the sGMM is designed for situations with

1. panels that are characterized by few time periods and many cross-sectional units
2. a linear functional relationship
3. one dynamic left-hand-side variable that depends on its own past values
4. explanatory variables that are not strictly exogeneous
5. fixed individual effects
6. heteroskedasticity and autocorrelation within cross-sectional units but not across them

The first, third and fifth characteristic on the list are matters of construction. A deviation from the first one typically drives the estimator into numerical issues, whereas without dynamics a simpler approach would suffice. The second item in turn is an assumption that is often relaxed by introducing for example interaction terms or splitwise regression techniques. The post-estimation diagnostics typically presented correspond to numbers three and four and evaluate the appropriateness of the instrumentation strategy. Namely, to inspect the validity of the lagged levels and differences of the regressors as instruments, the Arellano-Bond autocorrelation test, the Hansen test for overidentifying restrictions and the difference-in-Hansen tests are nowadays often reported alongside the number of instruments. This is a clear improvement on past practices, where the tractability of the choices regarding the use of the sGMM was occasionally poor. In this study, for each sGMM estimation, Windmeijer (2005) small sample correction is used for robust standard errors; in the a priori estimate of the covariance matrix, the upper right and lower left quadrants are zeroed out; and the two-step estimator is favored over the one-step one[12].

The final point on the list is often overlooked. Typically, the Windmeijer small sample correction is used to estimate standard errors robust to within-country heteroskedasticity and autocorrelation but possible correlation across countries in the idiosyncratic disturbances is not thoroughly examined. The assumption of no heteroskedasticity across countries is a strong one and since the Arellano-Bond autocorrelation test and the estimation of robust standard errors

[11] For the preceding work on GMM, see Hansen (1982), Holtz-Eakin et al. (1988) and Arellano and Bond (1991).

[12] The analysis is done using Stata's xtabond2 routine.

make the assumption, it is not innocent. In his influential guide for the use of the sGMM estimator, Roodman (2009) argues that that the inclusion of time dummies makes the assumption more likely to hold and that the time dummies should be treated as strictly exogenous, and thus, enter the model as standard instruments with one column in the instrument matrix. I believe this is not sufficient to convincingly state that the sGMM is a major improvement over standard panel estimation techniques, although Blundell and Bond (1998) demonstrate that under heteroskedasticity across countries, the sGMM performs better than its predecessors.

Unfortunately, in a GMM context, testing for conditional homoskedasticity is not straight-forward. For simpler estimators, the nR^2 test developed by White (1980) together with the approach introduced by Breusch and Pagan (1979) is informative, whereas for GMM, the nR^2 statistic does not have the desired statistical properties (Hayashi, 2000, p. 234). However, White (1982) notes that when the errors are symmetric, nR^2 is biased towards the rejection of the null hypothesis of conditional homoskedasticity. Hence, under symmetricity, the failure to reject the null is useful evidence in favor of the correctness of the specification. In practice, the test is constructed by regressing the squared residuals on a constant and second-order cross products of the instrumental variables.

Recently, concerns over the invalidity and weakness of the instruments used in panel growth regressions have been raised and techniques robust to the issues have been developed and applied. Following Bazzi and Clemens (2013), Kraay (2015) revisits four widely-cited studies on inequality and growth and finds that the specifications in all of these studies suffer from weak instruments. Bartak and Jabłoński (2019) apply the techniques when evaluating whether different measures give different results for the inequality-growth relationship in OECD countries, and Berg et al. (2018) also investigate the issue in detail in their analysis that covers both inequality and redistribution. Below, instrument strength is addressed for the central results, i.e. the "black box" of sGMM is unbundled into levels and differenced equations together with the diagnostics for weak instruments[13].

The quality, and consequently the comparability, of inequality data and the caveats of panel regression techniques shed doubts on attempts trying to find whether inequality enhances or suppresses economic growth. Thus, this study explicitly makes a distinction between a causal interpretation and a robust association or a conditional correlation throughout the text and places a heavy emphasis on testing the underlying assumptions of the system GMM estimator.

[13] The analysis is done using Stata's weakiv routine. Aart Kraay's help is gratefully acknowledged.

2.4 Results

The statistical specifications of this study follow equation (2.1) to investigate how income inequality is associated with the growth of per capita GDP. The emphasis is on the results given by the sGMM estimator, which estimates equation (2.1) in levels and in first-differences as a system using lagged observations as instrument variables (first-differences for the level equation, levels for the first-difference equation). The results are accompanied with testing for conditional homoskedasticity and instrument strength.

The analysis proceeds with allowing the inequality-growth relationship to depend on the level of economic development and the level of inequality. Then, results that rely on simpler panel techniques are presented to demonstrate how the estimates depend on whether we utilize variation within or across countries. Finally, a distinction between OECD and non-OECD countries is made. As the scope of the analysis is wide, only results central to the study are presented in this section while auxiliary evidence can be found in the Appendices.

2.4.1 System GMM estimates, full sample of 103 countries

The scarcity of the data on income inequality imposes limitations on the econometric model. Namely, the specifications follow the timing convention of equation (2.1), where inequality is observed during the five-year period that precedes the window for the growth of per capita GDP[14]. Using longer lags violates the assumption that suitably lagged observations are valid instruments, i.e. there is second-order autocorrelation in the error term. As argued by for example Halter et al. (2014), this limitation is problematic since many of the suggested growth-hurting mechanisms associated with inequality are likely to materialize slowly over time. These mechanisms include, among other forces, the accumulation of human capital through educational attainment, institutional development, political processes and, at extreme cases, socio-political unrest. Alternatively, the potential growth-boosting transmission channels manifest themselves via more direct economic mechanisms, such as a high savings rate of the top earners and responses to economic incentives.

At the presence of the limitation described above, the use of both cross-country and time variation seems essential. Since income inequality and the potential growth-dampening mechanisms of inequality typically evolve slowly over time, estimators that utilize only within-country variation are prone to ignore variation that is associated to the channels that may be harmful for overall economic activity. As the level equation in the sGMM does not remove the country-specific characteristics, it can make use of the cross-country variation,

[14] The implementation of the panel regression techniques has been heavily influenced by Berg et al. (2018). Their materials are available at https://link.springer.com/article/10.1007/s10887-017-9150-2 under Electronic supplementary material.

and thus, alleviates the limitations in lag structure.

Following the restriction imposed by Halter et al. (2014), the set of instruments is narrowed down to include only the second lag of the explanatory variables. Experiments with larger instrument sets have no effect on the main results, just the post-estimation diagnostics tend to indicate invalidity of the instrumentation strategy in a form of instrument proliferation (suspiciously high p-value of Hansen J), which weakens the tests of instrument validity (Roodman, 2009). In the preferred specifications, all explanatory variables are treated as endogenous. As a sensitivity check, I also report results for specifications, where investments to GDP and average schooling years are not instrumented[15].

TABLE 2.3 System GMM estimates for the Gini coefficient and top 20 % income share

System GMM estimation, dependent variable: growth of per capita GDP. Economic growth is measured over a five-year period, inequality measures are averages over the preceding five-year window, initial per capita GDP enters the model one year prior to the growth window, investment to GDP is observed during the growth window and is thus allowed to have a contemporaneous effect on growth while educational attainment is observed at $t-5$. Year fixed effects included. For columns (1) and (2), the set of instruments includes the second lags of the inequality measure, per capita GDP, investment to GDP and average years of schooling. For columns (3) and (4), the set of instruments includes the second and third lag of the inequality measure and per capita GDP. Robust standard errors in parantheses. See equation (2.1) for the growth regression and Chapter 2.3 for data sources. Intercept and coefficients for other growth determinants omitted. The coefficients for the level of per capita GDP are negative in all specification, whereas the coefficients for investment to GDP and schooling are positive.

	Investments and schooling treated as endogeneous		Investments and schooling treated as exogeneous	
	Gini, WIID4	Top 20 %, WIID4	Gini, WIID4	Top 20 %, WIID4
	(1)	(2)	(3)	(4)
Inequality	-0.0482	0.0550	0.0127	-0.0195
	(0.0532)	(0.0660)	(0.0719)	(0.1120)
Observations	673	627	673	627
Number of countries	103	103	103	103
Number of instruments	95	90	82	79
AR1 test (p-value)	<0.000	<0.000	<0.000	<0.000
AR2 test (p-value)	0.404	0.123	0.580	0.122
Hansen test of joint instr. validity (p-value)	0.601	0.606	0.402	0.244
Diff.-in-Hansen tests of instr. subsets (p-value)				
For levels	0.950	0.974	0.994	0.949
For initial per cap GDP	0.462	0.656	0.541	0.511
For IV-type (time dum.)	0.635	0.626	1.000	0.987

The main estimation results are presented in Table 2.3. The Gini coefficient and the income share of the highest-earning quintile were selected under particular focus for two reasons. First, the Gini is often used as a default statistic for income inequality and it has been the most commonly used measure when the inequality-growth relationship has been examined. It is meaningful to attach this

[15] These specifications suit well for testing for instrument strength (see below) because some of the tests address the endogenous explanatory variables jointly.

study to previous findings. The top income shares, on the other hand, have been heavily featured in the public debate not least due to the work by Piketty (2015) and his co-authors on the top percentile. Furthermore, a measure that addresses the right-tail of the income distribution complements the Gini, which has been criticized to put high emphasis on the middle income brackets that tend to remain relatively stable. Second, the Gini and top 20 % income share satisfy the most rudimentary criterion for the use of the sGMM: there is no second-order autocorrelation as indicated by the failure to reject the null hypothesis of no serial correlation (AR2 test). The highest quintile is chosen over the top decile and the Palma ratio (Top 10 / Bottom 40) as the latter ones fail to satisfy the property (see 2.A.2, Tables 2.11 and 2.14).

The key finding in Table 2.3 is that the reduced-form estimate for income inequality on subsequent economic growth is statistically insignificant. Taking the first estimate of roughly -0.05 (column (1)) means that one standard deviation change in the within-country variation of the Gini coefficient (0.0302)[16] results in 0.15 percentage point decrease in the annual growth of per capita GDP during the following five-year period.

The second interesting piece of information is that the signs of the point estimates change depending on whether investment to GDP and average years of schooling are treated as endogenous. More importantly, the convergence term is negative in all specifications, i.e. poorer countries tend to catch up, and the estimates for investment activity and educational attainment are positive irrespective of whether they are instrumented or not. When treated as exogenous, the coefficients are larger as can be expected. Thus, the sGMM estimates for the association between income inequality and growth seem to be sensitive to changes in the econometric specification that are not directly related to the treatment of inequality.

The Gini coefficient that relies on imputed data (the SWIID) performs better in this regard. The inequality estimate on growth is -0.0915 (standard error: 0.0615) when the controls are treated as endogenous (Appendix 2.A.2, Table 2.11, column (2)). Alternatively, when investment and schooling are not instrumented, the estimate is -0.1614 (0.0937), i.e. the estimate is statistically significant at 10 % level. However, the questions raised by Jenkins (2015) about the imputation model of the SWIID impose doubts on these relatively large negative estimates.

Appendix 2.A.2 includes the estimation results for a variety of inequality measures in addition to the Gini coefficient and top 20 % income share discussed above. In brief, none of the sGMM estimates are statistically significant. The first implication of these findings is that the conclusion does not change if the Gini coefficient is replaced with the Palma ratio (Table 2.11). Second, the combination of the sGMM and the WIID do not lend support for the findings of Litschig and Lombardi (2019) and Voitchovsky (2005), who studied how inequality in the tails of the distribution accounts for economic growth (Table 2.12). Third, none of the individual income shares by quintiles or deciles (Tables 2.13 and 2.14) show a sta-

[16] Some 15 % of the changes in the Gini coefficient between five-year windows meet this change, i.e. 0.03 corresponds to a relatively large increase in income inequality

tistically significant association with subsequent growth. Many of the specifications in 2.A.2 do not satisfy the assumption of no second-order serial correlation (AR2 test). If the set of instruments is sufficiently expanded, the assumption is satisfied. Importantly, this comes at the cost of suspiciously high Hansen J test p-values, which is a sign of instrument proliferation, which in turn weakens the tests of instrument validity.

Further evidence of sensitivity can be gained by introducing additional growth determinants sequentially. In columns (1) and (4) of Table 2.4, only the measure of inequality and convergence term are included, whereas in columns (2) & (5) and (3) & (6), the control variables are included in two blocks. The sample is restricted to 85 countries for which there are data for all variables to ensure that the results are not driven by the exclusion of countries that are short on data for the additional controls.

TABLE 2.4 Adding controls sequentially into the growth regression

System GMM estimation, dependent variable: growth of per capita GDP. See Table 2.3 for details on the statistical specification. The same limited sample (85 countries) across specifications.

	(1)	(2)	(3)	(4)	(5)	(6)
Gini, WIID4	0.0146	-0.0526	-0.0268			
	(0.0649)	(0.1265)	(0.0297)			
Top 20 %, WIID4				-0.0814	-0.0492	-0.0553
				(0.0563)	(0.0633)	(0.0399)
Ln(Initial	-0.0122***	-0.0278**	-0.0226***	-0.0111***	-0.0259***	-0.0205***
per capita GDP)	(0.0038)	(0.0142)	(0.0069)	(0.0041)	(0.0047)	(0.0068)
Ln(Investment		0.0306	0.0191**		0.0283**	0.0187
to GDP)		(0.0274)	(0.0092)		(0.0129)	(0.0121)
Ln(Avg yrs		0.0427	0.0385**		0.0379***	0.0306*
of schooling)		(0.0283)	(0.0156)		(0.0142)	(0.0157)
Ln(Political			-0.0159*			-0.0114
institutions)			(0.0095)			(0.0104)
Ln(Debt			-0.0030			-0.0018
to GDP)			(0.0034)			(0.0034)
Ln(Openness)			0.0130			0.0101
			(0.0093)			(0.0094)
Constant	0.0000	0.2701**	0.0000	0.0000	0.2606***	0.2450***
	(0.0000)	(0.1073)	(0.0000)	(0.0000)	(0.0652)	(0.0659)
Observations	425	425	425	425	425	425
Number of countr.	85	85	85	85	85	85
Number of instr.	73	73	117	73	73	117
AR1 test (p-value)	<0.000	<0.000	< 0.000	< 0.000	< 0.000	< 0.000
AR2 test (p-value)	0.084	0.100	0.163	0.104	0.109	0.240
Hansen test of joint						
instr. val. (p-value)	0.262	0.186	0.961	0.266	0.238	0.920

Notes: Robust standard errors in parentheses. *, ** and *** denote statistical significance at the 10%, 5% and 1% levels, respectively. Tests for instrument subsets omitted for readability.

Most notably, the sign of the estimate for the top 20 % income share changes from positive to negative when, in the baseline specification of two additional growth determinants (column (2) of Table 2.3, column (5) of Table 2.4), the sam-

ple of countries is restricted from 103 to 85. This finding clearly calls for subsample analysis that is presented in Section 2.4.3. Furthermore, the inclusion of controls reduces the estimated association between inequality and growth when moving from columns (2) to (3) and from (4) to (5). As argued by Berg et al. (2018), the introduced controls can represent some of the transmission channels through which inequality affects growth. The association between inequality, the potential mechanisms and economic growth is examined below in Section 2.5.

In addition to the tests of second-order serial correlation, the Hansen tests of joint instrument validity are also reported in every table. The tests indicate that the specifications of Tables 2.3 and 2.4 do not suffer from over-identification. Because the inclusion of additional controls creates additional moment conditions when the explanatory variables are treated as endogenous (Table 2.4, columns (3) and (6)), the number of instruments increases and the p-values of Hansen tests are close to one. This may be due to instrument proliferation, which weakens the tests of instrument validity. This result clearly demonstrates why the set of other growth determinants is restricted to two in the preferred specifications.

Beyond the assumptions of no second-order serial correlation and joint instrument validity, the sGMM also assumes that the idiosyncratic errors are not correlated across countries and that the instruments are strong. As discussed above, testing for cross-country heteroskedasticity is difficult in a GMM setting since the relevant statistic, specified above, is biased towards the rejection of the null hypothesis of conditional homoskedasticity. However, this indicates that the failure to reject is useful evidence in favor of the model specification given that the errors are symmetric. In practice, the tests are implemented by regressing the squared residuals on a constant and second-order cross products of the instrumental variables. In the specifications of Tables 2.3 and 2.4, I fail to reject the null. The p-values for the preferred models (Table 2.3, columns (1) and (2)) the p-values are 0.677 and 0.511, respectively. Moreover, the residuals seem to be symmetric.

Testing for instrument strength follows Kraay (2015), who revisits four studies that have found a negative and statistically significant relationship between inequality and growth. Following his footsteps, the sGMM estimator is unbundled into difference and level equations and three tests of instrument strength are introduced. To reduce the dimensions of the tests, I will build on the specifications of columns (3) and (4) in Table 2.3, where investment to GDP and schooling years are not instrumented.

First, Kleibergen and Paap (2006) under-identification test is used to test for a complete failure of identification (H_0: the first-stage coefficient matrix is not full rank). As the p-values in Table 2.5 show, I fail to reject the null hypothesis in all cases. Moreover, a possible rejection may still be compatible with a low explanatory power of the instruments on the endogenous variables. Thus, this first test is a strong indication of weak instrument problems.

Second, the weakness of instruments is examined in terms of the maximal bias of the two-stage least squares (2SLS) relative to the least squares by following the approach of Stock and Yogo (2005) (Cragg-Donald Wald F-statistic). In all cases, I fail to reject the null at the least demanding reported level of 30 %. How-

ever, the weakness in this approach is defined in terms of a weighted average of the biases, which may conceal some coefficients that are strongly identified.

Third, to circumvent the problematic average bias, testing for weak instruments can be done parameter by parameter (Sanderson and Windmeijer, 2016). For the Gini coefficient in the difference equation (column (1)), I reject the null at the most demanding level reported (10 %, critical value: 124.37). For the level equations, the null is not rejected, whereas for the income share of the highest-earning quintile in the difference equation, the statistic is not reported due to potential collinearities.

TABLE 2.5 Unbundling the system GMM estimator to test for instrument strength

Two-stage least squares estimation (2SLS), dependent variable: growth of per capita GDP. Economic growth is measured over a five-year period, inequality measures are averages over the preceding five-year window, initial per capita GDP enters the model one year prior to the growth window, investment to GDP is observed during the growth window and is thus allowed to have a contemporaneous effect on growth while educational attainment is observed at $t-5$. Year fixed effects included. Kleibergen-Paap H_0: the first-stage coefficient matrix is not full rank. Cragg-Donald (Stock and Yogo) H_0: the maximal bias of the 2SLS estimates relative to OLS is at least 30 %. Sanderson-Windmeijer H_0: maximal size distortion for a conventional Wald test is at least 25 %.

	Difference equation, 2SLS		Level equation, 2SLS	
	Gini, WIID4	Top 20 %, WIID4	Gini, WIID4	Top 20 %, WIID4
	(1)	(2)	(3)	(4)
Kleibergen-Paap under-identific. test (p-value)	0.166	0.186	0.260	0.667
Cragg-Donald Wald F (H_0: weak instruments)	1.57	1.62	2.93	0.84
Critical value for 30 % maximal relative bias	4.08	4.12	4.37	4.37
Sanderson-Windm. F (H_0: weak instruments)	133.87	n.a.	2.83	8.99
Critical value for 25 % maximal size	33.38	n.a.	18.20	18.20
Instruments$^{\diamond}$	Y_{it-2}, Y_{it-3} G_{it-2}, G_{it-3}	Y_{it-2}, Y_{it-3} $T20_{it-2}$, $T20_{it-3}$	ΔG_{it-2}, ΔG_{it-3}	$\Delta T20_{it-2}$, $\Delta T20_{it-3}$
Observations	510	465	673	627
Number of countries	101	101	103	103

Notes: Robust standard errors in parantheses. $^{\diamond}$ Y_{it}, G_{it} and $T20_{it}$ indicate per capita GDP, the Gini coefficient and top 20 % income share, respectively.

Overall, the evidence in Table 2.5 indicates weak instrument problems. In column (1), the Sanderson-Windmeijer test speaks for strong instruments but the finding collides with the evidence of failure of identification (Kleibergen-Paap). In the case of the imputed values (the SWIID Gini), the null hypothesis of failure of identification is rejected for the difference equation. Otherwise, the null of weak instruments cannot be rejected. The findings of weak instrument problems imply that the confidence intervals robust to the problems will include a wide range of both positive and negative values around the small point estimates. These findings are consistent with Bazzi and Clemens (2013) and Kraay (2015)[17].

[17] Bazzi and Clemens (2013) investigated instrument strength in Voitchovsky (2005) among

A large number of studies has focused on revealing whether the inequality-growth relationship is dependent on the level of inequality, the level of economic development or some other factor. Without introducing any new variables or mechanisms, this study incorporates the two first sources of potential non-linearity. This is done for the level of inequality by following Berg et al. (2018) and for the level of economic development by following Barro (2000). To reduce the number of specifications, the potential role of non-linearities is demonstrated only by focusing on the Gini coefficient, i.e. the specification (1) of Table 2.3 is augmented.

TABLE 2.6 Non-linearities to the level of inequality and economic development

System GMM estimation, dependent variable: growth of per capita GDP. Economic growth is measured over a five-year period, inequality measures are averages over the preceding five-year window, initial per capita GDP enters the model one year prior to the growth window, investment to GDP is observed during the growth window while educational attainment is observed at $t-5$. Year fixed effects included. In column (1), the coefficient for the Gini is allowed to differ when the level of inequality is already high. In column (2), the potential dependency to the level of economic development is modelled via an interaction term. In both specifications, the set of instruments includes the second lags of all explanatory variables. Robust standard errors in parantheses. Intercept and coefficients for investments and schooling omitted.

	(1)	(2)
Gini at the top 25 %	-0.0055	
	(0.0580)	
Gini at the bottom 75 %	0.0096	
	(0.0760)	
Gini		-0.0201
		(0.5978)
Gini × Ln(Initial per capita GDP)		-0.0027
		(0.0672)
Ln(Initial per capita GDP)	-0.0142**	-0.0177
	(0.0069)	(0.0226)
Observations	673	673
Number of countries	103	103
Test of equality of the top 25 % and bottom 75 % coeff. (p-value)	0.532	
Test of joint significance of the Gini and interaction term (p-value)		0.627
Number of instruments	116	117
AR1 test (p-value)	<0.000	<0.000
AR2 test (p-value)	0.349	0.350
Hansen test of joint instrument validity (p-value)	0.809	0.663

Notes: Robust standard errors in parantheses. *, ** and *** denote statistical significance at the 10%, 5% and 1% levels, respectively. Tests for instrument subsets omitted for readability.

In Table 2.6, the coefficient of the Gini coefficient is negative when the level of inequality is high and positive when inequality is modest or low (column (1)). However, neither of these estimates or the difference between the two are statistically significant. The cut-off point (top 25 %) is the same as in Berg et al. (2018). If

other panel growth studies that examined a different theme. Kraay (2015) focused solely on inequality-growth studies: Castelló-Climent (2010), Halter et al. (2014), Ostry et al. (2014), Dabla-Norris et al. (2015).

the cut-off value is chosen as the 90th percentile or the median of the distribution of the Gini coefficient, the "top" and "bottom" estimates are both negative and the difference between the two is statistically insignificant. The results of column (2) show that, in terms of just the point estimates, the association between income inequality and growth is negative and more pronounced in richer economies. Like in column (1), the coefficients are not individually or jointly significant. Thus, the two most obvious sources of non-linearity do not gain empirical support when the WIID and the sGMM are used in conjunction. Moreover, the conclusion is the same irrespective of the inequality measure.

2.4.2 Other panel techniques

The results above showed that the widely used sGMM estimator found no evidence for a clear-cut relationship between income inequality and subsequent growth of per capita GDP when the WIID serves as the data source for inequality. The results were shown to be sensitive to even small changes in the specifications and the internal instruments were shown to suffer from weakness. But, what do other widely applied panel estimation techniques tell and how should we interpret the coefficients?

The estimators considered here are the pooled OLS (POLS), the fixed effects (FE), the random effects (RE) and the so-called difference GMM (dGMM) estimator. The simplest estimator, POLS, ignores the country-specific fixed effects. FE, as the name suggests, removes the fixed effects by time-demeaning the data and thus effectively relies on time variation. RE makes the assumption that the individual effect does not correlate with the regressors. The dGMM uses the suitably lagged values of the regressors as instruments for the first-differenced transformation of equation (2.1) and like FE does not make use of the cross-country variation. The dGMM corresponds to one of the two equations in the sGMM.

The use of alternative estimators has been previously studied in the inequality-growth context. In their meta-analysis, Neves et al. (2016) found that using cross-country variation is associated with stronger negative association relative to studies that have used variation in time. Berg et al. (2018) document that, in their analysis, the FE and dGMM find positive estimates for inequality on growth, whereas the RE and sGMM estimates are negative. Halter et al. (2014) point out the differences between the dGMM and the sGMM. They argue that even though the former can control for lagged dependent variables and unobserved cross-country heterogeneity, its use may be problematic because within-country inequality and the potential transmission channels evolve slowly over time. On the contrary, these variables tend to vary substantially between countries. Consequently, their concern is that the dGMM may be associated with large biases and imprecision. Thus, based on the previous findings, it can be expected that the POLS and RE estimates are negative, whereas FE and the dGMM should find positive estimates.

To ensure comparable analysis to the sGMM estimations, I adopt the same panel data set of 103 countries together with the timing convention and control variables introduced in equation (2.1). The reduced-form estimates are collected

in Table 2.7 while the full regression tables can be found in 2.A.3. The first column of Table 2.7 shows the sGMM estimates discussed above and columns (2) - (5) report the estimates obtained by using other panel techniques. The variables considered are the Gini coefficient (surveys, imputations), the Palma ratio and two variants of the top income shares.

The evidence based on the WIID data is consistent with the previous findings regarding the estimators that utilize variation between countries: the sGMM (1) and RE (4) estimates are negative with the exception of the top 20 % income share (sGMM). POLS captures the negative partial correlation between income inequality and growth when convergence, investments, schooling and year fixed effects are controlled for. It does not include country-specific characteristics. The negative estimates of column (2) are compatible with Figure 2.1, where one could fit a gradually down-ward sloping line[18].

TABLE 2.7 Five panel estimation techniques, five inequality measures

The reduced-form estimates from 25 panel growth regressions, dependent variable: growth of per capita GDP. Economic growth is measured over a five-year period, inequality measures are averages over the preceding five-year window, initial per capita GDP enters the model one year prior to the growth window, investment to GDP is observed during the growth window while educational attainment is observed at $t-5$. Year fixed effects included. Column by column, the estimation techniques are system GMM, pooled OLS, random effects, fixed effects and difference GMM. The full regression tables available in 2.A.3

	sGMM	POLS	FE	RE	dGMM
	(1)	(2)	(3)	(4)	(5)
Gini, WIID4	-0.0482	-0.0561***	0.0228	-0.0617**	-0.0420
	(0.0532)	(0.0207)	(0.0576)	(0.0300)	(0.0799)
Gini, SWIID7	-0.0915	-0.0492***	0.2195**	-0.0554***	0.3442**
	(0.0615)	(0.0159)	(0.0903)	(0.0181)	(0.1745)
Palma ratio, WIID4	-0.0009	-0.0058***	-0.0040	-0.0064**	-0.0053
	(0.0028)	(0.0021)	(0.0032)	(0.0026)	(0.0071)
Top 20 %, WIID4	0.0550	-0.0674**	0.0194	-0.0808*	-0.0370
	(0.0660)	(0.0291)	(0.0823)	(0.0420)	(0.1138)
Top 10 %, WIID4	-0.0057	-0.0812**	0.0081	-0.0958**	-0.1036
	(0.0750)	(0.0349)	(0.0896)	(0.0483)	(0.1405)
Reduced-form estimate × The standard deviation of the inequality measure					
Gini, WIID4	-0.0048	-0.0056	0.0023	-0.0061	-0.0042
Gini, SWIID7	-0.0081	-0.0044	0.0195	-0.0049	0.0306
Palma ratio, WIID4	-0.0013	-0.0084	-0.0061	-0.0096	-0.0085
Top 20 %, WIID4	0.0045	-0.0055	0.0016	-0.0066	-0.0030
Top 10 %, WIID4	-0.0004	-0.0063	0.0006	-0.0074	-0.0080

Notes: Robust standard errors in parentheses. *, ** and *** denote statistical significance at the 10%, 5% and 1% levels, respectively.

[18] I also experiment with specifications that remove the panel structure and rely solely on cross-country variation: income inequality is observed during the window 1991-1995 and growth of per capita GDP is calculated over 1995 and 2015. The least squares estimates for inequality are negative and statistically significant across all measures like in column (2) of Table 2.7.

2.4.3 OECD and non-OECD subsamples

Many of the seminal studies on inequality and economic growth have emphasized the role of the stage of economic development. For example, the Kuznets curve (Kuznets, 1955) depicts the idea of how the level of inequality is dependent on economic development, and in the theoretical framework of Galor and Moav (2004), the importance of physical and human capital in different stages of the growth process is an important driver of the inequality-growth relationship. Empirically, the distinction between developing and developed countries seems to matter. One of the central findings of Neves et al. (2016) is that the negative association between inequality and growth, found in many studies, is stronger in less developed countries. Thus, complementing the full sample analysis by focusing on subsamples of developed and developing countries seems essential.

In this study, I differentiate between two stages of economic development by separating the OECD member countries from the rest (Table 2.8). To detect differences in patterns between the two subsamples and the full sample with respect to different measures of inequality and estimation techniques, the format of Table 2.7 is adopted[19].

The main result of Table 2.8 is that the preferred estimator, the sGMM, does not find a single statistically significant estimate in either of the samples. The second finding is that the signs of the estimates follow the predicted patterns associated with cross-country and time variation faithfully in the non-OECD sample (negative sGMM, POLS and RE estimates while the FE and dGMM estimates are positive with the exception of the Palma ratio & FE). In the sample of OECD members, the POLS, FE and dGMM estimates follow a similar pattern, whereas the signs of the sGMM and RE estimates depend on the measure of income inequality. Furthermore, none of the OECD sample estimates are statistically significant.

In terms of the sGMM estimates, differentiating between developed and developing countries does not change the big picture: no clear-cut relationship between income inequality and subsequent economic growth emerges. Yet, the simple estimation techniques that use both cross-country and time variation find a more pronounced negative association in the developing countries. This is consistent with the meta-analysis of Neves et al. (2016).

2.5 Transmission channels

The rediscovered empirical interest in the equity-efficiency trade-off was sparked by the seminal theoretical studies of the 1990s briefly presented in Chapter 2.2. Thus, it is natural to extend the reduced-form analysis of the previous section to address the relevance of the mechanisms introduced in the theoretical literature. In the language of the tug-of-war depicted in the introduction of the dissertation,

[19] The ten individual full regression tables are omitted but are available upon a request.

TABLE 2.8 Panel growth regressions in the samples of OECD and non-OECD countries

The reduced-form estimates from 50 panel growth regressions, dependent variable: growth of per capita GDP. See Table 2.7 for further details.

	sGMM	POLS	FE	RE	dGMM
	(1)	(2)	(3)	(4)	(5)
Panel A: OECD					
Gini, WIID4	0.1946	-0.0002	0.0428	0.0002	0.1658
	(0.1987)	(0.0225)	(0.0480)	(0.0233)	(0.1276)
Gini, SWIID7	-0.0948	-0.0297	0.0367	-0.0352	0.2571
	(0.2107)	(0.0272)	(0.0647)	(0.0300)	(0.1783)
Palma ratio, WIID4	-0.0033	-0.0022	0.0096	-0.0021	0.0130
	(0.0096)	(0.0022)	(0.0067)	(0.0024)	(0.0135)
Top 20 %, WIID4	0.0443	-0.0164	0.0392	-0.0172	0.2764
	(0.2564)	(0.0266)	(0.0603)	(0.0294)	(0.1965)
Top 10 %, WIID4	0.2194	-0.0198	0.0794	-0.0209	0.2115
	(0.2375)	(0.0318)	(0.0885)	(0.0349)	(0.2755)
Panel B: non-OECD					
Gini, WIID4	-0.0066	-0.0952***	0.0284	-0.0874**	0.0136
	(0.0715)	(0.0265)	(0.0826)	(0.0356)	(0.1313)
Gini, SWIID7	-0.1013	-0.0764***	0.3941***	-0.0713***	1.1758***
	(0.1473)	(0.0204)	(0.1280)	(0.0226)	(0.3329)
Palma ratio, WIID4	-0.0042	-0.0068***	-0.0034	-0.0069***	0.0096
	(0.0030)	(0.0023)	(0.0034)	(0.0026)	(0.0081)
Top 20 %, WIID4	-0.0618	-0.1115***	0.0382	-0.1087**	0.1686
	(0.0878)	(0.0378)	(0.1053)	(0.0493)	(0.2011)
Top 10 %, WIID4	-0.1017	-0.1244***	0.0353	-0.1215**	0.3306
	(0.0807)	(0.0442)	(0.1041)	(0.0555)	(0.2316)

Notes: Robust standard errors in parentheses. *, ** and *** denote statistical significance at the 10%, 5% and 1% levels, respectively.

the interest now covers not just the result of the contest but also the strength of some of the individuals pulling the rope.

The first two mechanisms considered come self-evidently from growth theory. The accumulation of physical and human capital are essential determinants for economic growth and if inequality has an effect on these processes, it also impacts GDP growth. More specific depictions of the channels are given by Galor and Zeira (1993) and Galor and Moav (2004), who analyze the role of physical and human capital in the relationship between inequality and the process of economic development. The data for these two potential mechanisms were already introduced for the preceding analysis when investment to GDP and educational attainment served as control variables in the growth regressions.

The three supplementary variables for the mechanism analysis are life expectancy, the quality of political institutions (Marshall et al., 2002) and fertility rate. The data for both life expectancy and fertility rate come from the World Development Indicators (WDI) provided by the WorldBank (2019). Life expectancy serves as an alternative measure for human capital, the role of political institutions in the equity-efficiency context is emphasized by Alesina and Perotti (1996) while De La Croix and Doepke (2003) introduce fertility as a potential underlying channel between inequality and growth. The set of mechanism could arguably be expanded or altered but the ones considered here are backed up by rigorous economic theory and, importantly for the empirical analysis, cross-country data with reasonably good coverage for these variables exist.

Two noteworthy caveats specific to the variables listed above need to be stated. First, the measure provided by the Polity IV project (Marshall et al., 2002) does not exactly match political instability as modelled by Alesina and Perotti (1996) since it addresses the quality of political institutions labelling them from autocratic to democratic in a scale from -10 to 10. Second, in the model of De La Croix and Doepke (2003), poor parents decide to have many children and neglect investments in education. As a result, what should matter is differential fertility instead of births per woman on average as in the fertility rate provided by the WDI for example. Interestingly though, Berg et al. (2018) find that average fertility and differential fertility are positively correlated and thus, they argue, the former can be useful in cross-country analysis until the data coverage of the differential fertility improves.

The statistical approach to evaluate the relevance of potential channelling mechanisms in the inequality-growth relationship follows a two-stage framework similar to Berg et al. (2018). First, letting X stand for inequality and stacking the channels in a matrix Z, give a growth regression

$$\begin{aligned} lnY_{i,t+4} - lnY_{i,t} = \beta_1(\frac{1}{5}\sum_{j=0}^{4} X_{i,t-10+j}) + \beta_2 lnY_{i,t-1} + \beta_3'(\frac{1}{5}\sum_{j=0}^{4} Z^k_{i,t-5+j}) \\ + \alpha_i + \eta_t + \varepsilon_{i,t}, \end{aligned} \tag{2.2}$$

where α_i and η_t are the vectors of fixed country and year effects and $\varepsilon_{i,t}$ is the overall error term. Second, for each channel Z^k, the the effect of income concen-

tration on the channel is given by

$$(\frac{1}{5}\sum_{j=0}^{4} Z^k_{i,t-5+j}) = \lambda_0 + \lambda^k_1(\frac{1}{5}\sum_{j=0}^{4} X_{i,t-10+j}) + \lambda^k_2 lnY_{i,t-1} + \mu_i + \kappa_t + \omega_{i,t}, \quad (2.3)$$

where λ^k_1 and λ^k_2 are the effect of the inequality measure and initial income on channel k. μ_i, κ_t and $\omega i, t$ are fixed country effects, fixed year effects and the error term, respectively. Substituting (2.3) into (2.2) gives

$$\begin{aligned} lnY_{i,t+4} - lnY_{i,t} = (\beta_1 + \beta^{'}_3 \sum_k \lambda^k_1)(\frac{1}{5}\sum_{j=0}^{4} X_{i,t-10+j}) + (\beta_2 + \beta^{'}_3 \sum_k \lambda^k_2) lnY_{i,t-1} \\ + \alpha_i + \eta_t + \varepsilon_{i,t} \end{aligned} \quad (2.4)$$

The sGMM estimation involves estimating equation (2.4) and its first-differenced transformation as a system. Contrary to the timing convention of the previous section, inequality is now observed during twice lagged five-year window while the candidate mechanisms enter the model as an average between $t-5$ and $t-1$ with the exception that educational attainment is observed at $t-5$. The underlying mechanisms likely require longer time periods to fully manifest themselves but given the data limitations the chosen timing convention is appropriate: inequality is observed before the channels it is assumed to effect while the channels are observed prior to the growth window.

In the full regression tables (2.A.4), the first columns report the coefficients that correspond to equation (2.2), the columns in the middle collect the λ^k_1 parameters of equation (2.3), whereas the column on the right corresponds to equation (2.4). The tables cover the Gini coefficient as the inequality measure with only physical and human capital channels, the Gini with full set of potential mechanisms and the income share of the top quintile as the measure of inequality with the same two sets of channels. The samples are the same throughout the four specifications and cover 83 countries. Table 2.9 collects the coefficients from the detailed tables of 2.A.4 into a single compact illustration. Column (1) reports the association between the candidate channels and growth, column (2) the association between inequality and the channels and column (3) the full decomposition of the growth regression.

The total effects displayed in the bottom-right corner of each panel replicate the null result of the previous section. However, panels A and C reveal that through physical investments, inequality is positively associated with per capita growth, whereas through education channel, inequality seems to dampen growth. Panels B and D show that the role of investment channel remains large when the supplementary variables are introduced while the fertility channel shifts much of the burden from schooling. Moreover, life expectancy as an alternative measure for human capital does not emerge as a relevant transmission mechanism. The direct effect should be interpreted as a combined residual of all the possible channels, potentially pulling in different directions, not addressed in this section.

TABLE 2.9 Transmission channels

System GMM estimation, decomposing the inequality-growth relationship into potential transmission channels. In columns (1) and (3), the dependent variable is growth of per capita GDP. In column (2), the dependent variables are the channels. See equations (2.2) - (2.4) for the timing convention. The estimates are collected from the full regression tables located in Appendix 2.A.4

	Association between channels and growth, $\beta_3^{'}$ of eq. (2.4) (1)	Association between ineq. and channels, λ_1^k of eq. (2.3) (2)	Panel growth regression decomposed, $\beta_1 + \beta_3^{'} \sum_k \lambda_1^k$ of eq. (2.4) (3)
Panel A: Gini, investment and schooling channels			
Direct effect			0.0084
			(0.0390)
Investment	0.0265**	2.1393**	0.0567
	(0.0111)	(0.8368)	
Schooling	0.0471***	-1.5238*	-0.0718
	(0.0125)	(0.9177)	
Total			-0.0066
			(0.0418)
Panel B: Gini, all candidate channels			
Direct effect			-0.0033
			(0.0289)
Investment	0.0244***	2.1393**	0.0522
	(0.0093)	(0.8368)	
Schooling	0.0210**	-1.5238*	-0.0320
	(0.0092)	(0.9177)	
Life expectancy	-0.0055	-0.4208**	0.0023
	(0.0373)	(0.1685)	
Political institutions	-0.0148	-0.2699	0.0040
	(0.0108)	(0.3858)	
Fertility	-0.0331***	1.2979***	-0.0430
	(0.0094)	(0.5013)	
Total			-0.0197
			(0.0327)

Table 2.9 continues.

	Association between channels and growth, β_3' of eq. (2.4) (1)	Association between ineq. and channels, λ_1^k of eq. (2.3) (2)	Panel growth regression decomposed, $\beta_1 + \beta_3' \sum_k \lambda_1^k$ of eq. (2.4) (3)
Panel C: Top 20 % income share, investment and schooling channels			
Direct effect			-0.0128
			(0.0617)
Investment	0.0263**	2.6878**	0.0707
	(0.0116)	(1.2374)	
Schooling	0.0386***	-1.6435	-0.0634
	(0.0112)	(1.0435)	
Total			0.0050
			(0.0678)
Panel D: Top 20 % income share, all candidate channels			
Direct effect			0.0085
			(0.0397)
Investment	0.0246**	2.6878**	0.0661
	(0.0099)	(1.2374)	
Schooling	0.0228**	-1.6435	-0.0375
	(0.0090)	(1.0435)	
Life expectancy	0.0028	-0.4948	-0.0014
	(0.0415)	(5.7035)	
Political institutions	-0.0177*	-0.9032	0.0160
	(0.0096)	(0.6069)	
Fertility	-0.0326***	1.3792*	-0.0450
	(0.0094)	(0.7695)	
Total			0.0067
			(0.0444)

Notes: Robust standard errors in parentheses. *, ** and *** denote statistical significance at the 10%, 5% and 1% levels, respectively.

How should the result of inequality supporting growth through physical investments be interpreted? First, if capital incomes play a large role behind rising income inequality, larger dispersion of income makes investments more attractive thus raising their level and contributing positively to aggregate output. Second, following Kaldor (1957) and Bourguignon (1981), the higher savings rate of the top earners may induce a positive linkage between inequality and investments. The result suggests that mechanisms of these type dominate over the ones where inequality creates a hostile economic environment for investments.

As discussed above, Table 2.9 paints a simplified picture of the analysis by collecting the key coefficients. The detailed diagnostics reported in 2.A.4 show that in many cases the assumptions of the instrumentation strategy are violated and thus the results should be interpreted with caution. Typically, at least either the autocorrelation assumption or the instrument non-proliferation can be met but often satisfying them both is out of reach. Furthermore, a brief unbundling exercise reveals that the analysis on the transmission channels, too, suffers from weak instruments.

The field of mechanisms underlying the equity-efficiency question is complex and introducing a two-stage approach using aggregate data in a cross-country

setting has its limitations beyond the estimator-specific issues. For example, instability induced by income or wealth inequality first affects investment decisions and then growth of output in the model by Alesina and Perotti (1996). Moreover, capturing incentive-based effects or disentangling separate channels with measures that do not precisely match the suggested mechanisms adds uncertainty into the analysis. Despite the limitations, cross-country investigation on the channels is valuable especially when new data sources and new suggested channels emerge. Alternatively, focusing on micro-based evidence in a specific institutional setting potentially gains our knowledge even more if the identification strategy succeeds in isolating a specific mechanism.

2.6 Conclusion

This study has revisited the much studied question of how income inequality affects economic growth. The aim has been to construct a comprehensive empirical analysis in a cross-country panel data setting to clarify the divergent results published over time. While relying on up-to-date data, different inequality measures, varying specifications for growth regressions and several estimation techniques have been considered. Furthermore, the properties of the preferred estimator, system GMM, have been examined in detail, subsample analysis has been conducted and the framework has allowed non-linearities to the level of inequality and the level of economic development. Finally, to complement the reduced-form growth regressions, analysis on potential transmission channels underlying the equity-efficiency dilemma has been implemented.

The main finding of the study is that there is no clear evidence suggesting that income inequality either promotes or dampens economic growth. Different estimators show patterns already documented by previous studies while the system GMM estimator, which aims to mitigate the issues caused by reverse causality and omitted variables, suggests that no relationship between inequality and growth can be found. The null result seems to be a result of different mechanisms pulling in different directions. Additionally, even if the typical diagnostics reported along with the system GMM supported the assumptions attached to the estimator, the point estimates cannot be interpreted as causal since testing for the assumptions has its caveats and the internal instruments tend to be weak. More profoundly, a causal interpretation from an identification strategy that is based on a large panel of countries offers little for policy recommendations because curbing (or promoting) income inequality is at the hands of individual countries.

The results of this paper can by no means invalidate the powerful arguments for devastating consequences that excessive inequality can have through socio-political instability or for incentive-based responses if the level of inequality rises in a very equal country. Despite the limitations of cross-country studies, I believe that they can offer much more by discovering new inter-dependencies and relevant transmission channels underlying the equity-efficiency question. How-

ever, perhaps even a more fruitful avenue is to focus on micro-level data. As the relationship between inequality and growth is determined by numerous mechanisms, which are likely to play different roles under different institutional settings, isolating specific mechanisms in a specific context can offer stronger results than can be established when the focus is set on aggregate data.

2.A Appendix

2.A.1 Data retrieval and evaluation

Data selection. The observation is defined as net income if the WIID4 variable resource_detailed, previously labeled as welfare definition, is one of the following: 'Earnings, net', 'Income, net', 'Monetary income, net', 'Monetary income, net (excluding property income)' or 'Taxable income, net'; as consumption income if resource_detailed is 'Consumption'; and as market income if resource_detailed is one of the following: 'Earnings, gross', 'Factor income', 'Income, gross', 'Market income', 'Monetary income, gross', 'Taxable income, gross' or 'Taxable income, gross (including deductions)'.

Based on the variable quality_score running from 3 to 13, I rank the observations and pick the highest to use the observations of best possible quality to form the final country panel and get rid of many of the duplicate observations. In case of observations tied on the quality score for a given country-year pair, a simple average is taken to obtain unique observations.

The quality score is defined in the following way by the WIID team (UNU-WIDER, 2018): *We award points to the observations based on their attributes in the following way (maximum is 13 points). Gini coefficient is available (1). Resource concept: Consumption, Income (net), Income (gross), Monetary income (gross), Monetary income (net) (5), Income, Monetary income, Market income (3), Factor income, Primary income, Taxable income, Earnings (1). Equivalence scale: Per capita or equivalized (3), No adjustment (2). Area coverage: All, Urban, Rural (1). Population coverage: All (1). Distributional share information: All of d1-q5 are available (2), All of q1-q5 are available (at least one of d1-d10 is missing) (1).*

Comparative analysis between different data sources. The OECD Income Distribution Database (OECD, 2019)[20] provides data on the net income Gini coefficients for its member states. All series correspond to same OECD income definitions and thus they should be more comparable across time and across the OECD countries than the WIID ones. Therefore, the OECD database offers a point of reference to evaluate whether the WIID series differ from series of likely higher quality in a subsample of OECD countries. For non-OECD countries, a comparative exercise would be a cumbersome task since the reference series would have

[20] Available at http://www.oecd.org/social/income-distribution-database.htm

to be gathered from various sources and improvements on comparability relative to the WIID would be difficult to establish.

Following Atkinson and Brandolini (2001), the WIID, the SWIID and the OECD data are used to form cross-country inequality rankings and to compare within-country inequality trends. The WIID series correspond to the result of the above-described data selection algorithm and thus the observations are averages over the periods 2000-2004 and 2010-2014. Due to gaps in the WIID and OECD data, the comparison is restricted to 14 countries. Other choices of reference years would reduce the ranking sample even further.

TABLE 2.9 Country rankings by the Gini coefficient

	Year 2000			Year 2010		
Country	WIID	SWIID	OECD	WIID	SWIID	OECD
Australia	8	9	9	11	10	10
Canada	9	8	8	8	8	8
Denmark	2	1	1	5	2	2
Finland	3	4	3	2	3	3
France	6	7	6	7	7	7
Germany	7	6	5	6	6	6
Israel	13	12	11	13	12	12
Italy	10	10	10	10	9	9
Mexico	14	14	14	14	14	14
Netherlands	5	5	7	4	5	5
Norway	4	2	4	1	1	1
Sweden	1	3	2	3	4	4
United Kingdom	11	11	12	9	11	11
United States	12	13	13	12	13	13

Inequality rankings in a subset of 14 OECD countries. Countries are ranked based on the value of the Gini coefficient. The smallest Gini is marked by 1, the largest by 14.

A single major glitch clearly emerges: the 2010 WIID ranking places Denmark as fifth while all others rank the country in the top two. As can be seen in Figure 2.2, the WIID very likely overestimates the level of inequality in Denmark in 1995 and 2000. Otherwise, the rankings are fairly stable although changes occur especially within the Nordic countries who share low levels of income inequality and whose values for the Ginis are close to one another irrespective of the data source. All pairwise correlations between the rankings in a point in time are well above 0.95.

Based on graphical analysis, of which Figure 2.2 is an example, the WIID in general matches the data provided by the OECD modestly well although some of the time variation is undoubtedly due to differences between surveys or calculations of the income distributions. Canada is an example of a case where all three alternatives paint a similar picture, the SWIID probably underestimates the extent of inequality in Mexico while the WIID series show lower values than the OECD ones for the US.

Next, a comparative approach is taken for the measures provided by the WIID. I consider the same base years as above, 2000 and 2010, while focus is set

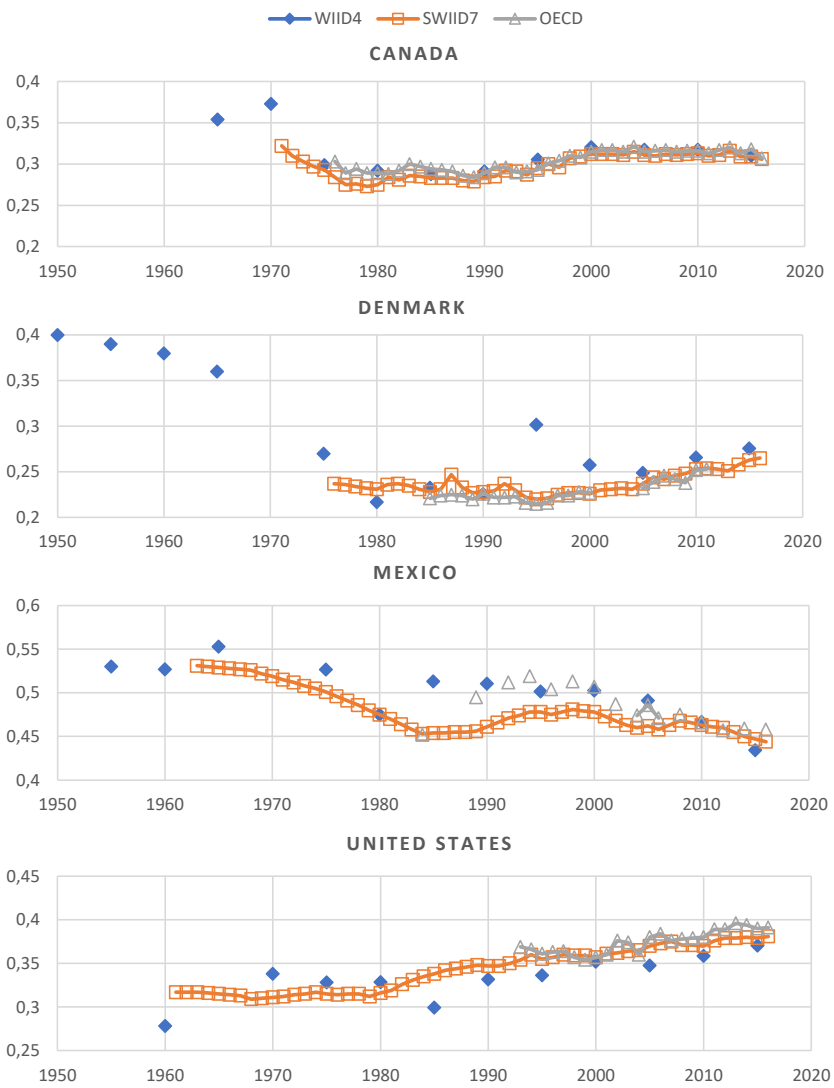

FIGURE 2.2 The net income Gini coefficients in Canada, Denmark, Mexico and the United States

on the net income Gini coefficient and the income share of the richest decile. As the Gini is by construction especially sensitive to changes in the middle of the income distribution and thus inherently incorporates values regarding how to measure inequality by giving a smaller weight for the tails of the distribution, it is essential to adopt alternative measures to complement the analysis. The top income shares have gained plenty of attention both in the media and in economics and are therefore chosen for the comparative analysis.

The country panel formed for this study has observations covering the two inequality measures in both 2000 and 2010 for 88 countries. Since tables and graphical time series analysis are not feasible in any practical manner for such a large set of countries, the countries are ranked according to their level of income inequality and the rankings are used to examine the dependencies in time and between the Gini coefficient and the top income shares.

The cross-national rankings show more changes in time for both inequality measures as illustrated in the lower panels of Figure 2.3 especially in the middle of the ranking. The countries that have either relatively low or high level of income inequality in 2000 are similarly ranked in 2010. The countries consistently at the low end of the ranking are the Nordic countries, Austria, Czech Republic, Hungary, Netherlands, Slovakia and Slovenia, whereas the high-inequality positions are occupied by for example Brazil, Guatemala, Namibia and South Africa. Overall, the cross-national rankings and graphical illustrations, such as Figure 2.3, show that within-country inequality is very persistent and the variation in inequality in the panel of countries used in this study comes predominantly from cross-country differences.

The upper panels of Figure 2.3 show that in both time periods the Gini coefficient and the income share of the richest decile rank the countries very similarly. The correlation between the rankings are 0.98 and 0.97 in 2000 and 2010, respectively. This observation is consistent with the study by Leigh (2007), who finds that the top income shares tend to track the broader measures of inequality. The connection between the relative incomes of the richest earners and the Gini speak for the use of the top income shares as a substitute for broader inequality measures if there are data available only for the right tail of the income distribution. The use of tax data to construct long time-series spanning over the 20th century and beyond has been most notably popularized by Piketty (2015). The country coverage of these data at this point of the project by the World Inequality Lab[21] is still small in comparison to the WIID but already offers an adequate data source for within-country analysis and the construction of panels with small number of countries.

[21] See https://wid.world/ for the project and the World Inequality Database.

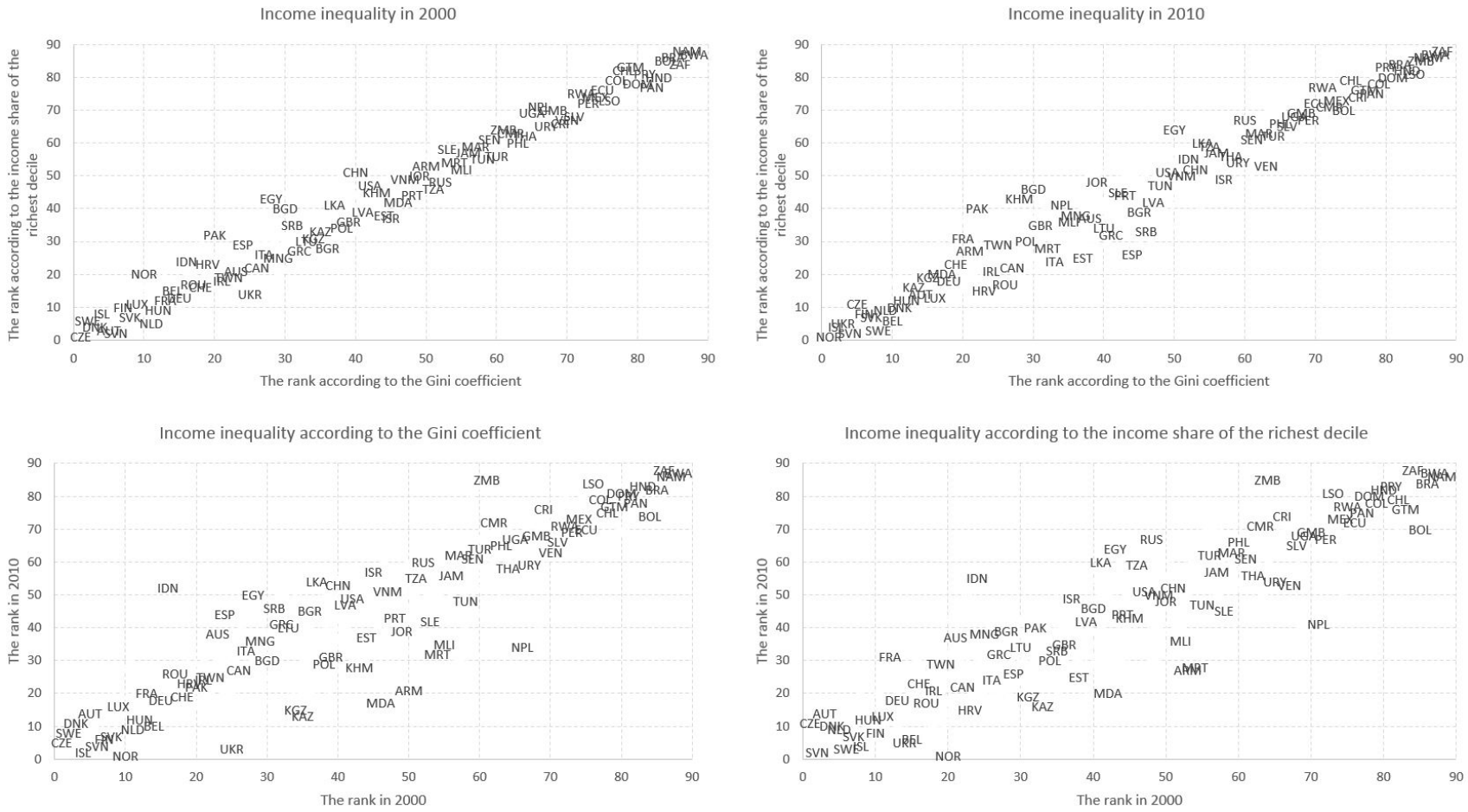

FIGURE 2.3 The WIID variables in comparison

TABLE 2.10 Samples for different sections of the analysis

The core analysis	Adding controls sequentially	Transmission channels
Armenia	Armenia	Armenia
Australia	Australia	Australia
Austria	Austria	Austria
Bangladesh	Bangladesh	Bangladesh
Belgium	Belgium	Belgium
Bolivia	Bolivia	Bolivia
Botswana	Botswana	Botswana
Brazil	Brazil	Brazil
Bulgaria	Bulgaria	Bulgaria
Burundi	Burundi	Burundi
Cambodia	Cambodia	Cambodia
Cameroon		
Canada	Canada	Canada
Central African Rep.	Central African Rep.	Central African Rep.
Chile	Chile	Chile
China		
Colombia	Colombia	Colombia
Costa Rica	Costa Rica	Costa Rica
Croatia	Croatia	Croatia
Czech Republic	Czech Republic	Czech Republic
Cote d'Ivoire		
Denmark	Denmark	Denmark
Dominican Republic	Dominican Republic	Dominican Republic
Ecuador	Ecuador	Ecuador
Egypt		
El Salvador	El Salvador	El Salvador
Estonia	Estonia	Estonia
Finland	Finland	Finland
France	France	France
Gambia		
Germany	Germany	Germany
Ghana	Ghana	Ghana
Greece	Greece	Greece
Guatemala	Guatemala	Guatemala
Honduras	Honduras	Honduras
Hungary	Hungary	Hungary
Iceland		
India	India	India
Indonesia	Indonesia	Indonesia
Iran (Islamic Republic of)		
Ireland	Ireland	Ireland
Israel	Israel	Israel
Italy	Italy	Italy
Jamaica	Jamaica	Jamaica
Jordan		
Kazakhstan		
Kenya	Kenya	Kenya
Kyrgyzstan	Kyrgyzstan	Kyrgyzstan
Latvia	Latvia	Latvia
Lesotho	Lesotho	Lesotho
Lithuania	Lithuania	Lithuania

Table 2.10 continues

Luxembourg	Luxembourg	Luxembourg
Malawi	Malawi	Malawi
Mali	Mali	Mali
Mauritania		
Mexico	Mexico	Mexico
Mongolia	Mongolia	Mongolia
Morocco		
Mozambique	Mozambique	Mozambique
Namibia	Namibia	Namibia
Nepal	Nepal	Nepal
Netherlands	Netherlands	Netherlands
Nicaragua	Nicaragua	Nicaragua
Niger	Niger	Niger
Norway	Norway	Norway
Pakistan	Pakistan	Pakistan
Panama	Panama	Panama
Paraguay	Paraguay	Paraguay
Peru	Peru	Peru
Philippines	Philippines	Philippines
Poland	Poland	Poland
Portugal	Portugal	Portugal
Republic of Korea	Republic of Korea	Republic of Korea
Republic of Moldova	Republic of Moldova	Republic of Moldova
Romania	Romania	Romania
Russian Federation	Russian Federation	Russian Federation
Rwanda		
Senegal	Senegal	Senegal
Serbia	Serbia	Serbia
Sierra Leone	Sierra Leone	Sierra Leone
Slovakia	Slovakia	Slovakia
Slovenia	Slovenia	Slovenia
South Africa	South Africa	South Africa
Spain	Spain	Spain
Sri Lanka	Sri Lanka	Sri Lanka
Sweden	Sweden	Sweden
Switzerland	Switzerland	Switzerland
Taiwan	Taiwan	
Tajikistan		
Thailand	Thailand	Thailand
Tunisia		
Turkey	Turkey	Turkey
Tanzania		
Uganda		
Ukraine	Ukraine	Ukraine
United Kingdom	United Kingdom	United Kingdom
United States	United States	United States
Uruguay	Uruguay	Uruguay
Venezuela	Venezuela	Venezuela
Viet Nam		
Yemen		
Zambia	Zambia	Zambia
Zimbabwe	Zimbabwe	
103 countries	85 countries	83 countries

2.A.2 Reduced-form sGMM estimates for all inequality measures

TABLE 2.11 The Gini coefficient (WIID, SWIID) and the Palma ratio

System GMM estimation, dependent variable: growth of per capita GDP. Economic growth is measured over a five-year period, inequality measures are averages over the preceding five-year window, initial per capita GDP enters the model one year prior to the growth window, investment to GDP is observed during the growth window and is thus allowed to have a contemporaneous effect on growth while educational attainment is observed at $t-5$. Year fixed effects included. In all specifications, the set of instruments includes the second lags of all explanatory variables. See equation (2.1) for the growth regression and Chapter 2.3 for data sources.

	Gini coefficient WIID4 (1)	Gini coefficient SWIID7 (2)	Palma ratio WIID4 (3)
Inequality	-0.0482	-0.0915	-0.0009
	(0.0532)	(0.0615)	(0.0028)
Ln(Initial per capita GDP)	-0.0158**	-0.0087	-0.0103
	(0.0077)	(0.0075)	(0.0082)
Ln(Investment to GDP)	0.0189**	0.0237***	0.0135***
	(0.0076)	(0.0074)	(0.0050)
Ln(Avg yrs of schooling)	0.0115	-0.0026	0.0072
	(0.0137)	(0.0113)	(0.0150)
Constant	0.0000	0.0000	0.1267*
	(0.0000)	(0.0000)	(0.0665)
Observations	673	744	594
Number of countries	103	103	103
Number of instruments	95	82	82
AR1 test (p-value)	<0.000	<0.000	<0.000
AR2 test (p-value)	0.404	0.787	0.064
Hansen test of joint instr. validity (p-value)	0.601	0.125	0.488
Diff.-in-Hansen tests of instr. subsets (p-value)			
For levels	0.950	0.920	0.910
For initial per cap GDP	0.462	0.813	0.584
For IV-type (time dum.)	0.635	0.875	0.383

Notes: Robust standard errors in parantheses. *, ** and *** denote statistical significance at the 10%, 5% and 1% levels, respectively.

TABLE 2.12 Inequality measures of Litschig and Lombardi (2019) and Voitchovsky (2005)

System GMM estimation, dependent variable: growth of per capita GDP. See Table 2.11 for details on the statistical specification.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
5th quintile	-0.2079						
	(0.5348)						
4th quintile	-0.2010						
	(0.8508)						
2nd quintile	-0.0761						
	(1.0530)						
1st quintile	-0.5076						
	(0.8230)						
P90/P70		0.4181		-10.9459		-2.1635	-8.3020
		(3.6853)		(17.5888)		(2.6007)	(8.1873)
P50/P10			0.0234		-0.0031	0.0358	0.0202
			(0.0719)		(0.0708)	(0.0694)	(0.0961)
Gini				0.1614	-0.0181		0.0997
				(0.3147)	(0.0584)		(0.1469)
Ln(Initial per capita GDP)	-0.0135**	-0.0121	-0.0077	-0.0129	-0.0131	-0.0129	-0.0136*
	(0.0063)	(0.0092)	(0.0090)	(0.0091)	(0.0082)	(0.0089)	(0.0074)
Ln(Investment to GDP)	0.0161***	0.0149***	0.0151***	0.0107**	0.0133**	0.0135***	0.0127***
	(0.0050)	(0.0057)	(0.0041)	(0.0045)	(0.0055)	(0.0029)	(0.0043)
Ln(Avg yrs of schooling)	0.0106	0.0107	0.0030	0.0149	0.0126	0.0105	0.0144
	(0.0116)	(0.0156)	(0.0166)	(0.0215)	(0.0146)	(0.0145)	(0.0133)
Constant	0.0000	0.0000	0.1113	0.2529	0.1524**	0.1808*	0.2481**
	(0.0000)	(0.0000)	(0.0713)	(0.2069)	(0.0775)	(0.1077)	(0.1219)
Observations	623	595	594	595	594	594	594
Number of countries	103	103	103	103	103	103	103
Test for joint significance of the ineq. terms (p-value)	0.750			0.657	0.934	0.647	0.507
Number of instruments	145	82	82	101	101	100	119
AR1 test (p-value)	<0.000	<0.000	<0.000	<0.000	<0.000	<0.000	<0.000
AR2 test (p-value)	0.131	0.052	0.056	0.062	0.067	0.066	0.057
Hansen test of joint instr. validity (p-value)	0.996	0.449	0.542	0.451	0.484	0.731	0.790

Notes: Robust standard errors in parantheses. *, ** and *** denote statistical significance at the 10%, 5% and 1% levels, respectively. Tests for instrument subsets omitted for readability.

TABLE 2.13 Income shares by quintiles

System GMM estimation, dependent variable: growth of per capita GDP. Economic growth is measured over a five-year period, inequality measures are averages over the preceding five-year window, initial per capita GDP enters the model one year prior to the growth window, investment to GDP is observed during the growth window and is thus allowed to have a contemporaneous effect on growth while educational attainment is observed at $t-5$. Year fixed effects included. In all specifications, the set of instruments includes the second lags of all explanatory variables. See equation (2.1) for the growth regression and Chapter 2.3 for data sources.

	Income share				
	1st quintile	2nd quintile	3rd quintile	4th quintile	5th quintile
	(1)	(2)	(3)	(4)	(5)
Inequality	-0.0942	-0.1288	0.0010	0.0910	0.0550
	(0.2694)	(0.2163)	(0.2147)	(0.2072)	(0.0660)
Ln(Initial per capita GDP)	-0.0111	-0.0097	-0.0131	-0.0152**	-0.0120
	(0.0085)	(0.0079)	(0.0080)	(0.0062)	(0.0074)
Ln(Investment to GDP)	0.0171***	0.0164***	0.0154**	0.0162**	0.0165***
	(0.0049)	(0.0054)	(0.0068)	(0.0063)	(0.0045)
Ln(Avg yrs of schooling)	0.0094	0.0093	0.0128	0.0132	0.0127
	(0.0144)	(0.0144)	(0.0157)	(0.0134)	(0.0140)
Constant	0.0000	0.0000	0.0000	0.0000	0.1167*
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0675)
Observations	626	623	623	624	627
Number of countries	103	103	103	103	103
Number of instruments	89	89	89	90	90
AR1 test (p-value)	<0.000	<0.000	<0.000	<0.000	<0.000
AR2 test (p-value)	0.131	0.135	0.087	0.069	0.123
Hansen test of joint instrument validity (p-value)	0.490	0.433	0.370	0.460	0.606
Difference-in-Hansen tests of instrument subsets (p-value)					
For levels	0.959	0.981	0.959	0.969	0.974
For initial per cap GDP	0.429	0.629	0.392	0.912	0.656
For IV-type (time dummies)	0.199	0.377	0.156	0.234	0.626

Notes: Robust standard errors in parantheses. *, ** and *** denote statistical significance at the 10%, 5% and 1% levels, respectively.

TABLE 2.14 Income shares by deciles

System GMM estimation, dependent variable: growth of per capita GDP. Economic growth is measured over a five-year period, inequality measures are averages over the preceding five-year window, initial per capita GDP enters the model one year prior to the growth window, investment to GDP is observed during the growth window and is thus allowed to have a contemporaneous effect on growth while educational attainment is observed at $t-5$. Year fixed effects included. In all specifications, the set of instruments includes the second lags of all explanatory variables. See equation (2.1) for the growth regression and Chapter 2.3 for data sources.

	1st decile	2nd decile	3rd decile	4th decile	5th decile	6th decile	7th decile	8th decile	9th decile	10th decile
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Inequality	-0.3520	-0.1185	0.0103	0.0258	0.2990	0.5512	0.0225	1.3532	-0.0604	-0.0057
	(0.4585)	(0.4447)	(0.4021)	(0.3719)	(0.5186)	(0.4096)	(1.9617)	(0.9667)	(0.3854)	(0.0750)
Ln(Initial per cap GDP)	-0.0065	-0.0106	-0.0111	-0.0120	-0.0124	-0.0127	-0.0102	-0.0136*	-0.0079	-0.0130*
	(0.0089)	(0.0083)	(0.0078)	(0.0076)	(0.0084)	(0.0079)	(0.0084)	(0.0078)	(0.0071)	(0.0077)
Ln(Investment to GDP)	0.0120*	0.0125**	0.0127**	0.0125**	0.0129**	0.0134**	0.0130	0.0152**	0.0139*	0.0127**
	(0.0068)	(0.0058)	(0.0063)	(0.0057)	(0.0060)	(0.0065)	(0.0122)	(0.0068)	(0.0072)	(0.0063)
Ln(Avg yrs of schooling)	0.0034	0.0092	0.0092	0.0102	0.0084	0.0066	0.0083	0.0068	0.0077	0.0120
	(0.0166)	(0.0150)	(0.0145)	(0.0148)	(0.0163)	(0.0156)	(0.0247)	(0.0160)	(0.0134)	(0.0139)
Constant	0.1086*	0.1344**	0.1347**	0.1401**	0.1237**	0.1042*	0.1102	-0.0119	0.1239	0.1300
	(0.0646)	(0.0573)	(0.0548)	(0.0550)	(0.0595)	(0.0619)	(0.1532)	(0.1341)	(0.0910)	(0.1103)
Observations	594	594	594	594	594	594	595	595	596	596
Number of countries	103	103	103	103	103	103	103	103	103	103
Number of instruments	82	82	82	82	82	82	82	82	114	85
AR1 test (p-value)	<0.000	<0.000	<0.000	<0.000	<0.000	<0.000	<0.000	<0.000	<0.000	<0.000
AR2 test (p-value)	0.058	0.064	0.071	0.071	0.074	0.084	0.077	0.146	0.055	0.075
Hansen test of joint instr. validity (p-value)	0.456	0.463	0.431	0.406	0.476	0.521	0.477	0.450	0.868	0.456
Diff.-in-Hansen tests of instr. subsets (p-value)										
For levels	0.815	0.736	0.770	0.630	0.689	0.746	0.801	0.804	0.999	0.940
For initial per cap GDP	0.322	1.000	0.268	0.770	0.895	0.863	0.855	0.504	0.700	0.342
For IV (time dummies)	1.000	0.164	0.114	0.152	1.000	1.000	0.334	0.177	1.000	0.462

Notes: Robust standard errors in parantheses. *, ** and *** denote statistical significance at the 10%, 5% and 1% levels, respectively.

2.A.3 Other estimation techniques

TABLE 2.15 The Gini coefficient (WIID) and growth, five different estimators

Dependent variable: growth of per capita GDP. Economic growth is measured over a five-year period, inequality measures are averages over the preceding five-year window, initial per capita GDP enters the model one year prior to the growth window, investment to GDP is observed during the growth window while educational attainment is observed at $t-5$. Year fixed effects included. Column by column, the estimation techniques are system GMM, pooled OLS, random effects, fixed effects and difference GMM.

	sGMM	POLS	FE	RE	dGMM
	(1)	(2)	(3)	(4)	(5)
Gini, WIID4	-0.0482	-0.0561***	0.0228	-0.0617**	-0.0420
	(0.0532)	(0.0207)	(0.0576)	(0.0300)	(0.0799)
Ln(Initial per capita GDP)	-0.0158**	-0.0135***	-0.0647***	-0.0171***	-0.0761***
	(0.0077)	(0.0021)	(0.0084)	(0.0026)	(0.0166)
Ln(Investment to GDP)	0.0189**	0.0209***	0.0283***	0.0254***	0.0140**
	(0.0076)	(0.0047)	(0.0085)	(0.0057)	(0.0057)
Ln(Avg yrs of schooling)	0.0115	0.0140***	0.0003	0.0167**	0.0149
	(0.0137)	(0.0048)	(0.0147)	(0.0067)	(0.0178)
Constant	0.0000	0.1745***	0.5749***	0.2135***	
	(0.0000)	(0.0232)	(0.0901)	(0.0311)	
Observations	673	673	673	673	510
R-squared		0.157	0.304	0.179	
Number of countries	103	103	103	103	101
Number of instruments	95				100
AR1 test (p-value)	<0.000				<0.000
AR2 test (p-value)	0.404				0.768
Hansen test of joint instr. validity (p-value)	0.601				0.492

Notes: Robust standard errors in parantheses. *, ** and *** denote statistical significance at the 10%, 5% and 1% levels, respectively. Tests for instrument subsets omitted for readability.

TABLE 2.16 The Gini coefficient (SWIID) and growth, five different estimators

Dependent variable: growth of per capita GDP. Economic growth is measured over a five-year period, inequality measures are averages over the preceding five-year window, initial per capita GDP enters the model one year prior to the growth window, investment to GDP is observed during the growth window while educational attainment is observed at $t-5$. Year fixed effects included. Column by column, the estimation techniques are system GMM, pooled OLS, random effects, fixed effects and difference GMM.

	sGMM	POLS	FE	RE	dGMM
	(1)	(2)	(3)	(4)	(5)
Gini, SWIID7	-0.0915	-0.0492***	0.2195**	-0.0554***	0.3442**
	(0.0615)	(0.0159)	(0.0903)	(0.0181)	(0.1745)
Ln(Initial per capita GDP)	-0.0087	-0.0124***	-0.0659***	-0.0149***	-0.0790***
	(0.0075)	(0.0023)	(0.0071)	(0.0023)	(0.0140)
Ln(Investment to GDP)	0.0237***	0.0219***	0.0249***	0.0245***	0.0229***
	(0.0074)	(0.0040)	(0.0059)	(0.0043)	(0.0085)
Ln(Avg yrs of schooling)	-0.0026	0.0122***	-0.0190	0.0131***	-0.0384***
	(0.0113)	(0.0040)	(0.0156)	(0.0049)	(0.0147)
Constant	0.0000	0.1753***	0.5404***	0.2020***	
	(0.0000)	(0.0253)	(0.0778)	(0.0258)	
Observations	744	744	744	744	641
R-squared		0.149	0.324	0.172	
Number of countries	103	103	103	103	103
Number of instruments	82				89
AR1 test (p-value)	<0.000				<0.000
AR2 test (p-value)	0.787				0.482
Hansen test of joint instr. validity (p-value)	0.125				0.189

Notes: Robust standard errors in parantheses. *, ** and *** denote statistical significance at the 10%, 5% and 1% levels, respectively. Tests for instrument subsets omitted for readability.

TABLE 2.17 Palma ratio and growth, five different estimators

Dependent variable: growth of per capita GDP. Economic growth is measured over a five-year period, inequality measures are averages over the preceding five-year window, initial per capita GDP enters the model one year prior to the growth window, investment to GDP is observed during the growth window while educational attainment is observed at $t-5$. Year fixed effects included. Column by column, the estimation techniques are system GMM, pooled OLS, random effects, fixed effects and difference GMM.

	sGMM	POLS	FE	RE	dGMM
	(1)	(2)	(3)	(4)	(5)
Palma ratio	-0.0009	-0.0058***	-0.0040	-0.0064**	-0.0053
	(0.0028)	(0.0021)	(0.0032)	(0.0025)	(0.0071)
Ln(Initial per capita GDP)	-0.0103	-0.0147***	-0.0801***	-0.0172***	-0.0916***
	(0.0082)	(0.0022)	(0.0108)	(0.0026)	(0.0191)
Ln(Investment to GDP)	0.0135***	0.0211***	0.0246***	0.0244***	0.0098
	(0.0050)	(0.0047)	(0.0080)	(0.0057)	(0.0069)
Ln(Avg yrs of schooling)	0.0072	0.0161***	-0.0173	0.0173**	0.0069
	(0.0150)	(0.0055)	(0.0180)	(0.0073)	(0.0242)
Constant	0.1267*	0.1944***	0.7548***	0.2216***	
	(0.0665)	(0.0217)	(0.1014)	(0.0260)	
Observations	594	594	594	594	437
R-squared		0.1989	0.3715	0.208	
Number of countries	103	103	103	103	103
AR1 test (p-value)	<0.000				<0.000
AR2 test (p-value)	0.064				0.149
Hansen test of joint instr. validity (p-value)	0.488				0.284

Notes: Robust standard errors in parantheses. *, ** and *** denote statistical significance at the 10%, 5% and 1% levels, respectively. Tests for instrument subsets omitted for readability.

TABLE 2.18 Top 20 % income share and growth, five different estimators

Dependent variable: growth of per capita GDP. Economic growth is measured over a five-year period, inequality measures are averages over the preceding five-year window, initial per capita GDP enters the model one year prior to the growth window, investment to GDP is observed during the growth window while educational attainment is observed at $t-5$. Year fixed effects included. Column by column, the estimation techniques are system GMM, pooled OLS, random effects, fixed effects and difference GMM.

	sGMM	POLS	FE	RE	dGMM
	(1)	(2)	(3)	(4)	(5)
Top 20 % income share	0.0550	-0.0674**	0.0194	-0.0808*	-0.0370
	(0.0660)	(0.0291)	(0.0823)	(0.0420)	(0.1138)
Ln(Initial per capita GDP)	-0.0120	-0.0139***	-0.0742***	-0.0178***	-0.0761***
	(0.0074)	(0.0022)	(0.0105)	(0.0027)	(0.0205)
Ln(Investment to GDP)	0.0165***	0.0218***	0.0259***	0.0262***	0.0135**
	(0.0045)	(0.0050)	(0.0084)	(0.0063)	(0.0059)
Ln(Avg yrs of schooling)	0.0127	0.0147***	-0.0043	0.0174**	-0.0003
	(0.0140)	(0.0053)	(0.0163)	(0.0074)	(0.0229)
Constant	0.1167*	0.1871***	0.6534***	0.2338***	
	(0.0675)	(0.0279)	(0.1135)	(0.0389)	
Observations	627	627	627	627	465
R-squared		0.159	0.334	0.187	
Number of countries	103	103	103	103	101
Number of instruments	90				89
AR1 test (p-value)	<0.000				<0.000
AR2 test (p-value)	0.123				0.190
Hansen test of joint instr. validity (p-value)	0.606				0.505

Notes: Robust standard errors in parantheses. *, ** and *** denote statistical significance at the 10%, 5% and 1% levels, respectively. Tests for instrument subsets omitted for readability.

TABLE 2.19 Top 10 % income share and growth, five different estimators

Dependent variable: growth of per capita GDP. Economic growth is measured over a five-year period, inequality measures are averages over the preceding five-year window, initial per capita GDP enters the model one year prior to the growth window, investment to GDP is observed during the growth window while educational attainment is observed at $t-5$. Year fixed effects included. Column by column, the estimation techniques are system GMM, pooled OLS, random effects, fixed effects and difference GMM.

	sGMM	POLS	FE	RE	dGMM
	(1)	(2)	(3)	(4)	(5)
Top 10 % income share	-0.0057	-0.0812**	0.0081	-0.0958**	-0.1036
	(0.0750)	(0.0349)	(0.0896)	(0.0483)	(0.1405)
Ln(Initial per capita GDP)	-0.0130*	-0.0147***	-0.0825***	-0.0179***	-0.0906***
	(0.0077)	(0.0022)	(0.0111)	(0.0027)	(0.0199)
Ln(Investment to GDP)	0.0127**	0.0218***	0.0239***	0.0255***	0.0101
	(0.0063)	(0.0051)	(0.0080)	(0.0062)	(0.0069)
Ln(Avg yrs of schooling)	0.0120	0.0153***	-0.0099	0.0172**	0.0045
	(0.0139)	(0.0057)	(0.0180)	(0.0077)	(0.0253)
Constant	0.1300	0.1927***	0.7280***	0.2291***	
	(0.1103)	(0.0277)	(0.1128)	(0.0367)	
Observations	596	596	596	596	438
R-squared		0.168	0.354	0.185	
Number of countries	103	103	103	103	101
Number of instruments	85				82
AR1 test (p-value)	<0.000				<0.000
AR2 test (p-value)	0.075				0.187
Hansen test of joint instr. validity (p-value)	0.456				0.294

Notes: Robust standard errors in parantheses. *, ** and *** denote statistical significance at the 10%, 5% and 1% levels, respectively. Tests for instrument subsets omitted for readability.

2.A.4 Transmission channels

TABLE 2.20 Transmission channels: Gini together with investment and schooling

System GMM estimation, decomposing the inequality-growth relationship into potential transmission channels. Dependent variable in columns (1) and (4): growth of per capita GDP. In columns (3) and (4), the dependent variables are the channels. See equations (2.2) - (2.4) for the timing convention.

	Growth regression	Inequality on the channels		Growth regression
		Investment	Schooling	
	(1)	(2)	(3)	(4)
Gini	0.0084	2.1393**	-1.5238*	-0.0066
	(0.0390)	(0.8368)	(0.9177)	(0.0418)
Ln(Investment)	0.0265**			
	(0.0111)			
Ln(Schooling)	0.0471***			
	(0.0125)			
Ln(Initial per capita GDP)	-0.0277***	0.1408**	0.2890***	-0.0103***
	(0.0045)	(0.0590)	(0.0943)	(0.0029)
Residual of investment				0.0265**
				(0.0111)
Residual of schooling				0.0471***
				(0.0125)
Constant	0.0000	-3.7402***	0.0000	0.0000
	(0.0000)	(0.7879)	(0.0000)	(0.0000)
Countries	83	83	83	83
Observations	391	391	391	391
Number of instruments	82	63	63	82
AR1 test (p-value)	<0.000	0.858	0.374	<0.000
AR2 test (p-value)	0.024	0.070	0.792	0.024
Hansen test of joint instr. validity (p-value)	0.696	0.464	0.306	0.696
Difference-in-Hansen tests of instr. subsets (p-value)				
For levels	0.998	0.958	0.723	0.998
For initial per cap GDP	0.445	1.000	0.639	0.445
For IV-type (time dummies)	0.991	0.696	0.803	0.991

Notes: Robust standard errors in parantheses. *, ** and *** denote statistical significance at the 10%, 5% and 1% levels, respectively.

TABLE 2.21 Transmission channels: Gini and all candidate channels

System GMM estimation, decomposing the inequality-growth relationship into potential transmission channels. Dependent variable in columns (1) and (7): growth of per capita GDP. In columns (3) - (6), the dependent variables are the channels. See equations (2.2) - (2.4) for the timing convention.

	Growth regression	Inequality on the channels					Growth regression
		Investment	Schooling	Life expect.	Political inst.	Fertility	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Gini	-0.0033	2.1393**	-1.5238*	-0.4208**	-0.2699	1.2979***	-0.0197
	(0.0289)	(0.8368)	(0.9177)	(0.1685)	(0.3858)	(0.5012)	(0.0327)
Ln(Investment)	0.0244***						
	(0.0093)						
Ln(Schooling)	0.0210**						
	(0.0092)						
Ln(Life expectancy)	-0.0055						
	(0.0373)						
Ln(Political institutions)	-0.0148						
	(0.0108)						
Ln(Fertility)	-0.0331***						
	(0.0094)						
Ln(Initial per capita GDP)	-0.0235***	0.1408**	0.2890***	0.0680***	0.1949***	-0.1063	-0.0137***
	(0.0053)	(0.0590)	(0.0943)	(0.0141)	(0.0465)	(0.0664)	(0.0024)
Residual of investment							0.0244***
							(0.0093)
Residual of schooling							0.0210**
							(0.0092)

Table 2.21 continues.

	Growth regression	Inequality on the channels					Growth regression
		Investment	Schooling	Life expect.	Political inst.	Fertility	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Residual of life expectancy							-0.0055
							(0.0373)
Residual of political institutions							-0.0148
							(0.0108)
Residual of fertility							-0.0331***
							(0.0094)
Constant	0.0000	0.0000	-0.5954	3.7258***	0.0000	0.0000	0.0000
	(0.0000)	(0.0000)	(1.1457)	(0.1739)	(0.0000)	(0.0000)	(0.0000)
Countries	83	83	83	83	83	83	83
Observations	391	391	391	391	391	391	391
Number of instruments	133	63	63	60	62	60	133
AR1 test (p-value)	<0.000	0.858	0.374	0.047	0.150	<0.000	<0.000
AR2 test (p-value)	0.101	0.070	0.792	0.760	0.150	0.242	0.101
Hansen test of joint instrument validity (p-value)	0.999	0.464	0.306	0.235	0.940	0.047	0.999
Difference-in-Hansen tests of instrument subsets (p-value)							
For levels	1.000	0.958	0.723	0.382	1.000	0.358	1.000
For initial per cap GDP	0.999	1.000	0.639	0.726	0.790	0.550	0.999
For IV-type (time dummies)	1.000	0.696	0.803	0.817	0.959	0.987	1.000

Notes: Robust standard errors in parantheses. *, ** and *** denote statistical significance at the 10%, 5% and 1% levels, respectively.

TABLE 2.21 Transmission channels: Top 20 % income share together with investment and schooling

System GMM estimation, decomposing the inequality-growth relationship into potential transmission channels. Dependent variable in columns (1) and (4): growth of per capita GDP. In columns (3) and (4), the dependent variables are the channels. See equations (2.2) - (2.4) for the timing convention.

	Growth regression	Inequality on the channels		Growth regression
		Investment	Schooling	
	(1)	(2)	(3)	(4)
Top 20 % income share	-0.0128	2.6878**	-1.6435	0.0050
	(0.0617)	(1.2374)	(1.0435)	(0.0678)
Ln(Investment)	0.0263**			
	(0.0116)			
Ln(Schooling)	0.0386***			
	(0.0112)			
Ln(Initial per capita GDP)	-0.0238***	0.1605***	0.3352***	-0.0072
	(0.0055)	(0.0536)	(0.0809)	(0.0048)
Residual of investment				0.0258**
				(0.0127)
Residual of schooling				0.0386***
				(0.0117)
Constant	0.0000	-4.0470***	0.0000	0.1288**
	(0.0000)	(0.9386)	(0.0000)	(0.0596)
Countries	83	83	83	83
Observations	391	391	391	391
Number of instruments	80	62	62	80
AR1 test (p-value)	0.000	0.950	0.024	0.000
AR2 test (p-value)	0.024	0.168	0.877	0.024
Hansen test of joint instrument validity (p-value)	0.498	0.492	0.168	0.498
Difference-in-Hansen tests of instrument subsets (p-value)				
For levels	0.950	0.672	0.293	0.950
For initial per cap GDP	0.357	0.859	0.745	0.357
For IV-type (time dummies)	0.896	0.610	0.700	0.896

Notes: Robust standard errors in parantheses. *, ** and *** denote statistical significance at the 10%, 5% and 1% levels, respectively.

TABLE 2.22 Transmission channels: Top 20 % income share and all candidate channels

System GMM estimation, decomposing the inequality-growth relationship into potential transmission channels. Dependent variable in columns (1) and (7): growth of per capita GDP. In columns (3) - (6), the dependent variables are the channels. See equations (2.2) - (2.4) for the timing convention.

	Growth regression	Inequality on the channels					Growth regression
		Investment	Schooling	Life expect.	Political inst.	Fertility	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Top 20 % income share	0.0085	2.6878**	-1.6435	-0.4949	-0.9032	1.3792*	0.0067
	(0.0397)	(1.2290)	(1.0435)	(23.2732)	(0.6069)	(0.7695)	(0.0444)
Ln(Investment)	0.0246**						
	(0.0099)						
Ln(Schooling)	0.0228**						
	(0.0090)						
Ln(Life expectancy)	0.0028						
	(0.0415)						
Ln(Political institutions)	-0.0177*						
	(0.0096)						
Ln(Fertility)	-0.0326***						
	(0.0094)						
Ln(Initial per capita GDP)	-0.0228***	0.1605***	0.3352***	0.0723	0.1486***	-0.1377*	-0.0092***
	(0.0060)	(0.0530)	(0.0809)	(5.3216)	(0.0551)	(0.0815)	(0.0027)
Residual of investment							0.0246**
							(0.0099)
Residual of schooling							0.0228**
							(0.0090)

Table 2.22 continues

	Growth regression	Inequality on the channels					Growth regression
		Investment	Schooling	Life expect.	Political inst.	Fertility	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Residual of life expectancy							0.0028
							(0.0415)
Residual of political institutions							-0.0177*
							(0.0096)
Residual of fertility							-0.0326***
							(0.0094)
Constant	0.2894*	-4.0470***	0.0000	0.0000	0.0000	0.0000	0.0000
	(0.1635)	(0.9276)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Countries	83	83	83	83	83	83	83
Observations	391	391	391	391	391	391	391
Number of instruments	131	62	62	59	61	59	131
AR1 test (p-value)	<0.000	0.950	0.024	0.951	0.150	<0.000	<0.000
AR2 test (p-value)	0.112	0.168	0.877	0.992	0.150	0.480	0.112
Hansen test of joint instrument validity (p-value)	0.999	0.492	0.168	0.575	0.846	0.058	0.999
Difference-in-Hansen tests of instrument subsets (p-value)							
For levels	1.000	0.672	0.293	0.810	1.000	0.381	1.000
For initial per cap GDP	1.000	0.859	0.745	0.495	0.834	0.612	1.000
For IV-type (time dummies)	1.000	0.610	0.700	0.917	0.431	0.914	1.000

Notes: Robust standard errors in parantheses. *, ** and *** denote statistical significance at the 10%, 5% and 1% levels, respectively.

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3 THE ROLE OF FINANCIAL DEVELOPMENT IN THE RELATIONSHIP BETWEEN INCOME INEQUALITY AND ECONOMIC GROWTH

Abstract*
The study adds to the literature on the role of credit constraints in the interplay between income inequality and economic growth. The question "what type of financial development matters for the inequality-growth relationship?" is answered empirically by adopting a multi-dimensional index of financial development. The analysis covers 35 OECD member countries and 34 non-OECD economies from 1980, with varying coverage across countries. The results obtained using panel estimation techniques suggest that in the non-OECD countries, income inequality is positively associated with the subsequent growth of per capita GDP under sufficiently developed financial markets. If the markets are poorly developed, the partial correlation between inequality and growth is statistically insignificant. For OECD countries, the association seems to be non-existent although weak evidence of growth-dampening inequality is found if both the level of inequality is high and financial markets are highly developed. The results imply that promoting the development of financial markets – rather than institutions – may alleviate the adverse effects of income inequality on economic growth in under-developed countries.

Keywords: Economic growth, Income inequality, Financial development, Panel data

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3.1 Introduction

A large body of economic literature has emphasized the role of credit market imperfections in how income distribution affects economic development. In short, the central argument of the branch pushed forward most notably by Galor and Zeira (1993) and Galor and Moav (2004) states that, under credit constraints, income inequality may suppress the accumulation of human capital at low income levels, which may eventually be harmful for economic growth. Thus, development of financial institutions and markets may alleviate the growth-dampening effects of inequality.

Moreover, setting up new firms or expanding existing ones may require sufficiently concentrated income or wealth for the entrepreneurs to cover the sunk costs associated with entrepreneurial activity. By channelling funds to the low income individual with business ideas, financial development may help to disconnect the link between economic inequality and entrepreneurial activity. Aghion et al. (1999) go even further and note that under credit frictions, inequality may be negatively associated with investment opportunities. They argue that due to decreasing returns to individual capital investment, the marginal productivity of an investment made by the rich is lower than an investment made by the poor. On the contrary, it is also possible that financial development under high income inequality may hurt growth. For example, the poorer households might overleverage themselves[1], which creates an additional layer of complexity in the interplay between economic growth, inequality and financial development.

This paper aims to add to the existing literature by asking what type of – if any – financial development matters for the inequality-growth relationship. The question is answered empirically. A multi-dimensional index of financial development (Svirydzenka, 2016) is adopted. The index not only provides an aggregate measure but also separates the institutional evolutions from the development of financial markets. Furthermore, it provides measures of depth, access and efficiency for the institutions and markets and thus follows the characterization of financial systems by Cihak et al. (2012)[2]. The objective of this study is not to isolate specific mechanisms, such as the human capital channel or overleveraging discussed above, but rather to analyze the partial correlation between income inequality and per capita growth of GDP conditional on financial development. The empirical analysis relies on a panel data set that includes 69 countries, of which 35 are the members of the OECD. The study makes use of the structure of the data by disentangling the OECD member countries from the less-developed economies. Dictated by data coverage, the analysis uses observations from 1980 to 2017 at best though many countries are observed for shorter time periods.

The findings of the empirical analysis suggest that there exists a positive

1 The role of "NINJA loans" (no income, no job, no assets) has been widely discussed in the aftermath of the global financial crisis.

2 The original characterization includes stability as the fourth dimension.

partial correlation between income inequality and subsequent growth of per capita GDP in the non-OECD countries given that the financial markets are sufficiently developed. The evidence for an association between inequality and growth is weak in the OECD countries. Only under high inequality and highly developed financial markets, there are traces of a negative relationship between inequality and growth. The results of this paper complement (i) the earlier studies on the role of credit constraints in the interplay between inequality and growth and (ii) the vast literature that has used reduced-form cross-country and panel growth regressions to understand whether inequality matters for economic growth[3]. Although the methodological approach cannot isolate causal mechanisms, novel evidence for the role of financial markets in the inequality-growth relationship is found.

The next section of the study introduces the data and econometric techniques while the third section presents the results of the empirical analysis. The fourth section concludes the findings. Many of the regression tables and figures are located in the appendices.

3.2 Data and methodology

The three key data sources of this study are the version 9.1 of the Penn World Table (Feenstra et al., 2015, PWT), the fourth version of the World Income Inequality Database (UNU-WIDER, 2018, WIID) and the multi-dimensional index of financial development by Svirydzenka (2016). The coverage of these sources and the control variables narrow down the sample to include 35 OECD member economies and 34 non-OECD countries.

The aim of the multi-dimensional financial development index (Svirydzenka, 2016) is to overcome the shortcomings of the use of single indicators to track financial development. As summarized in Figure 3.1[4], the sub-indices capture the size and liquidity (depth), the ability of individuals and companies to access financial services (access) and the ability of institutions to provide the services with sustainable revenues and the activity of the capital markets (efficiency). The sub-indices are constructed for banks, insurance companies, mutual funds and pension funds as a group (financial institutions) and for stock and bond markets (financial markets). Finally, the development of institutions and markets are

[3] For a comprehensive review, see Neves et al. (2016), whose meta-analysis suggests that the literature suffers from publication bias: statistically significant results are more willingly reported and published following a predictable time pattern with cyclically alternating positive and negative reduced-form estimates. Their results also suggest that the estimation technique, data quality and the specification choice for the growth regression are not significant drivers of the varying estimates. Rather, cross-sectional analyses tend to find a stronger negative association than panel studies, the negative association is stronger in less developed countries, the inclusion of regional dummies soak up much of the previous finding and the concept of inequality significantly affects the results.

[4] See Figure 1 in Svirydzenka (2016) for the original artwork.

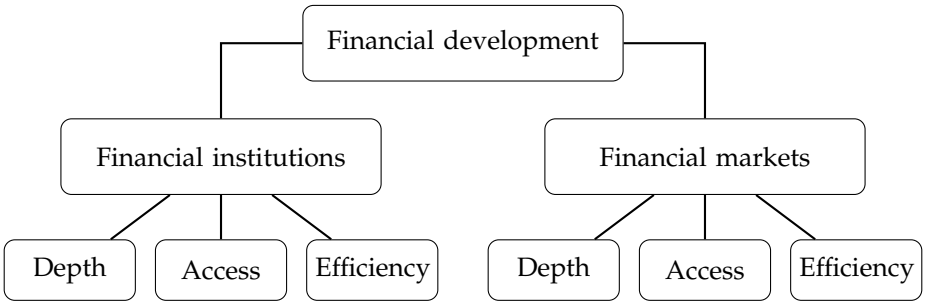


FIGURE 3.1 Financial development index pyramid

gathered into the aggregate index.

Table 3.1 presents the variables that are used to form the sub-indices. The two largely used proxies for financial development – private sector credit to GDP and stock market capitalization to GDP – are included as the underlying variables. The former for the depth of institutions, the latter for the depth of markets. The construction of the indices follows a four-stage approach. First, the underlying variables are normalized, second, the normalized variables are aggregated into the sub-indices, third, the sub-indices are aggregated into the indices of institutional and market development, and finally, the aggregate index is constructed. In her paper, Svirydzenka (2016) offers a detailed discussion on the methodology, portrays overall trends and discusses differences between countries and country groups.

TABLE 3.1 The underlying variables for depth, access and efficiency of Figure 3.1

Financial institutions	
Depth	Private sector credit to GDP
	Pension fund assets to GDP
	Mutual fund assets to GDP
	Insurance premiums, life and non-life to GDP
Access	Bank branches per 100,000 adults
	ATMs per 100,000 adults
Efficiency	Net interest margin
	Lending-deposits spread
	Non-interest income to total income
	Overhead costs to total assets
	Return on assets
	Return on equity
Financial markets	
Depth	Stock market capitalization to GDP
	Stocks traded to GDP
	International debt securities of government to GDP
	Total debt securities of financial corporations to GDP
	Total debt securities of non-financial corporations to GDP
Access	Percent of market capitalization outside of top 10 largest companies
	Total number of issuers of debt
Efficiency	Stock market turnover ratio (stocks traded to capitalization)
In access to financial markets, the total number of issuers of debt includes domestic and external and non-financial and financial corporations	

The primary data source for income inequality in this study is the fourth version of the World Income Inequality Database (WIID) maintained by the United Nations University World Institute for Development Economics Research (UNU-WIDER, 2018). It is a secondary database combining information from several sources[5] and builds on the work by Deininger and Squire (1996). Each update has aimed at improving data comparability, both within countries over time and across countries, by taking seriously the issues raised in the evaluative studies by for example Atkinson and Brandolini (2001) and Jenkins (2015). The data set includes not only information on the Gini coefficient but also on the income shares of each decile. Even though the data issues cannot be fully removed, I believe that the newest version of the WIID is the best available data source for income inequality in a cross-country setting. This conclusion is founded on the well-documented choices that account for the influential critique directed to the construction of secondary databases.

As informatively summarized by Jenkins (2015), Atkinson and Brandolini (2001) state that non-comparability in secondary data sets may arise because of differences in the definitions of income, in the data sources or in the processing of the income data in the original source. Differences both within countries in time and across countries may emerge. Many of the differences are associated with predictable patterns on inequality if their nature is not drastically heterogeneous over time and across countries. Unfortunately, the assumption of homogeneity is unlikely to hold for the WIID despite major improvements on the earlier databases and thus the practical implications need to assessed by comparing the WIID series with other sources of at least as good a quality. This is presented together with the data selection algorithm in Appendix 2.A.1 of Chapter 2.

The empirical studies on the linkage between income inequality and economic growth have predominantly focused on disposable income, also referred to as net or post-tax & post-transfer income. Since the aim of this study is to complement the previous empirical literature by introducing a novel measure of financial development, the same concept of inequality is adopted. Although many of the suggested mechanisms in the theoretical literature emphasize wealth inequality rather than the dispersion of income, the focus on disposable income is well-founded as our consumption, saving and investing decisions are based on income after taxes and transfers. The listed economic decisions in turn are relevant for aggregate economic activity.

In the WIID, each observation is labeled as one of possible income, consumption or expenditure concepts as strongly recommended by the seminal evaluative studies. Following the assertive conclusion of Jenkins (2015), I explicitly report the data selection algorithm inspired by Jäntti et al. (2018). To avoid repetition in this dissertation, the algorithm is reported in Appendix 2.A.1 of Chapter 2. After separating the net income observations from the rest, two issues remain for

[5] The Organisation for Economic Co-operation and Development (OECD), The EU-Statistics on Income and Living Conditions (EU-SILC), The Luxembourg Income Study (LIS), The World Bank, The Socio-Economic Database for Latin America and the Caribbean (SEDLAC), national statistical offices and independent research papers.

empirical work: the observations are of varying quality and there are often multiple observations for each country-year pair. Some of the multiple observations are due to multiple surveys but predominantly the measurements come from the same survey and it is just the computation (and the statisticians in charge) that change. Helpfully, the WIID team has introduced a variable called a quality score, which ranks the observations from 3 to 13. By ranking the observations based on this score, and picking the highest, I can use the observations of best possible quality to form the final country panel and get rid of many of the duplicate observations. In case of observations tied on the quality score for a given country-year pair, a simple average is taken to obtain unique observations. I believe that this data selection procedure may be helpful for future researchers who need to merge the WIID into some other cross-country panel.

Many recent studies, of which some have received much attention (Ostry et al., 2014), have used the Standardized World Income Inequality Database (Solt, 2016, SWIID) as their source for data on the Gini coefficients. The SWIID is based on the WIID, supplemented by other sources and all observations come from its imputation model. In his conclusions, Jenkins (2015) states that costs associated with the use of the WIID are present for the SWIID too. Additionally, he urges to set questions about the imputation model against the benefits of coverage and draws a conclusion that the WIID should be used instead of the SWIID given that the use of the WIID is accompanied by a tractable data selection algorithm.

For data on economic growth, I rely on the Penn World Table (Feenstra et al., 2015, PWT), which is a standard data source for empirical cross-country studies offering annual data on numerous variables in a global scope. Economic activity is defined as expenditure-side per capita gross domestic product (GDP) and the rate of growth corresponds to logarithmic differences.

Following a standard convention in the literature, the baseline statistical model addresses growth of per capita GDP inside five-year non-overlapping windows. The last growth window is a three-year one (2015-2017). The aim of the choice is to (i) move away from a short-run scope influenced by business cycles (ii) and to mitigate the issues of missing observation and noisiness stemming from potential measurement error in the income inequality (*Gini*) and financial development (*Svir*, Svirydzenka (2016)) time series. The panel growth regression can be written as

$$\begin{aligned}\frac{1}{4}(lnY_{i,t+4} - lnY_{i,t}) &= \gamma lnY_{i,t-1} + \boldsymbol{\delta}'\boldsymbol{X}_{i,t} \\ &+ \beta_1(\frac{1}{5}\sum_{j=0}^{4} Gini_{i,t-5+j}) + \beta_2(\frac{1}{5}\sum_{j=0}^{4} Svir_{i,t-5+j}) \\ &+ \beta_3(\frac{1}{5}\sum_{j=0}^{4}(Gini \times Svir)_{i,t-5+j}) + \alpha_i + \eta_t + \varepsilon_{i,t},\end{aligned} \tag{3.1}$$

where α_i and η_t are the vectors of fixed country and year effects and $\varepsilon_{i,t}$ is the overall error term. $Y_{i,t}$ stands for expenditure-side real per capita GDP in country

i in year t while $X_{i,t}$ contains a set of control variables[6]. The purpose of including both the country and year fixed effects is to control for the bias stemming from both the unobservable variables that change over time but are constant over countries – such as large shifts in technology or educational attainment not captured by the years of schooling – and the factors that are different across countries but are constant over time. The latter effectively means that the empirical analysis relies on variation within countries[7]. So far, the modelling choices follow standard approaches, whereas the novelty comes from the inclusion of the terms *Svir* and $Gini \times Svir$ to evaluate the dependency of the inequality-growth relationship on financial development. Moreover, the empirical analysis aims to fully utilize the richness of the financial development index (Svirydzenka, 2016) introduced above. Consequently,the aggregate index, the development of financial institutions, the development of financial markets and the sub-indices (Figure 3.1 and Table 3.1) enter the panel regressions one after another.

TABLE 3.2 Descriptive statistics, five-year non-overlapping windows

Variable	Mean	Std. Dev.	Observations	Countries
Full sample				
Growth of per capita GDP	2.97 %	2.68 %	318	69
Level of per capita GDP (2011 USD)	21 068	15 915		
Gini coefficient	0.36	0.10		
Financial development, aggregate index	0.38	0.22		
Development of financial institutions	0.48	0.24		
Development of financial markets	0.27	0.24		
OECD				
Growth of per capita GDP	2.50 %	2.13 %	177	35
Level of per capita GDP (2011 USD)	31 369	13 938		
Gini coefficient	0.31	0.06		
Financial development, aggregate index	0.51	0.20		
Development of financial institutions	0.63	0.21		
Development of financial markets	0.38	0.25		
non-OECD				
Growth of per capita GDP	3.56 %	3.16 %	141	34
Level of per capita GDP (2011 USD)	8 137	5 170		
Gini coefficient	0.43	0.09		
Financial development, aggregate index	0.22	0.10		
Development of financial institutions	0.31	0.12		
Development of financial markets	0.13	0.14		

Table 3.2 shows the sample means and associated standard deviations for the focal variables of this study. Clearly, the OECD and non-OECD countries are substantially different from another, which comes as a no surprise. The higher growth rates of per capita GDP in the less developed countries depict the styl-

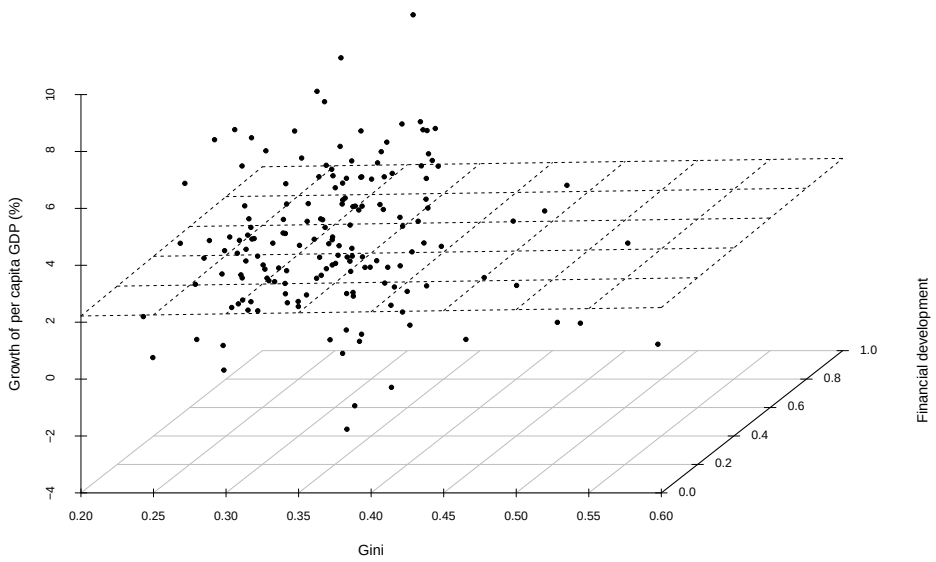
6 Investment to GDP (Feenstra et al., 2015), average years of schooling to GDP (Barro and Lee, 2013), the quality of political institutions (Marshall et al., 2002), trade volume to GDP (Feenstra et al., 2015) and debt to GDP (Lane and Milesi-Ferretti, 2007).

7 As a robustness check, a widely-used system GMM estimator is also used. The properties of this panel estimation technique are briefly discussed in the next section when the results of the empirical analysis are presented.

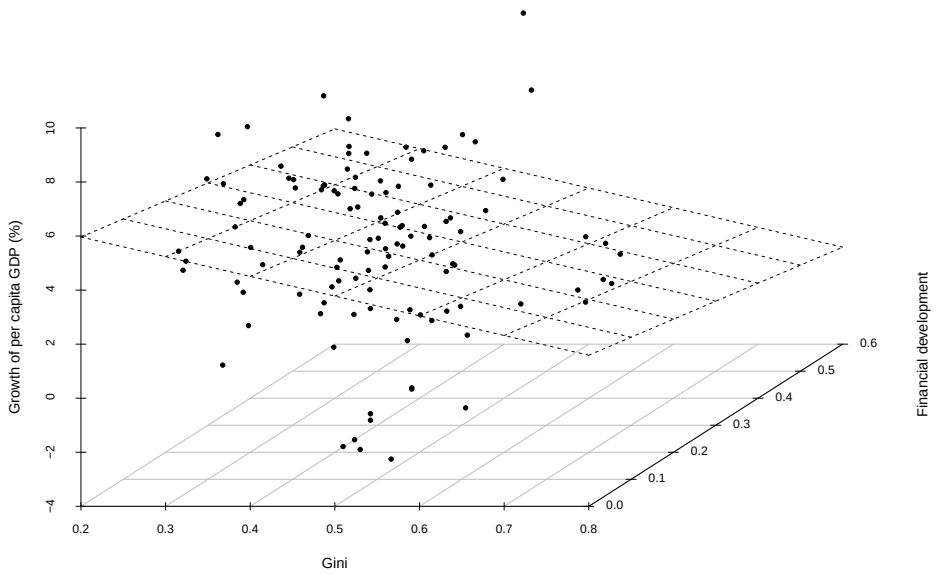
ized fact of growth convergence: poorer countries tend to catch up and grow faster. The sample means for the levels of economic activity are not as informative since they have been growing over time and thus portray the level of development in the middle of the sample. Still, the large difference between the groups paints the big picture. The differences also exist for the Gini coefficients and financial development. The non-OECD countries tend to be more unequal while both the financial institutions and markets are more developed in the OECD member states. The substantial differences immediately suggest that the analysis relying in the full sample of 69 countries should be complemented by focusing on the two groups separately.

As the first step to examine the interplay between economic growth, income inequality and financial development, the observations are plotted in three-dimensional illustrations (Figures 3.2 - 3.4) separately for the OECD and non-OECD countries. Regression planes from pooled least squares regressions, where the growth of per capita GDP is regressed on the contemporaneous Gini coefficient and varying indices of financial development, are also fitted over the observations. This approach does not account for growth convergence, other growth determinants, country-specific characteristics or the time that the potential effects of inequality on growth takes to manifest themselves. Rather, the illustrations offer the first glance at the inter-dependencies between the variables under investigation.

Again, differences between the OECD and non-OECD countries emerge. In the former, the regression planes are fairly flat for the aggregate index and institutional development, whereas Figure 3.4a portrays how the growth rates of per capita GDP are lowest when the contemporaneous values of the Gini coefficient and market development are low. This naïve approach thus suggests that inequality and financial market development are good for economic growth in the rich countries. In the non-OECD countries alternatively, all planes tilt towards the right indicating that the contemporaneous correlation between economic growth and the Gini is negative. As can be seen below, this finding is largely due to the fact that the least developed economies in the group of the non-OECD countries tend to be more unequal but also grow faster as they are catching up (growth convergence). The aggregate index plane tilts slightly towards high values of the index, the feature is more prevalent for the financial institutions, whereas the inclination is the opposite for the development of the financial markets. Altogether, the inter-dependencies between growth, inequality and financial development seem to be heterogeneous between the aggregate index, the development of institutions and the development of markets in both country groups.

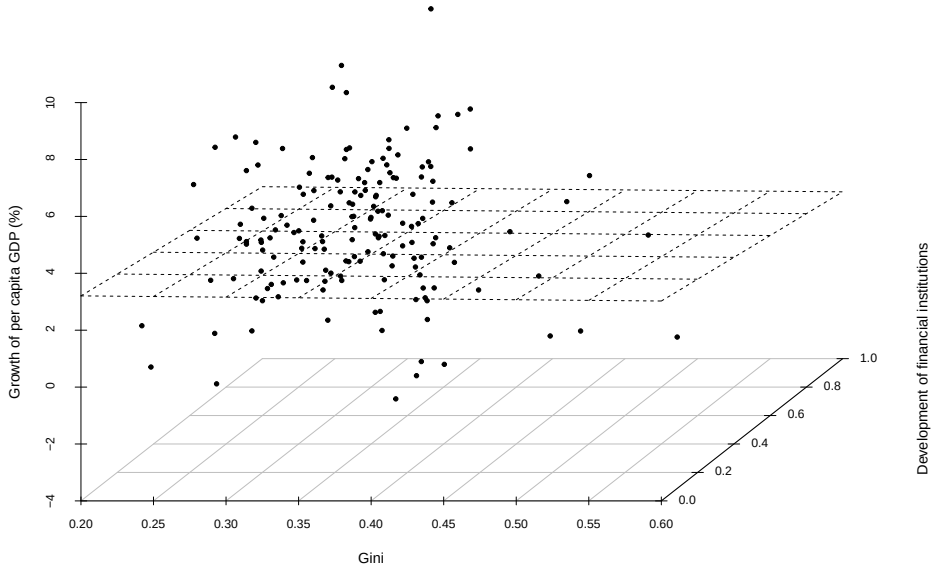


(a) OECD countries

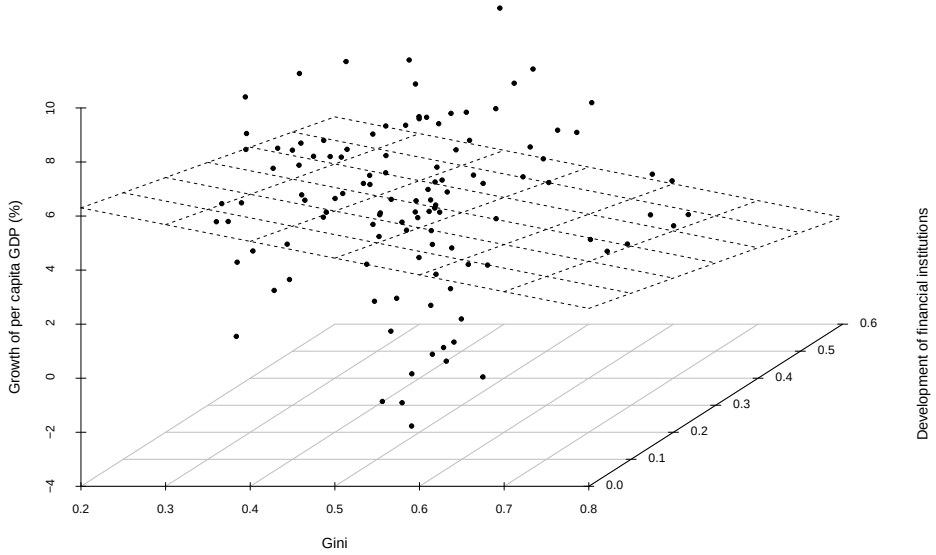


(b) Non-OECD countries

FIGURE 3.2 Pooled least squares regression planes, per capita growth regressed on Gini and aggregate financial development (5-year non-overlapping windows)

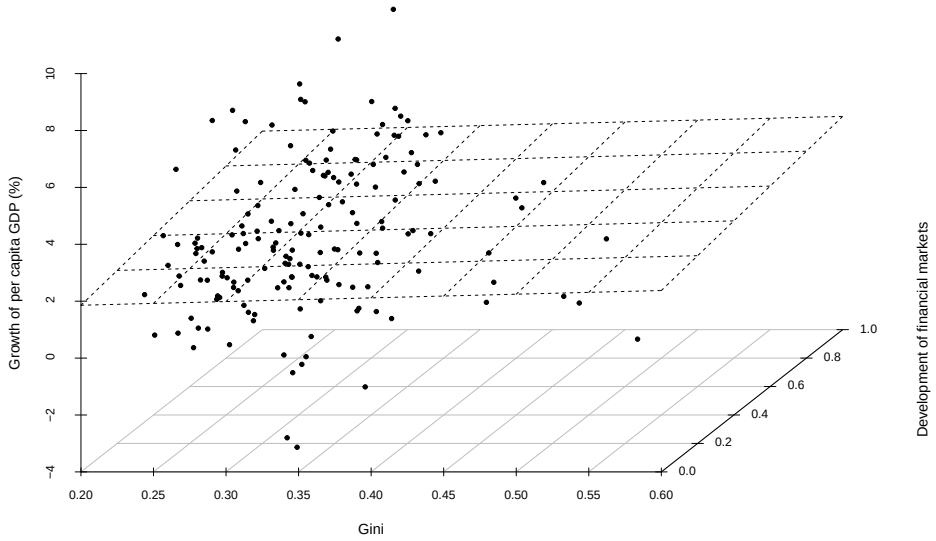


(a) OECD countries

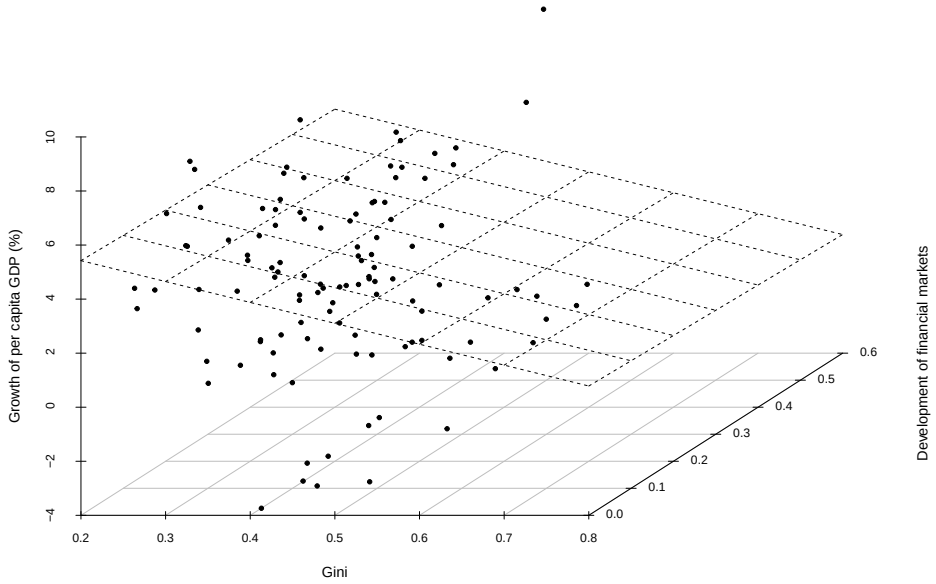


(b) Non-OECD countries

FIGURE 3.3 Pooled least squares regression planes, per capita growth regressed on Gini and aggregate financial development (5-year non-overlapping windows)



(a) OECD countries



(b) Non-OECD countries

FIGURE 3.4 Pooled least squares regression planes, per capita growth regressed on Gini and aggregate financial development (5-year non-overlapping windows)

3.3 Results

This section presents the results of the empirical analysis, which builds on the panel growth regression laid out in equation (3.1). Results corresponding to a linear functional form and further extensions are also considered. The extensions include introducing alternative measures of income inequality, incorporating the potential effect of the extent of inequality on the results and using a panel estimation technique that can under certain conditions mitigate the potential issues stemming from omitted variables and reverse causality. Finally, instead of the multi-dimensional index, private credit to GDP and stock market capitalization to GDP are taken as the proxies of financial development.

Table 3.3 displays the estimates of specification (3.1) for the aggregate index, the development of financial institutions and the development of financial markets. Because of large differences in economic development, income inequality and financial development between the OECD and non-OECD countries and the rudimentary correlational evidence of Figures 3.2 - 3.4, the panel regressions are run for the full sample and the two sub-samples separately to investigate whether the relationship is dependent on the country coverage. Moreover, this distinction seems important based on the findings of previous studies. In their meta-analysis, Neves et al. (2016) document that the association between inequality and growth seems to be negative and more pronounced in less developed countries than in rich countries. The table – not the statistical specifications themselves – excludes the estimates for the other growth determinants while Appendix 3.A.1 provides the full regression tables with controls. Moreover, the results for the sub-indices depth, access and efficiency are also located in the appendix.

In a linear form, the association between income inequality and growth of per capita GDP is statistically insignificant in the full sample (column (1)) and in the sub-sample of OECD countries (column (3)). In the non-OECD countries however, the Gini coefficient is positively related with subsequent economic growth (column (5)). The patterns hold irrespective of whether the set of control variables include the aggregate index of financial development, the development of markets, the development of institutions or whether the level of economic development is the only control alongside the country and year fixed effects (Table 3.5 in Appendix 3.A.1). Institutions and growth seem to be unrelated while a positive and significant association emerges between the markets and growth in the full sample and in the OECD countries. Moreover, the aggregate index is positively related with growth in the full sample.

Columns (2), (4) and (6) of Table 3.3 correspond to the statistical model of equation (3.1). Panels A and C show evidence that overall financial development and the development of markets play a role in the inequality-growth relationship in the full sample and in the non-OECD countries as many of the coefficients are individually and jointly statistically significant. This does not hold for institutions (Panel B) or in the sub-sample of OECD countries for any of the measures of financial development. Yet, based on the parameter estimates, standard errors

TABLE 3.3 The association between the Gini and economic growth conditional on the level of financial development

Fixed effects panel estimation, dependent variable: growth of per capita GDP inside non-overlapping five-year growth windows. Columns (2), (4) and (6) correspond to equation (3.1) while columns (1), (3) and (5) correspond to specifications without an interaction term. Control variables are included in the regressions but not reported in the table.

Panel A: Financial development, aggregate index (FD)

	All		OECD		non-OECD	
	(1)	(2)	(3)	(4)	(5)	(6)
Gini	0.0485	0.1887*	-0.1091	0.0756	0.1712**	-0.0650
	(0.0702)	(0.1126)	(0.0795)	(0.1959)	(0.0825)	(0.1616)
FD	0.0493**	0.1502***	0.0384	0.1185	-0.0694	-0.4241**
	(0.0188)	(0.0559)	(0.0234)	(0.0891)	(0.0580)	(0.1952)
Gini × FD		-0.3052*		-0.2706		0.7620*
		(0.1716)		(0.2910)		(0.3977)
Joint signif. of Gini and FD (p values)	0.036		0.064		0.109	
Joint signif. of Gini and Gini × FD (p values)		0.195		0.353		0.007
Joint signif. of FD and Gini × FD (p values)		0.002		0.178		0.095
Joint signif. of Gini, FD and Gini × FD (p values)		0.006		0.115		0.017
Observations	318	318	177	177	141	141
Number of countries	69	69	35	35	34	34

Panel B: Development of financial institutions (FI)

	All		OECD		non-OECD	
	(1)	(2)	(3)	(4)	(5)	(6)
Gini	0.0355	0.2055*	-0.1146	0.1178	0.1775**	0.0678
	(0.0694)	(0.1111)	(0.0773)	(0.2326)	(0.0849)	(0.1678)
FI	0.0124	0.1267**	0.0089	0.1011	-0.0382	-0.1583
	(0.0176)	(0.0531)	(0.0204)	(0.0937)	(0.0393)	(0.1887)
Gini × FI		-0.3092**		-0.3073		0.2630
		(0.1436)		(0.3035)		(0.3793)
Joint signif. of Gini and FI (p values)	0.674		0.298		0.100	
Joint signif. of Gini and Gini × FI (p values)		0.104		0.282		0.138
Joint signif. of FI and Gini × FI (p values)		0.062		0.556		0.583
Joint signif. of Gini, FI and Gini × FI (p values)		0.131		0.417		0.230
Observations	318	318	177	177	141	141
Number of countries	69	69	35	35	34	34

Table 3.3 continues.

Panel C: Development of financial markets (FM)

	All		OECD		non-OECD	
	(1)	(2)	(3)	(4)	(5)	(6)
Gini	0.0537	0.1190	-0.1026	0.0139	0.1679**	0.0646
	(0.0711)	(0.0996)	(0.0808)	(0.1375)	(0.0810)	(0.1059)
FM	0.0446***	0.1009*	0.0321**	0.0901	-0.0544	-0.2840**
	(0.0122)	(0.0540)	(0.0142)	(0.0679)	(0.0526)	(0.1124)
Gini × FM		-0.1822		-0.1941		0.5416*
		(0.1773)		(0.2291)		(0.3061)
Joint signif. of Gini and FM (p values)	0.002		0.025		0.127	
Joint signif. of Gini and Gini × FM (p values)		0.477		0.415		0.010
Joint signif. of FM and Gini × FM (p values)		0.001		0.050		0.014
Joint signif. of Gini, FM and Gini × FM (p values)		0.002		0.042		0.004
Observations	318	318	177	177	141	141
Number of countries	69	69	35	35	34	34

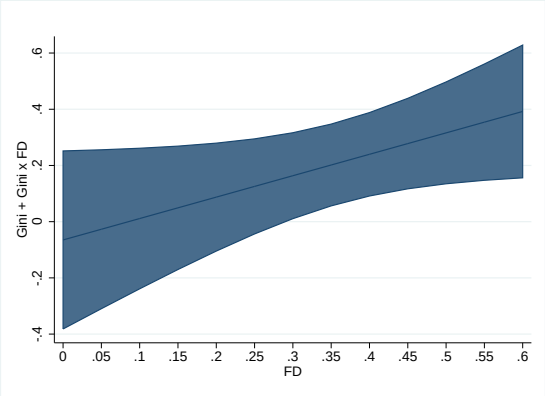
Robust standard errors in parantheses. *, ** and *** indicate statistical significance at 10 %, 5 % and 1 % levels, respectively.

and tests of joint significance in Table 3.3, it is difficult to interpret the results in terms of the relationship between the Gini coefficient and subsequent economic growth conditional on the financial development index.

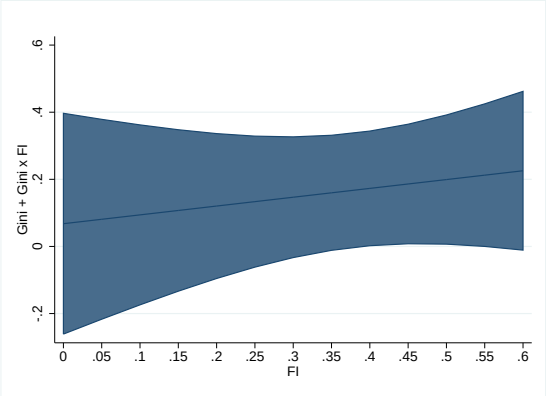
To visualize the interplay between income inequality, economic growth and financial development, interaction plots, which display the point estimate of $Gini + Gini \times Svir$ along with the 95 % confidence intervals for different values of financial development, are introduced. Again, the interest not only lies in the aggregate index but instead the richness of the data source (Svirydzenka, 2016) is allowed to flourish. Moreover, the OECD and non-OECD countries are separated, which seems essential given the results of Table 3.3.

The results for the sample of OECD countries are blunt: there is no evidence for a statistically significant association between the Gini coefficient and subsequent economic growth in the quadratic specifications conditional on any of the measures of financial development. The interaction plots for OECD countries, in which zero is included in the confidence intervals for all cases, are omitted. In the non-OECD countries, both the aggregate index (Figure 3.5a) and development of financial markets (3.5c) seem to play a significant role in the inequality-growth relationship, whereas modelling the interaction through the development of institutions (3.5b) suggests that inequality and growth are not related. Furthermore, the sub-indices of market development (3.5d, 3.5e and 3.5f) replicate the main result of market development: under sufficiently highly developed markets, the association between the Gini coefficient and subsequent growth is positive.

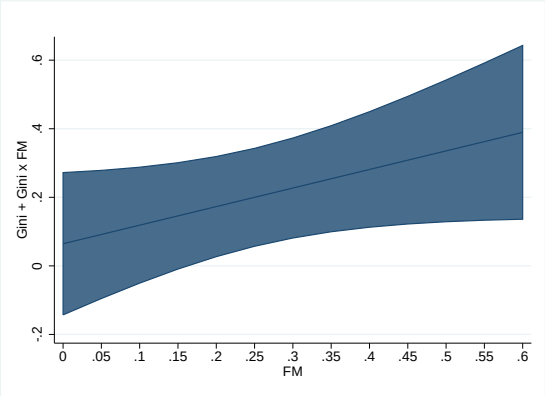
The interaction plots of Figure 3.5 immediately raise the question of how relevant the regions right from the cut-off, where the lower bound of the confidence interval is above zero, are. For the aggregate index, the highest quintile of the sample values is above the cut-off, whereas the corresponding share is 25



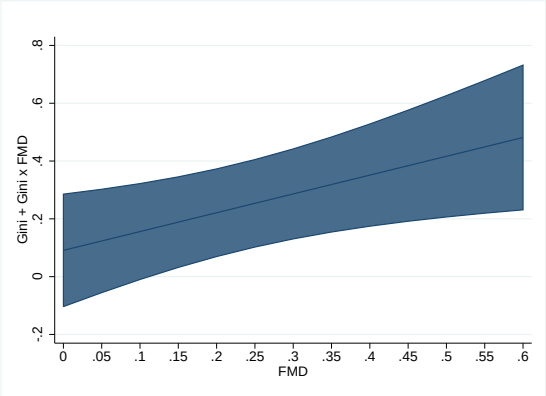
(a) Financial development (FD)



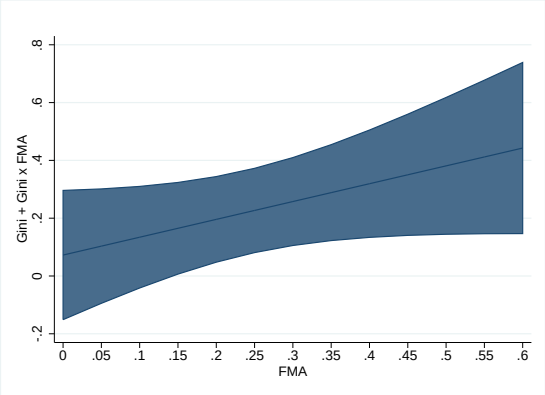
(b) Development of financial institutions (FI)



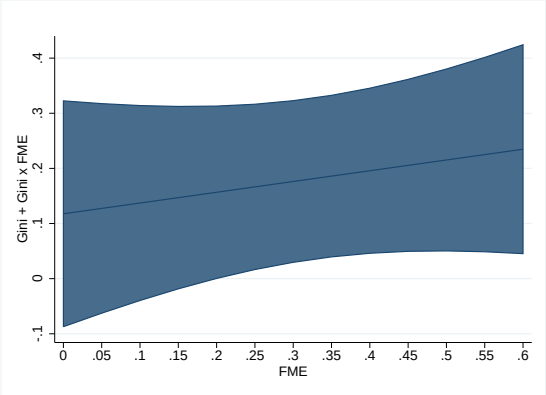
(c) Development of financial markets (FM)



(d) Depth of financial markets (FMD)



(e) Access to financial markets (FMA)



(f) Efficiency of financial markets (FME)

FIGURE 3.5 Estimated association (95 % level confidence interval) between the Gini coefficient and per capita growth conditional on different measures of financial development, non-OECD countries

% for market development[8]. For the sub-indices depth, access and efficiency, the shares are approximately 25 %, 30 % and 23 %, respectively. If the point estimates are considered, 90 % of the sample values of the aggregate measure are above the cut-off, whereas for the measures of financial market development, the association is always positive.

The functional form of equation (3.1) also produces estimates for the relationship between financial development and growth conditional on the level of the Gini coefficient. In the OECD countries, under low income inequality, there is a positive association between the development of financial markets and growth, whereas in the non-OECD countries, the association is negative for low levels of the Gini coefficient. Such dependencies are not present for aggregate development or institutional development. As the emphasis of this study is to complement the previous reduced-form analysis on the interplay between income inequality and subsequent economic growth, the potential growth-promoting or growth-dampening effect of financial development is not thoroughly examined here.

TABLE 3.3 Correlation between per capita GDP and financial development

Panel level correlations between $lnY_{i,t-1}$ and $\frac{1}{5}\sum_{j=0}^{4} Svir_{i,t-5+j}$							
OECD				non-OECD			
	FD	FI	FM		FD	FI	FM
Per capita GDP	0.23	0.40	0.05	Per capita GDP	-0.03	0.19	-0.21

The dependency of the inequality-growth relationship to the level of economic development. A potential worry over the results is whether the inequality-growth relationship in the non-OECD countries is simply conditional on the level of economic development rather than the development of financial markets. The panel level correlations reported in Table 3.3 mitigate this worry: there is no strong correlation between per capita GDP and the measures of financial development in either of the country samples. If the annual observations were used instead, relatively high positive correlations emerge. This is an additional benefit of using the five-year intervals. Moreover, the interaction plot (Figure 3.6) shows that the upward-sloping profile of Figure 3.5 does not emerge if the estimated model is the following:

$$\begin{aligned}\frac{1}{4}(lnY_{i,t+4} - lnY_{i,t}) &= \gamma lnY_{i,t-1} + \boldsymbol{\delta}'\boldsymbol{X}_{i,t} \\ &+ \beta_1(\frac{1}{5}\sum_{j=0}^{4} Gini_{i,t-5+j}) \\ &+ \beta_2(\frac{1}{5}\sum_{j=0}^{4} Gini_{i,t-5+j} \times lnY_{i,t-1}) + \alpha_i + \eta_t + \varepsilon_{i,t},\end{aligned} \tag{3.2}$$

8 Six of the 34 countries are always above the cut-off, 13 are both over and under during the observation period while 15 are always under.

where the notation follows equation (3.1). Rather, in the non-OECD countries, the association between the Gini coefficient and subsequent growth is positive (negative) for low (high) levels of per capita GDP.

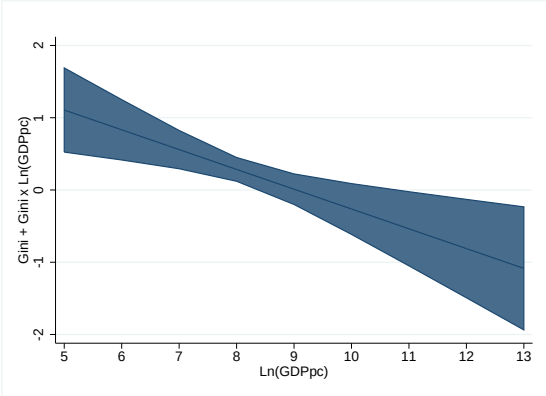


FIGURE 3.6 Estimated association (95 % level confidence interval) between the Gini coefficient and per capita growth conditional on per capita GDP, non-OECD countries

Using top income shares. The main results are robust to considering the disposable income shares of either the highest-earning quintile or decile. First, for OECD countries, per capita GDP growth shows no dependency on the concentration of income. Second, in non-OECD countries, the association between income inequality and growth seems to depend on the development of financial markets irrespective of the measure of inequality. Graphical illustrations – similar to Figure 3.5 – in Appendix 3.A.2 portray the results for the top income shares in the sample of non-OECD countries. The similarities in results are hardly surprising as the Gini coefficient and the top income shares follow one another closely[9]. The main results remain unchanged if the Palma ratio (top 10 % income share divided by the bottom 40 % income share) is used instead of the Gini coefficient or the top income shares.

Addressing the extent of inequality. One aspect that may affect the above-stated results, is potential dependency on the extent of income inequality. To investigate this possibility, piece-wise panel growth regressions are introduced:

[9] In the set of countries of this study, the country-specific correlations between the Gini coefficient and the top income shares are on average above 0.97 when the five-year non-overlapping windows are considered. Although the correlations show cross-country variation, the OECD and non-OECD sub-samples share similar characteristics. Similarly to the Gini coefficient, the WIID serves as the source of data for the top income shares. Previously, Leigh (2007) studied the top incomes and broader measures of income inequality, such as the Gini, and found that the former track the latter closely.

$$\begin{aligned}\frac{1}{4}(lnY_{i,t+4} - lnY_{i,t}) &= \gamma lnY_{i,t-1} + \boldsymbol{\delta}'\boldsymbol{X}_{i,t} \\ &+ \beta_1(\frac{1}{5}\sum_{j=0}^{4} Gini^{top25}_{i,t-5+j}) + \beta_2(\frac{1}{5}\sum_{j=0}^{4} Gini^{bottom75}_{i,t-5+j}) \\ &+ \beta_3(\frac{1}{5}\sum_{j=0}^{4} Svir_{i,t-5+j}) + \beta_4(\frac{1}{5}\sum_{j=0}^{4}(Gini^{top25} \times Svir)_{i,t-5+j}) \\ &+ \beta_5(\frac{1}{5}\sum_{j=0}^{4}(Gini^{bottom75} \times Svir)_{i,t-5+j}) + \alpha_i + \eta_t + \varepsilon_{i,t},\end{aligned} \tag{3.3}$$

where the notation follows equation (3.1). This approach allows for different coefficients above and below a certain cut-off in the distribution of the Gini coefficient. The analysis uses the 75th percentile as the cut-off while the results show only little sensitivity to alternative choices. The reported one is consistent with the study by Berg et al. (2018). As above, the development of financial markets seems to play a role in the inequality-growth relationship while institutional development does not.

Table 3.4 reports the piece-wise panel regression results for the OECD and non-OECD countries separately when the relationship between income inequality and subsequent growth is allowed to depend on financial market development and the extent of inequality. Again, the additional growth determinants are excluded from the table for readability. Clearly, the parameter estimates for the Gini coefficient and for the interaction term are different conditional on the level of the Gini in the OECD countries. In the less developed economies, the two coefficients for the Gini are not statistically different from one another while the null hypothesis of equality of the interaction terms is rejected.

As above, the interaction plots are more suitable than regression tables to demonstrate the inter-dependencies studied in this paper. The results for the non-OECD countries (Figures 3.7b and 3.7d) are very similar between the low and high inequality cases and portray a very similar picture to Figure 3.5c. In the sub-sample of OECD countries, however, the results are dependent on the extent of income inequality as the results of Table 3.4 already suggested. At the bottom 75 % of the distribution of the Gini coefficient, the association between income inequality and growth seems non-existent (Figure 3.7c). This holds across specifications with linear functional form and ones that incorporate non-linearities to different measures provided by Svirydzenka (2016). Under both high inequality and high financial market development, income inequality is negatively associated with subsequent growth. This non-linearity is not present for the aggregate index or the development of institutions.

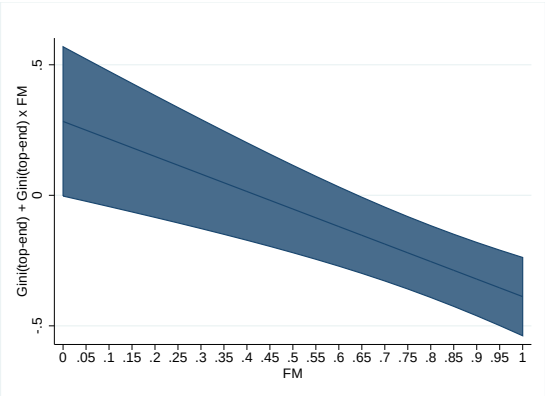
The panel regressions of this analysis suggest that financial markets, rather than institutions, matter for the interplay between income inequality and per capita growth of GDP. For the non-OECD countries the relationship is found not to depend on the level of income, whereas for the OECD countries, incorporating the extent of inequality seems essential to get the right picture. However, the

TABLE 3.4 The association between the Gini and economic growth conditional on financial market development and the extent of inequality

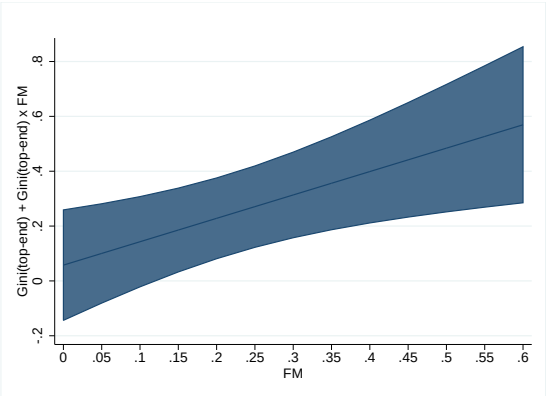
Fixed effects panel estimation (equation (3.3)), dependent variable: growth of per capita GDP inside non-overlapping five-year growth windows. Control variables are included in the regressions but not reported in the table.

	OECD	non-OECD
	(1)	(2)
Gini at the top 25 %	0.2831*	0.0576
	(0.1459)	(0.1027)
Gini at the bottom 75 %	-0.0460	0.0344
	(0.1288)	(0.1110)
Development of financial markets (FM)	0.0362	-0.4402***
	(0.0560)	(0.1365)
Gini at the top 25 % × FM	-0.6712***	0.8530**
	(0.1586)	(0.3244)
Gini at the bottom 75 % × FM	-0.0123	1.0760***
	(0.1890)	(0.3847)
Test for equality of the Gini_{top} and Gini_{bottom} coefficients (p values)	<0.000	0.286
Test for equality of the Gini_{top} × FM and Gini_{bottom} × FM coefficients (p values)	<0.000	0.019
Joint significance of Gini_{top} and Gini_{top} × FM (p values)	<0.000	0.001
Joint significance of Gini_{bottom} and Gini_{bottom} × FM (p values)	0.820	0.001
Joint significance of FM and Gini_{top} × FM (p values)	<0.000	0.004
Joint significance of FM and Gini_{bottom} × FM (p values)	0.109	0.006
Joint significance of Gini_{top}, FM and Gini_{top} × FM (p values)	<0.000	0.002
Joint significance of Gini_{bottom}, FM and Gini_{bottom} × FM (p values)	0.117	0.002
Observations	177	141
Number of countries	35	34

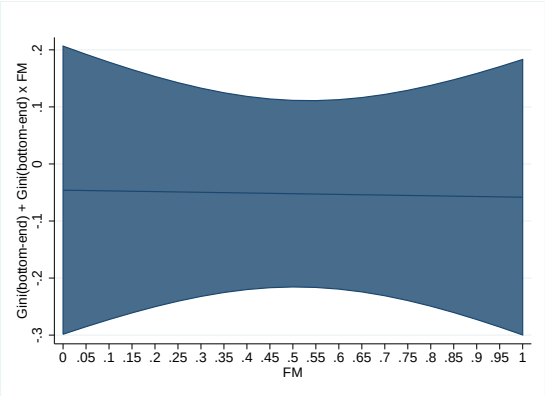
Robust standard errors in parantheses. *, ** and *** indicate statistical significance at 10 %, 5 % and 1 % levels, respectively.



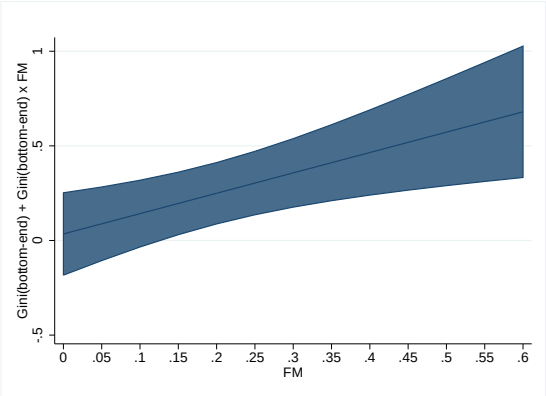
(a) Gini at the top 25 %, OECD



(b) Gini at the top 25 %, non-OECD



(c) Gini at the bottom 75 %, OECD



(d) Gini at the bottom 75 %, non-OECD

FIGURE 3.7 Estimated association (95 % level confidence interval) between the Gini coefficient at the top 25 % and at the bottom 75 % percent and per capita growth conditional on development of financial markets (FM)

statistical approach used so far can only capture a partial correlation between the variables of interest despite the chosen timing convention and controlling for several other determinants of economic growth and country and year fixed effects.

Controlling for endogeneity. The limitations of simple panel estimation techniques are well-recognized in the literature. To address the identification issues caused by both omitted variables and reverse causality, researchers have increasingly started to apply generalized method of moments (GMM) estimators. The so-called system GMM or sGMM (Arellano and Bover, 1995; Blundell and Bond, 1998)[10] has been particularly popular. In short, the sGMM estimates equation (3.1) and its first-difference as a system using suitably lagged values of the regressors as instrument variables for the first-differenced equation and lagged variables of first-differences as instruments for the level equation. The estimator can therefore exploit both variation in time and across individuals since the individual-specific characteristics are not removed from the equation in levels.

To inspect the validity of the lagged levels and differences of the regressors as instruments, the Arellano-Bond autocorrelation test, the Hansen test for overidentifying restrictions and the difference-in-Hansen tests are nowadays often reported alongside the number of instruments. This is a clear improvement on past practices, where the tractability of the choices regarding the use of the sGMM was often poor. In this study, for each sGMM estimation, Windmeijer (2005) small sample correction is used for robust standard errors; in the a priori estimate of the covariance matrix, the upper right and lower left quadrants are zeroed out; and the two-step estimator is favored over the one-step one. Moreover, the set of instruments is narrowed down to include only the observations during twice lagged windows for the regressors to reduce the risk of instrument proliferation.

Despite restricting the size of the instrument matrix, the sGMM tends to run into issues in small samples. Namely, the p-value of Hansen J can be suspiciously high implying that the estimator suffers from instrument proliferation, which weakens the power of testing for the validity of the instruments. Consequently, dividing the sample into OECD and non-OECD countries is out of reach. Moreover, as the instrument counts increases with the number of regressors, only the level of economic development is included as an additional growth determinant. To circumvent the problem, an approach, which uses the full sample of 69 countries together with cross-terms that indicate whether a country is a member of the OECD or not, is introduced (see equation (3.4) in Appendix 3.A.3). These choices of modelling reduce the number of instruments relative to the number of countries compared to the sub-sample analysis. Still, the tests for overidentifying restrictions speak for proliferation and the number of instruments clearly exceeds the number of countries (Table 3.12 in Appendix 3.A.3) violating the rule of thumb provided by Roodman (2009), who offers an influential guide for the use of the sGMM.

[10] For the preceding work on GMM, see Hansen (1982), Holtz-Eakin et al. (1988) and Arellano and Bond (1991).

The results of the sGMM estimations are illustrated by interaction plots familiar from above. Figure 3.11 in Appendix 3.A.3 replicates Figure 3.7. The results for the non-OECD countries are very similar between the fixed effects estimator and the sGMM. On the contrary, the result of growth-hurting inequality under high inequality and high development of financial markets in the OECD countries is not robust to the introduction of the sGMM.

The sGMM allows for heteroskedasticity and autocorrelation within countries but not across them. The assumption of no heteroskedasticity across countries is a strong one and since the Arellano-Bond autocorrelation test and the estimation of robust standard errors make the assumption, it is not innocent. Unfortunately, testing for conditional homoskedasticity is not straight-forward in a GMM framework[11] and thus it is not clear whether the sGMM improves on the simple panel estimation techniques even if the autocorrelation test and Hansen J were to support appropriateness of the model specification. Moreover, it has been shown that the sGMM estimates tend to be associated with wide weak-instrument robust confidence intervals (Bazzi and Clemens, 2013; Kraay, 2015).

3.4 Conclusion

This study investigated the role of financial development in the interplay between income inequality and growth of per capita GDP. The empirical analysis relied on panel data techniques and a multi-dimensional index of financial development together with survey-based evidence on the distribution of disposable income and a standard data source for overall economic activity. A positive partial correlation was found between income inequality and subsequent growth of per capita GDP in the non-OECD countries given that the financial markets are sufficiently developed. The evidence for an association between inequality and growth was weak in the sample of OECD countries.

Typically, panel growth regressions have two main limitations. First, it is not clear whether a parameter estimate corresponds to causal mechanisms or whether it is for example driven by some underlying institutional traits not captured by the controls. Second, the policy relevance of a finding that could be read as inequality causing a decrease or an increase in economic growth would still be limited. The policy actions aiming to affect income inequality are controlled by national policy-makers and the set of possible tools is large and associated with country-specific limitations, whereas the result necessarily relies on data

[11] For simpler estimators, the nR^2 test developed by White (1980) together with the approach introduced by Breusch and Pagan (1979) is informative, whereas for GMM, the nR^2 statistic does not have the desired statistical properties (Hayashi, 2000, p. 234). However, White (1982) notes that when the errors are symmetric, nR^2 is biased towards the rejection of the null hypothesis of conditional homoskedasticity. Hence, under symmetricity, the failure to reject the null is useful evidence in favor of the correctness of the specification. In practice, the test is constructed by regressing the squared residuals on a constant and second-order cross products of the instrumental variables.

that have been pooled from many countries.

The first concern is relevant in the context of this study while the second is perhaps less so as it is possible to focus on the development of financial markets as a tool to mitigate the potential adverse effects of income inequality on economic growth. The distinction is important if policies affecting financial markets are easier to coordinate supra-nationally than predistributive and redistributive actions.

3.A Appendix

3.A.1 Full fixed effects panel regression tables

TABLE 3.5 Parsimonious linear panel growth regression

Fixed effects panel estimation results with only convergence term and the Gini coefficient as explanatory variables, dependent variable: growth of per capita GDP inside non-overlapping five-year growth windows.

	All	OECD	non-OECD
	(1)	(2)	(3)
Initial per capita GDP	-0.0692***	-0.0752***	-0.0817***
	(0.0136)	(0.0117)	(0.0193)
Gini	0.0579	-0.0682	0.1889**
	(0.0740)	(0.0697)	(0.0824)
Constant	0.6491***	0.7961***	0.6175***
	(0.1388)	(0.1224)	(0.1629)
Observations	318	177	141
R-squared	0.2196	0.3840	0.4090
Number of countries	69	35	34

Robust standard errors in parantheses. *, ** and *** indicate statistical significance at 10 %, 5 % and 1 % levels, respectively.

TABLE 3.6 Financial development (aggregate index)

Fixed effects panel estimation, dependent variable: growth of per capita GDP inside non-overlapping five-year growth windows. Columns (2), (4) and (6) correspond to equation (3.1), where *Svir* is replaced with *FD*. Columns (1), (3) and (5) correspond to specifications without an interaction term.

	All		OECD		non-OECD	
	(1)	(2)	(3)	(4)	(5)	(6)
Initial per capita GDP	-0.1007***	-0.0989***	-0.1045***	-0.1040***	-0.0984***	-0.1111***
	(0.0130)	(0.0123)	(0.0139)	(0.0140)	(0.0235)	(0.0209)
Gini	0.0485	0.1887*	-0.1091	0.0756	0.1712**	-0.0650
	(0.0702)	(0.1126)	(0.0795)	(0.1959)	(0.0825)	(0.1616)
Financial development (FD)	0.0493**	0.1502***	0.0384	0.1185	-0.0694	-0.4241**
	(0.0188)	(0.0559)	(0.0234)	(0.0891)	(0.0580)	(0.1952)
Gini × FD		-0.3052*		-0.2706		0.7620*
		(0.1716)		(0.2910)		(0.3977)
Log(Investment to GDP)	0.0395***	0.0343**	0.0453**	0.0459**	0.0187	0.0265*
	(0.0136)	(0.0143)	(0.0208)	(0.0210)	(0.0145)	(0.0140)
Log(Schooling)	0.0300	0.0196	-0.0006	-0.0067	0.0047	0.0032
	(0.0201)	(0.0216)	(0.0263)	(0.0279)	(0.0296)	(0.0295)
Log(Political institutions)	0.0084	0.0061	0.0005	0.0013	0.0005	0.0040
	(0.0062)	(0.0057)	(0.0183)	(0.0169)	(0.0050)	(0.0050)
Log(Trade volume to GDP)	0.0176	0.0177	0.0200*	0.0179*	0.0184	0.0132
	(0.0109)	(0.0108)	(0.0102)	(0.0094)	(0.0164)	(0.0150)
Log(Debt to GDP)	-0.0026	-0.0015	-0.0083	-0.0076	0.0066	0.0064
	(0.0038)	(0.0037)	(0.0070)	(0.0070)	(0.0049)	(0.0047)
Constant	0.9129***	0.8628***	1.1281***	1.0779***	0.8475***	1.0632***
	(0.1339)	(0.1354)	(0.1639)	(0.1825)	(0.2155)	(0.2033)
Joint significance of Gini and FD (p values)	0.036		0.064		0.109	
Joint significance of Gini and Gini × FD (p values)		0.195		0.353		0.007
Joint significance of FD and Gini × FD (p values)		0.002		0.178		0.095
Joint significance of Gini, FD and Gini × FD (p values)		0.006		0.115		0.017
Observations	318	318	177	177	141	141
R-squared	0.3413	0.3541	0.5004	0.5064	0.4501	0.4749
Number of countries	69	69	35	35	34	34

Robust standard errors in parantheses. *, ** and *** indicate statistical significance at 10 %, 5 % and 1 % levels, respectively.

TABLE 3.7 Development of financial institutions

Fixed effects panel estimation, dependent variable: growth of per capita GDP inside non-overlapping five-year growth windows. Columns (2), (4) and (6) correspond to equation (3.1), where *Svir* is replaced with *FI*. Columns (1), (3) and (5) correspond to specifications without an interaction term.

	All		OECD		non-OECD	
	(1)	(2)	(3)	(4)	(5)	(6)
Initial per capita GDP	-0.0990***	-0.0974***	-0.1012***	-0.1008***	-0.0970***	-0.0999***
	(0.0132)	(0.0125)	(0.0156)	(0.0154)	(0.0226)	(0.0228)
Gini	0.0355	0.2055*	-0.1146	0.1178	0.1775**	0.0678
	(0.0694)	(0.1111)	(0.0773)	(0.2326)	(0.0849)	(0.1678)
Development of financial institutions (FI)	0.0124	0.1267**	0.0089	0.1011	-0.0382	-0.1583
	(0.0176)	(0.0531)	(0.0204)	(0.0937)	(0.0393)	(0.1887)
Gini × FI		-0.3092**		-0.3073		0.2630
		(0.1436)		(0.3035)		(0.3793)
Log(Investment to GDP)	0.0419***	0.0356**	0.0467**	0.0458**	0.0178	0.0210
	(0.0141)	(0.0150)	(0.0204)	(0.0203)	(0.0146)	(0.0151)
Log(Schooling)	0.0275	0.0178	-0.0076	-0.0103	0.0129	0.0155
	(0.0199)	(0.0208)	(0.0249)	(0.0255)	(0.0280)	(0.0286)
Log(Political institutions)	0.0097	0.0082	0.0065	0.0049	0.0006	0.0011
	(0.0069)	(0.0062)	(0.0173)	(0.0169)	(0.0049)	(0.0051)
Log(Trade volume to GDP)	0.0171	0.0191*	0.0203*	0.0196*	0.0201	0.0172
	(0.0107)	(0.0109)	(0.0105)	(0.0104)	(0.0174)	(0.0174)
Log(Debt to GDP)	-0.0051	-0.0040	-0.0095	-0.0088	0.0065	0.0063
	(0.0039)	(0.0038)	(0.0068)	(0.0069)	(0.0049)	(0.0047)
Constant	0.9227***	0.8562***	1.1196***	1.0518***	0.8180***	0.8876***
	(0.1381)	(0.1425)	(0.1800)	(0.1984)	(0.1986)	(0.2215)
Joint significance of Gini and FI (p values)	0.674		0.298		0.100	
Joint significance of Gini and Gini × FI (p values)		0.104		0.282		0.138
Joint significance of FI and Gini × FI (p values)		0.062		0.556		0.583
Joint significance of Gini, FI and Gini × FI (p values)		0.131		0.417		0.230
Observations	318	318	177	177	141	141
R-squared	0.3260	0.3390	0.4906	0.4964	0.4451	0.4486
Number of countries	69	69	35	35	34	34

Robust standard errors in parantheses. *, ** and *** indicate statistical significance at 10 %, 5 % and 1 % levels, respectively.

TABLE 3.8 Development of financial markets

Fixed effects panel estimation, dependent variable: growth of per capita GDP inside non-overlapping five-year growth windows. Columns (2), (4) and (6) correspond to equation (3.1), where *Svir* is replaced with *FM*. Columns (1), (3) and (5) correspond to specifications without an interaction term.

	All		OECD		non-OECD	
	(1)	(2)	(3)	(4)	(5)	(6)
Initial per capita GDP	-0.1011***	-0.0999***	-0.1051***	-0.1049***	-0.0966***	-0.1073***
	(0.0125)	(0.0122)	(0.0139)	(0.0140)	(0.0238)	(0.0214)
Gini	0.0537	0.1190	-0.1026	0.0139	0.1679**	0.0646
	(0.0711)	(0.0996)	(0.0808)	(0.1375)	(0.0810)	(0.1059)
Development of financial markets (FM)	0.0446***	0.1009*	0.0321**	0.0901	-0.0544	-0.2840**
	(0.0122)	(0.0540)	(0.0142)	(0.0679)	(0.0526)	(0.1124)
Gini × FM		-0.1822		-0.1941		0.5416*
		(0.1773)		(0.2291)		(0.3061)
Log(Investment to GDP)	0.0364***	0.0347**	0.0439**	0.0453**	0.0210	0.0255*
	(0.0131)	(0.0134)	(0.0200)	(0.0204)	(0.0150)	(0.0140)
Log(Schooling)	0.0305	0.0238	0.0045	-0.0023	0.0047	0.0035
	(0.0199)	(0.0216)	(0.0263)	(0.0286)	(0.0302)	(0.0295)
Log(Political institutions)	0.0071	0.0055	-0.0036	-0.0017	0.0008	0.0048
	(0.0059)	(0.0057)	(0.0184)	(0.0166)	(0.0049)	(0.0049)
Log(Trade volume to GDP)	0.0175	0.0165	0.0196*	0.0170*	0.0180	0.0179
	(0.0111)	(0.0109)	(0.0102)	(0.0095)	(0.0162)	(0.0157)
Log(Debt to GDP)	-0.0014	-0.0010	-0.0078	-0.0072	0.0066	0.0066
	(0.0037)	(0.0037)	(0.0071)	(0.0069)	(0.0048)	(0.0048)
Constant	0.9189***	0.8967***	1.1359***	1.1075***	0.8252***	0.9593***
	(0.1334)	(0.1343)	(0.1603)	(0.1747)	(0.2142)	(0.1860)
Joint significance of Gini and FM (p values)	0.002		0.025		0.127	
Joint significance of Gini and Gini × FM (p values)		0.477		0.415		0.010
Joint significance of FM and Gini × FM (p values)		0.001		0.050		0.014
Joint significance of Gini, FM and Gini × FM (p values)		0.002		0.042		0.004
Observations	318	318	177	177	141	141
R-squared	0.3502	0.3560	0.5047	0.5099	0.4466	0.4699
Number of countries	69	69	35	35	34	34

Robust standard errors in parantheses. *, ** and *** indicate statistical significance at 10 %, 5 % and 1 % levels, respectively.

TABLE 3.9 Depth of financial markets

Fixed effects panel estimation, dependent variable: growth of per capita GDP inside non-overlapping five-year growth windows. Columns (2), (4) and (6) correspond to equation (3.1), where *Svir* is replaced with *FMD*. Columns (1), (3) and (5) correspond to specifications without an interaction term.

	All		OECD		non-OECD	
	(1)	(2)	(3)	(4)	(5)	(6)
Initial per capita GDP	-0.1024***	-0.1017***	-0.1060***	-0.1060***	-0.0951***	-0.1069***
	(0.0120)	(0.0121)	(0.0141)	(0.0141)	(0.0241)	(0.0237)
Gini	0.0538	0.0837	-0.1010	-0.0389	0.1789**	0.0909
	(0.0686)	(0.0868)	(0.0794)	(0.1305)	(0.0875)	(0.0993)
Depth of financial markets (FMD)	0.0506***	0.0754*	0.0298**	0.0568	-0.0279	-0.3068***
	(0.0120)	(0.0422)	(0.0137)	(0.0574)	(0.0575)	(0.1110)
Gini × FMD		-0.0849		-0.0954		0.6509**
		(0.1428)		(0.2016)		(0.2744)
Log(Investment to GDP)	0.0368***	0.0358**	0.0452**	0.0464**	0.0190	0.0234
	(0.0131)	(0.0136)	(0.0204)	(0.0208)	(0.0146)	(0.0140)
Log(Schooling)	0.0318	0.0275	0.0043	0.0007	0.0088	0.0051
	(0.0204)	(0.0221)	(0.0257)	(0.0288)	(0.0318)	(0.0299)
Log(Political institutions)	0.0077	0.0069	0.0022	0.0020	0.0006	0.0048
	(0.0058)	(0.0056)	(0.0179)	(0.0176)	(0.0047)	(0.0049)
Log(Trade volume to GDP)	0.0141	0.0139	0.0162	0.0149	0.0204	0.0193
	(0.0110)	(0.0110)	(0.0099)	(0.0097)	(0.0169)	(0.0156)
Log(Debt to GDP)	-0.0008	-0.0006	-0.0083	-0.0081	0.0064	0.0056
	(0.0037)	(0.0037)	(0.0071)	(0.0070)	(0.0048)	(0.0045)
Constant	0.9171***	0.9088***	1.1285***	1.1191***	0.7997***	0.9382***
	(0.1309)	(0.1329)	(0.1648)	(0.1738)	(0.2178)	(0.2106)
Joint significance of Gini and FMD (p values)	<0.000		0.027		0.137	
Joint significance of Gini and Gini × FMD (p values)		0.630		0.467		0.002
Joint significance of FMD and Gini × FMD (p values)		<0.000		0.081		0.030
Joint significance of Gini, FMD and Gini × FMD (p values)		0.001		0.056		0.002
Observations	318	318	177	177	141	141
R-squared	0.3629	0.3646	0.5035	0.5053	0.4404	0.4723
Number of countries	69	69	35	35	34	34

Robust standard errors in parantheses. *, ** and *** indicate statistical significance at 10 %, 5 % and 1 % levels, respectively.

TABLE 3.10 Access to financial markets

Fixed effects panel estimation, dependent variable: growth of per capita GDP inside non-overlapping five-year growth windows. Columns (2), (4) and (6) correspond to equation (3.1), where *Svir* is replaced with FMA. Columns (1), (3) and (5) correspond to specifications without an interaction term.

	All		OECD		non-OECD	
	(1)	(2)	(3)	(4)	(5)	(6)
Initial per capita GDP	-0.0988***	-0.0960***	-0.1004***	-0.1006***	-0.0945***	-0.1096***
	(0.0131)	(0.0122)	(0.0163)	(0.0150)	(0.0225)	(0.0225)
Gini	0.0331	0.1345	-0.1064	0.1304	0.1779**	0.0725
	(0.0699)	(0.0985)	(0.0738)	(0.1139)	(0.0864)	(0.1141)
Access to financial markets (FMA)	0.0167	0.1116**	-0.0126	0.1098*	-0.0257	-0.3357*
	(0.0143)	(0.0522)	(0.0129)	(0.0587)	(0.0463)	(0.1716)
Gini × FMA		-0.2865*		-0.4117**		0.6171*
		(0.1616)		(0.1976)		(0.3636)
Log(Investment to GDP)	0.0391***	0.0358**	0.0490**	0.0519**	0.0209	0.0276*
	(0.0138)	(0.0139)	(0.0195)	(0.0192)	(0.0150)	(0.0138)
Log(Schooling)	0.0243	0.0146	-0.0045	-0.0117	0.0151	0.0200
	(0.0193)	(0.0203)	(0.0248)	(0.0252)	(0.0282)	(0.0290)
Log(Political institutions)	0.0094	0.0067	0.0070	0.0052	0.0005	0.0027
	(0.0067)	(0.0064)	(0.0169)	(0.0166)	(0.0046)	(0.0050)
Log(Trade volume to GDP)	0.0163	0.0156	0.0211*	0.0213**	0.0195	0.0217
	(0.0109)	(0.0106)	(0.0106)	(0.0104)	(0.0174)	(0.0162)
Log(Debt to GDP)	-0.0044	-0.0034	-0.0102	-0.0084	0.0063	0.0069
	(0.0040)	(0.0038)	(0.0070)	(0.0067)	(0.0048)	(0.0049)
Constant	0.9241***	0.8792***	1.1190***	1.0741***	0.7854***	0.9676***
	(0.1385)	(0.1352)	(0.1824)	(0.1832)	(0.1935)	(0.2063)
Joint significance of Gini and FMA (p values)	0.493		0.302		0.131	
Joint significance of Gini and Gini × FMA (p values)		0.214		0.080		0.007
Joint significance of FMA and Gini × FMA (p values)		0.068		0.109		0.112
Joint significance of Gini, FMA and Gini × FMA (p values)		0.141		0.159		0.016
Observations	318	318	177	177	141	141
R-squared	0.3280	0.3449	0.4926	0.5185	0.4400	0.4603
Number of countries	69	69	35	35	34	34

Robust standard errors in parantheses. *, ** and *** indicate statistical significance at 10 %, 5 % and 1 % levels, respectively.

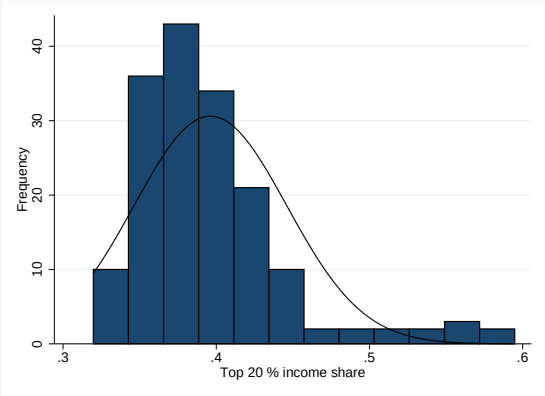
TABLE 3.11 Efficiency of financial markets

Fixed effects panel estimation, dependent variable: growth of per capita GDP inside non-overlapping five-year growth windows. Columns (2), (4) and (6) correspond to equation (3.1), where *Svir* is replaced with *FME*. Columns (1), (3) and (5) correspond to specifications without an interaction term.

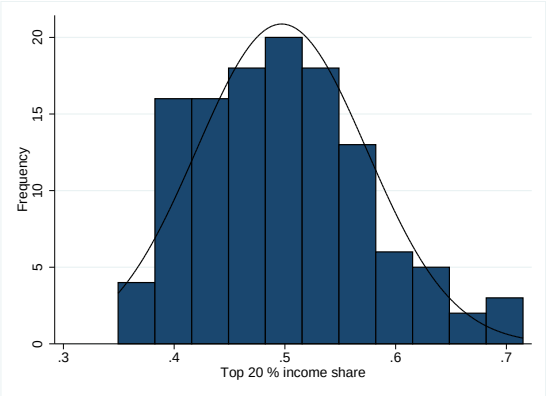
	All		OECD		non-OECD	
	(1)	(2)	(3)	(4)	(5)	(6)
Initial per capita GDP	-0.0999***	-0.0998***	-0.1048***	-0.1049***	-0.0959***	-0.0984***
	(0.0127)	(0.0126)	(0.0136)	(0.0139)	(0.0227)	(0.0213)
Gini	0.0499	0.0706	-0.0901	-0.0976	0.1647*	0.1177
	(0.0714)	(0.0846)	(0.0788)	(0.1062)	(0.0810)	(0.1045)
Efficiency of financial markets (FME)	0.0158**	0.0338	0.0192**	0.0151	-0.0200	-0.0916
	(0.0077)	(0.0385)	(0.0073)	(0.0501)	(0.0168)	(0.0781)
Gini × FME		-0.0558		0.0134		0.1952
		(0.1244)		(0.1685)		(0.2245)
Log(Investment to GDP)	0.0398***	0.0394***	0.0464**	0.0463**	0.0216	0.0225
	(0.0136)	(0.0137)	(0.0188)	(0.0190)	(0.0147)	(0.0145)
Log(Schooling)	0.0319	0.0306	0.0115	0.0122	0.0128	0.0117
	(0.0194)	(0.0199)	(0.0262)	(0.0266)	(0.0270)	(0.0277)
Log(Political institutions)	0.0075	0.0071	-0.0091	-0.0096	0.0014	0.0034
	(0.0064)	(0.0064)	(0.0183)	(0.0158)	(0.0049)	(0.0047)
Log(Trade volume to GDP)	0.0193*	0.0188*	0.0237**	0.0241**	0.0188	0.0187
	(0.0111)	(0.0110)	(0.0099)	(0.0088)	(0.0166)	(0.0167)
Log(Debt to GDP)	-0.0035	-0.0035	-0.0081	-0.0081	0.0066	0.0066
	(0.0037)	(0.0037)	(0.0068)	(0.0068)	(0.0048)	(0.0049)
Constant	0.9252***	0.9186***	1.1422***	1.1454***	0.8026***	0.8412***
	(0.1358)	(0.1362)	(0.1561)	(0.1609)	(0.1924)	(0.1760)
Joint significance of Gini and FME (p values)	0.120		0.025		0.091	
Joint significance of Gini and Gini × FME (p values)		0.707		0.493		0.048
Joint significance of FME and Gini × FME (p values)		0.070		0.039		0.196
Joint significance of Gini, FME and Gini × FME (p values)		0.142		0.056		0.038
Observations	318	318	177	177	141	141
R-squared	0.3364	0.3374	0.5126	0.5127	0.4444	0.4511
Number of countries	69	69	35	35	34	34

Robust standard errors in parantheses. *, ** and *** indicate statistical significance at 10 %, 5 % and 1 % levels, respectively.

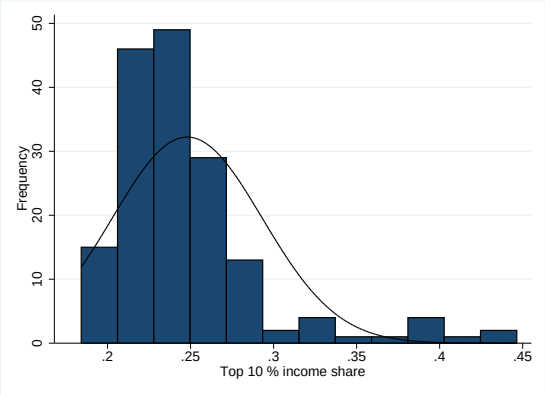
3.A.2 Association between the top income shares and growth of per capita GDP



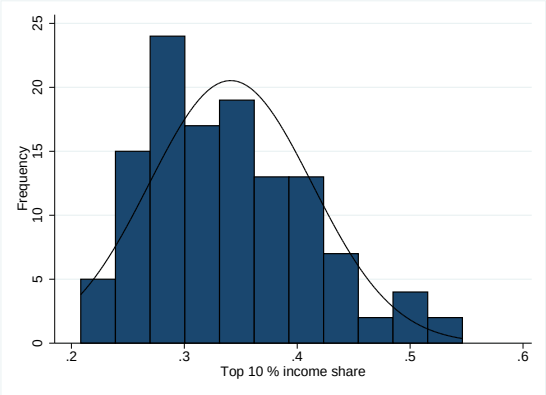
(a) Top 20 %, OECD



(b) Top 20 %, non-OECD

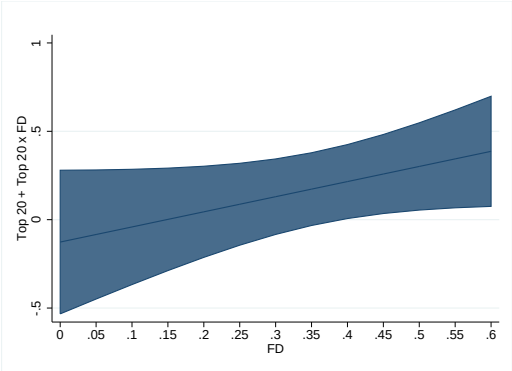


(c) Top 10 %, OECD

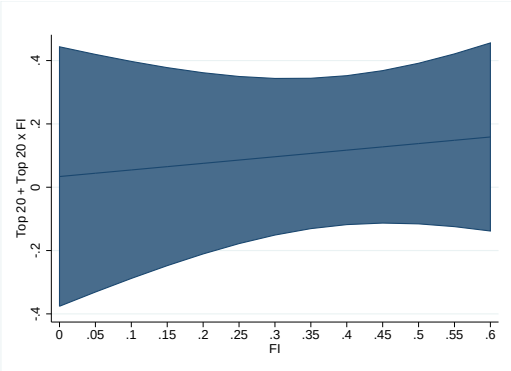


(d) Top 10 %, non-OECD

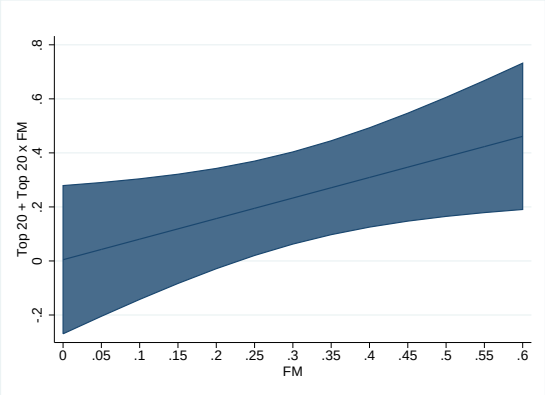
FIGURE 3.8 The distributions of top disposable income shares in OECD and non-OECD countries



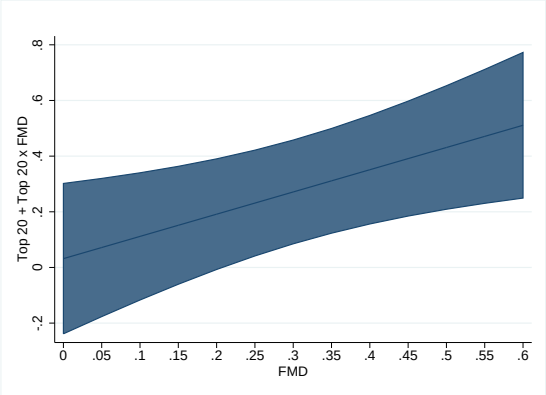
(a) Financial development (FD)



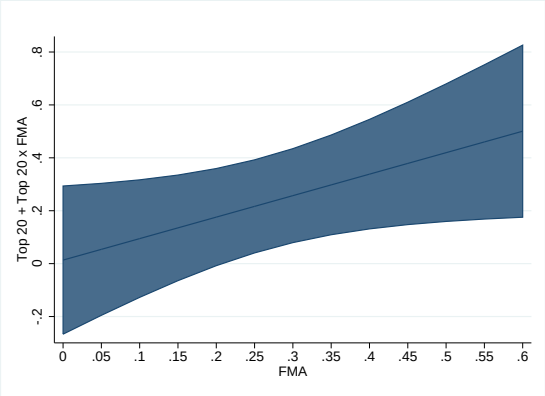
(b) Development of financial institutions (FI)



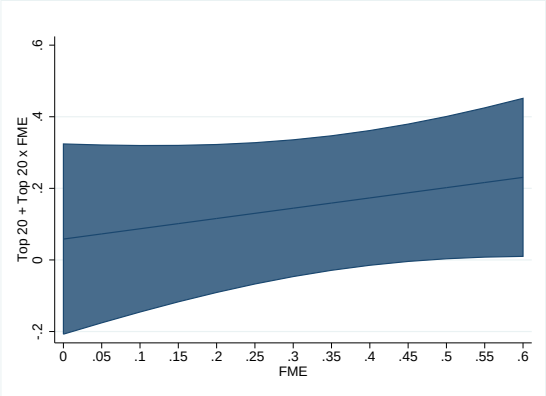
(c) Development of financial markets (FM)



(d) Depth of financial markets (FMD)

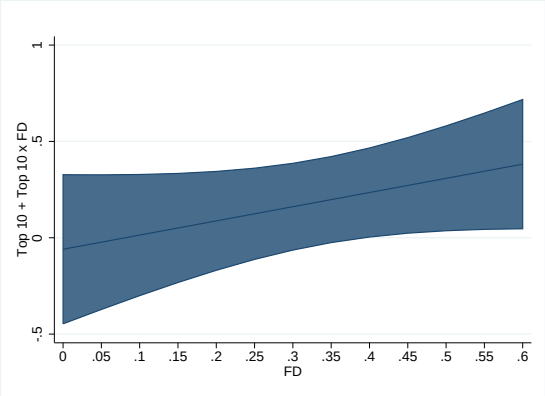


(e) Access to financial markets (FMA)

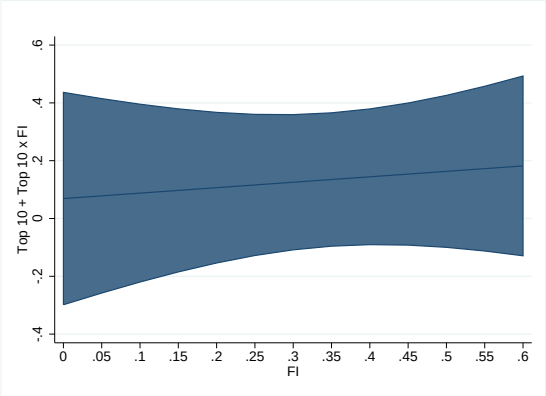


(f) Efficiency of financial markets (FME)

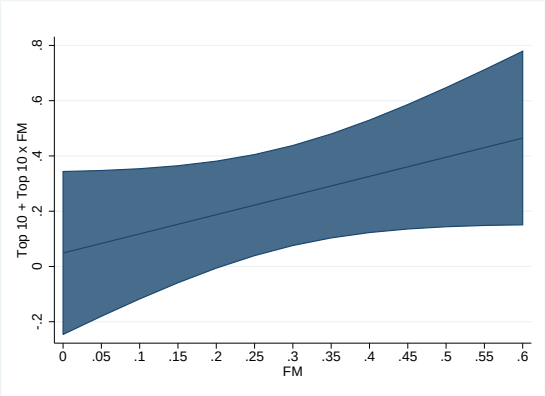
FIGURE 3.9 Estimated association (95 % level confidence interval) between the top 20 % income share and per capita growth conditional on different measures of financial development, non-OECD countries



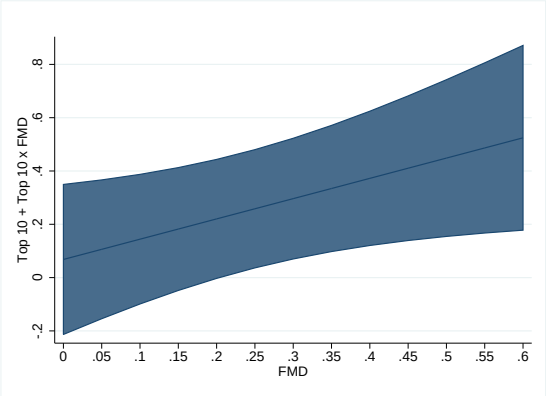
(a) Financial development (FD)



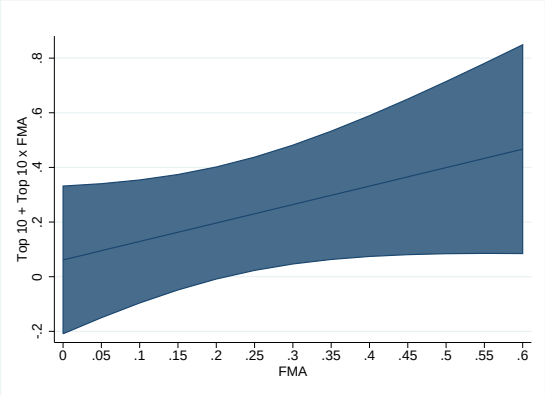
(b) Development of financial institutions (FI)



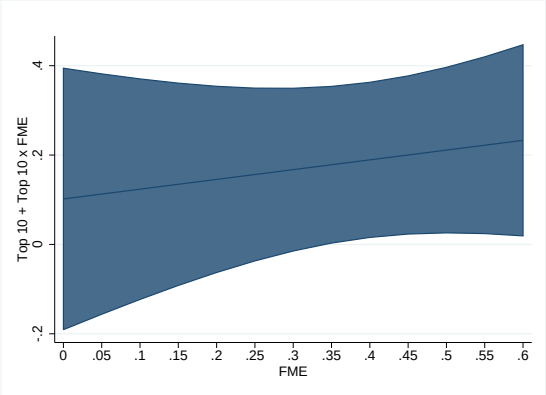
(c) Development of financial markets (FM)



(d) Depth of financial markets (FMD)



(e) Access to financial markets (FMA)



(f) Efficiency of financial markets (FME)

FIGURE 3.10 Estimated association (95 % level confidence interval) between the top 10 % income share and per capita growth conditional on different measures of financial development, non-OECD countries

3.A.3 Controlling for endogeneity: system GMM

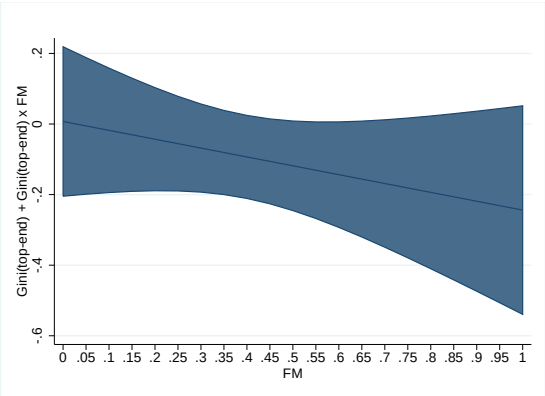
$$
\begin{aligned}
\frac{1}{4}(lnY_{i,t+4} - lnY_{i,t}) = \gamma lnY_{i,t-1} + \beta_1(\frac{1}{5}\sum_{j=0}^{4} Gini_{i,t-5+j}^{top25}) \\
+ \beta_2(\frac{1}{5}\sum_{j=0}^{4} Gini_{i,t-5+j}^{bottom75}) + \beta_3(\frac{1}{5}\sum_{j=0}^{4} FM_{i,t-5+j}) \\
+ \beta_4(\frac{1}{5}\sum_{j=0}^{4} Gini_{i,t-5+j}^{top25} \times OECD) + \beta_5(\frac{1}{5}\sum_{j=0}^{4} Gini_{i,t-5+j}^{bottom75} \times OECD) \\
+ \beta_6(\frac{1}{5}\sum_{j=0}^{4} FM_{i,t-5+j} \times OECD) + \beta_7(\frac{1}{5}\sum_{j=0}^{4} Gini_{i,t-5+j}^{top25} \times FM) \\
+ \beta_8(\frac{1}{5}\sum_{j=0}^{4} Gini_{i,t-5+j}^{bottom75} \times FM) \\
+ \beta_9(\frac{1}{5}\sum_{j=0}^{4} (Gini^{top25} \times FM)_{i,t-5+j} \times OECD) \\
+ \beta_{10}(\frac{1}{5}\sum_{j=0}^{4} (Gini^{bottom75} \times FM)_{i,t-5+j} \times OECD) + \alpha_i + \eta_t + \varepsilon_{i,t}
\end{aligned}
\tag{3.4}
$$

TABLE 3.12 System GMM estimates for the association between the Gini coefficient and economic growth conditional on financial market development and the level of inequality

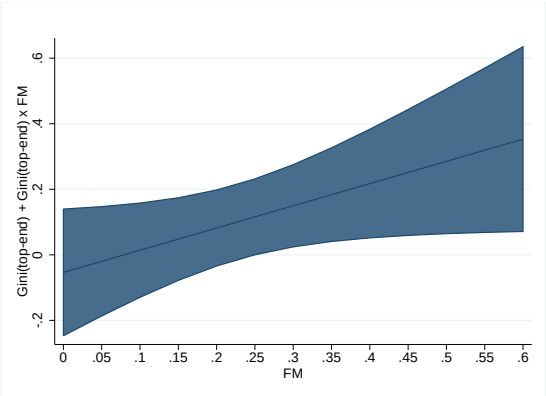
System GMM panel estimation, dependent variable: growth of per capita GDP inside non-overlapping five-year growth windows. The model is given in equation (3.4)

Initial per capita GDP	-0.0457***
	(0.0110)
Gini at the top 25 %	-0.0536
	(0.0986)
Gini at the bottom 75 %	-0.0372
	(0.1374)
Development of financial markets (FM)	-0.3814**
	(0.1873)
Gini at the top 25 % × OECD	0.0665
	(0.0958)
Gini at the bottom 75 % × OECD	0.0490
	(0.0499)
FM × OECD	0.5087***
	(0.1488)
Gini at the top 25 % × FM	0.6778*
	(0.3513)
Gini at the bottom 75 % × FM	0.8157*
	(0.4730)
Gini at the top 25 % × FM × OECD	-1.0491***
	(0.3234)
Gini at the bottom 75 % × FM × OECD	-1.0393***
	(0.3696)
Constant	0.0000
	(0.0000)
Observations	318
Number of countries	69
Number of instruments	126
AR1 test (p values)	<0.000
AR2 test (p values)	0.193
Hansen test of joint instrument validity (p values)	1.000
Difference-in-Hansen tests of instrument subsets (p values)	
For levels	1.000
For initial per cap GDP	0.970
For IV-type (time dummies)	0.693

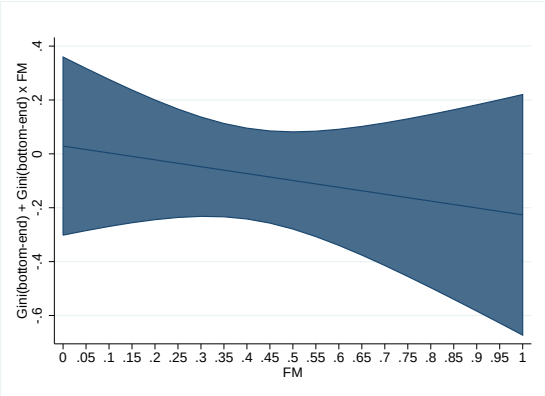
Robust standard errors in parantheses. *, ** and *** indicate statistical significance at 10 %, 5 % and 1 % levels, respectively.



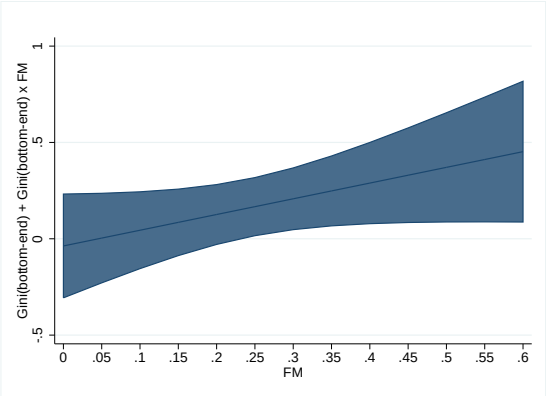
(a) Gini at the top 25 %, OECD



(b) Gini at the top 25 %, non-OECD



(c) Gini at the bottom 75 %, OECD



(d) Gini at the bottom 75 %, non-OECD

FIGURE 3.11 System GMM estimates (95 % level confidence interval) for the Gini coefficient at the top 25 % and at the bottom 75 % percent on per capita growth conditional on development of financial markets (FM)

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4 INCOME INEQUALITY AND ECONOMIC GROWTH: DIFFERENCE BETWEEN RISING AND FALLING TOP INCOME SHARES

Abstract*
This study contributes to the vast empirical literature on the interplay between income inequality and economic growth in two ways. First, potential cross-country heterogeneity, which is concealed in studies that use panel data, is addressed by using data from the World Inequality Database. Second, the adoption of a flexible autoregressive distributed lag model allows the growth of per capita GDP to have asymmetric responses to rising and falling top income shares. The analysis covers six countries over the period between 1950 and 2010, namely: Australia, Canada, France, India, Japan and the United States. In France and the United States, falls in the income shares of the highest-earning percentile were associated with lower subsequent economic growth. In India, growth was positively associated with a rising top income share. Thus, evidence is found of both cross-country heterogeneity and asymmetries. Adjustments to changes in inequality occured quickly in all countries suggesting that the empirical approach captures relatively direct economic mechanisms rather than slow-moving transmission channels. Furthermore, up-to-date data on top income shares are used to revisit panel estimation techniques that have been used in the past.

Keywords: Economic growth, Top income shares, Non-linear autoregressive distributed lag model, Panel cointegration, Panel regression

* I wish to thank Juha Junttila, who has supervised my work on the top income shares and economic growth since September 2016. I also benefited from methodological discussions with Jani-Petri Laamanen. The work was financially supported by the Finnish Cultural Foundation under Grant 12181963 and by the OP Group Research Foundation under Grant 20190078.

4.1 Introduction

The effect of economic inequality on growth has been proven to be a notoriously difficult research question. Although many theoretical papers have provided valuable insights on different mechanisms and even offered synthesis on the competing transmission channels, the empirical evidence remains inconclusive. Neves et al. (2016) document how the results depend on the structure of the data (panel, cross-section), the inequality concept (wealth, income, consumption), the sample of countries and the estimation technique. Interestingly, one of their main finding is evidence for publication bias, i.e. statistically significant results are more likely to be published and the signs of the reduced-form estimates follow a predictable time pattern. Moreover, establishing a causal interpretation to the results seems impossible.

This study aims to complement the existing empirical literature in two fronts. First, by focusing on the top income shares in six countries, the likely cross-country heterogeneity concealed in panel studies is addressed. Second, as there are no conclusive arguments why the response of economic growth should be symmetrical to rising and falling top income shares, a flexible autoregressive distributed lag (ARDL) model is adopted. Consequently, there is no need for a priori assumption on whether the inequality-growth relationship is linear or whether positive and negative changes in the top income shares should be treated separately. After the model specification, the empirical approach can be used to evaluate short-run and long-run responses and trace the process of adjustment from the initial equilibrium to the new one. Datawise, the study makes use of the top income shares freely available in the World Inequality Database.

The results of this study suggest that the long-run relationship between inequality and growth is indeed characterized by cross-country heterogeneity and asymmetries. First, in France and the United States, a decrease in the income share of the highest-earning percentile is associated with lower subsequent growth of per capita GDP while the growth-response to rising inequality is small and statistically insignificant. Second, in India, growth responds positively to rising inequality but shows no significant response to falling inequality. Third, changes in the top income shares seem not to translate into the growth process in Australia, Canada and Japan. Though, in Japan, the statistically insignificant point estimates for both positive and negative changes are negative. As a result, there is evidence for asymmetry. The short-run responses are larger than the long-run ones in all countries. The adjustments take place in two to seven years depending on the country, which suggests that the empirical models can capture mechanisms related to relatively direct economic mechanisms rather than slow-moving factors.

The next section of the study presents the data, while Section 4.3 briefly discusses related previous literature, introduces the non-linear ARDL model and shows the results of the empirical analysis. Sections 4.4 and 4.5 are distinct from the rest of the study by briefly revisiting two empirical approaches used in previ-

ous studies. Namely, Section 4.4 focuses on a panel cointegration framework and Section 4.5 demonstrates the use of panel growth regressions that rely on five-year non-overlapping growth windows, which has been the most-widely used approach in previous studies. The study is written so that a reader interested solely on the asymmetry analysis can skip Sections 4.4 and 4.5, which are in turn written to serve readers interested in the reproducibility of previous studies that have used similar long-run data on top income shares to examine the inequality-growth nexus.

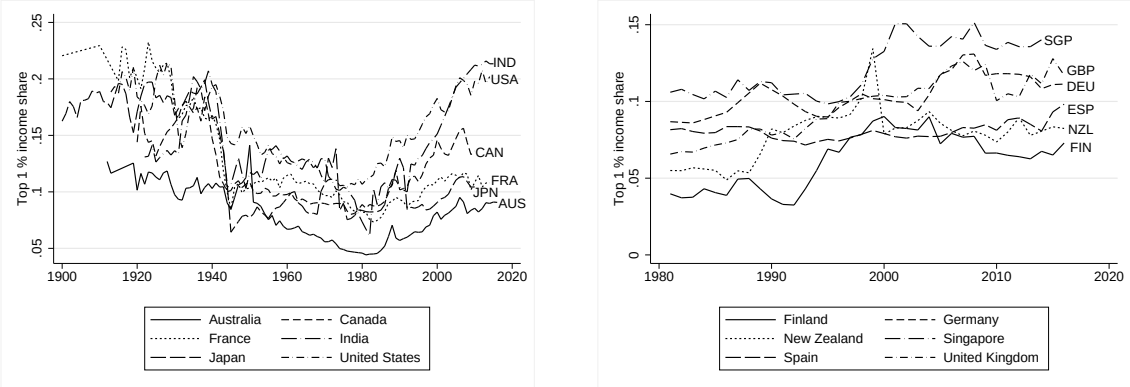
4.2 Data

The data on income inequality for this study come from the World Inequality Database (World Inequality Lab, 2020, WID), which is freely accessible at their web page WID.world. For an empirical researcher two alternatives for data retrieval exist. First, one can enter the web page, pick the variables and years of interest and then download the data in one's favorite format. Alternatively and more efficiently, Stata users can make use of the 'wid' routine. Using the additional materials of this study, the reader can either retrieve the data and merge them with data on gross domestic product (Bolt et al., 2018, the Maddison Project) or access the merged data straight away.

Essentially, the work on the top income share gathered into the WID builds on the groundbreaking work by Kuznets and Jenks (1953), i.e. income tax data, national accounts and Pareto interpolation methods are used. The studies on individual countries, which are used to form the WID, can be found in the WID web page under 'Methodology, Library'. The predecessor of the WID, the World Top Incomes Database, was released in January 2011 while the WID, which combines the top income shares, wealth-income ratios and data on the distribution of wealth, was launched in December 2015. The user friendly web page was introduced in January 2017.

Recently, the WID team has continued its work to improve the database in three fronts. First, and most importantly for this study, data coverage has increased notably both in terms of the time span and geographically. Second, much effort has been dedicated to track capital-income ratios and wealth inequality. Third, the scope has been broadened to account for the entire distribution of wealth and income instead of just the top income shares. Despite the admirable efforts on other inequality concepts, the top income shares still remain the best option if one wishes to track economic inequality over a long time period.

This study focuses on the pre-tax & pre-transfer income share of the highest-earning percentile for two reasons. First, this concept of inequality provides the best data coverage. Second, the time series on the top 1 % has been popularized especially by Piketty (2014) and these data have gained much attention in the public debate as well. Figure 4.1a shows how the top income shares fell during the 1920s-1940s, remained in a low level until the 1980s and then started to rise



(a) Countries with more than 90 annual observations

(b) Recent evolutions in six developed countries

FIGURE 4.1 Pre-tax & pre-transfer income share of the top 1 % in selected countries

again. The evolutions show large differences between countries but the big picture is clear. In his book, Piketty (2014) suggests an interpretative historical synthesis for these turns and the changes in the division of income between capital and labor. The six countries selected for the figure form the core of the empirical analysis of this study. Figure 4.1b illustrates the recent evolutions in six other countries.

The WID has two key advantages over the much-used databases that rely on self-reported survey data. First, the length of the WID time series makes it possible to apply time series techniques and focus on individual countries. Second, surveys may not capture the top income shares adequately due to for example under-reporting of income and refusal to take part in surveys. Burkhauser et al. (2017) document that the British household survey data under-estimates the top income shares when compared with tax data. Thus, the tax-based WID is likely to suffer less from the under-coverage of the top incomes than the survey-based alternatives. The first disadvantage associated with the WID is the relatively low country coverage during the past few decades. For this study, this defect does not materialize as the scope is set on the inequality-growth nexus in six individual countries. Moreover, the WID has been catching up the survey-based databases recently and the work proceeds constantly. Second, the WID time series capture the pre-tax & pre-transfer income, whereas many of the alternatives include different income concepts. In particular, as our consumption and savings decisions are done based on net rather than gross income, data on disposable income would be desirable.

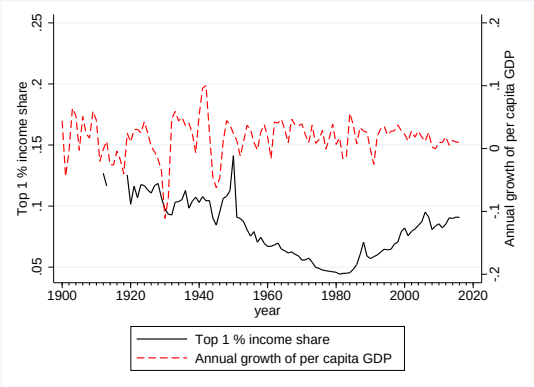
In this paper, the precise concept of inequality is the pre-tax & pre-transfer top 1 % income share of total national income earned by the adults (over 20 year-olds, including elderly). The population categories (individuals, tax units, equal-split adults) vary between countries. If there are more than one available, the category with the best coverage is chosen. If different categories are tied in terms of coverage, equal-split adults (income is split equally between adults who belong to the same couple) is the preferred category. For France, there is data for

FIGURE 4.2 Top 1 % income share in France by different population categories

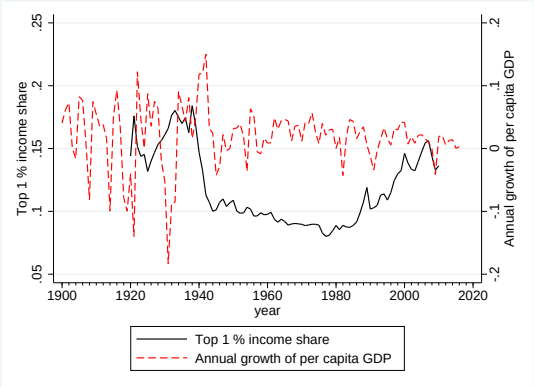
individuals, tax units and equal-split adults and therefore, the top income shares that correspond to different categories can be compared. Figure 4.2 shows that the three alternative time series follow one another fairly closely, which suggests that measures corresponding different categories paint similar pictures. In the countries under particular focus, the population categories in the final time series used are the following: individuals for Australia, Canada and Japan, and equal-splits for France, India and the United States. As the household structures, among many other factors, vary across countries, the comparability of the time series is likely lower between countries than over time within countries. Thus, data-wise, the use of time variation is preferable over cross-country variation.

The focal data used in this study are plotted in Figure 4.3. Economic growth is defined as the logarithmic difference between consecutive observations of per capita GDP. The GDP data come from the Maddison Project (Bolt et al., 2018). Both variables in the plots are expressed in decimals, i.e. a value of 0.02 for per capita GDP growth indicates 2 % annual growth and a value of 0.1 for the top 1 % income share means that the highest-earning percentile got 10 % of the total national income.

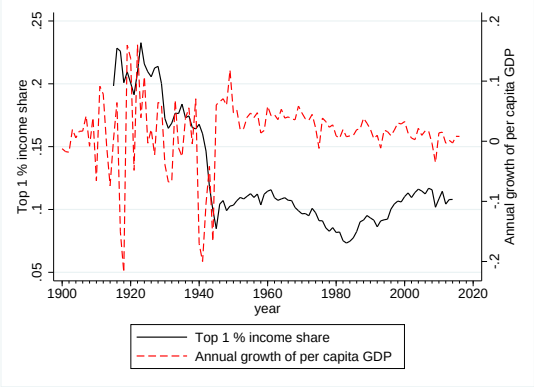
Figure 4.3 shows clearly how the growth rates of per capita GDP were much more volatile during the first half of the 20th century in comparison to the period 1950-2016 largely due to the two World Wars and the Great Depression. The turmoil during the 1930s and 1940s coincides with sharp drops in all six countries except Australia after which the top income shares remained in relatively low levels for roughly four decades in every country. Starting from the 1980s, the evolutions of the top income shares started to diverge. Namely, especially in India and the United States and less pronouncedly in Australia and Canada, the income shares started to rise. In France and Japan, the time series show some spikes but the trend is not increasing like in the four countries specified above. Piketty (2014) offers a detailed discussion on the potential drivers of these turns. On a first glance, the variables seem not to move together over time in any notable fashion. This is no surprise as the two probably affect one another through various economic mechanisms with substantially varying lags across mechanisms. The simple contemporaneous correlations are between -0.14 (Canada) and 0.16 (India).



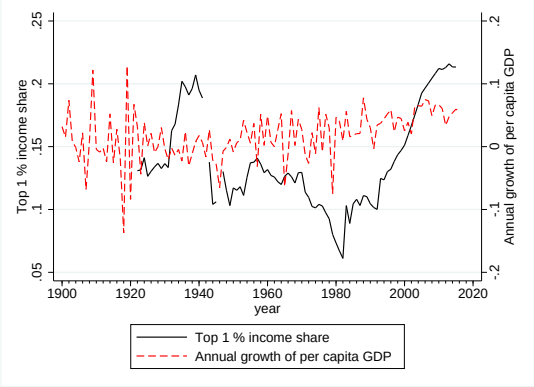
(a) Australia



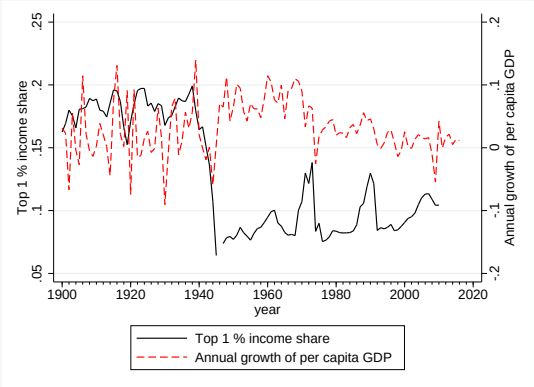
(b) Canada



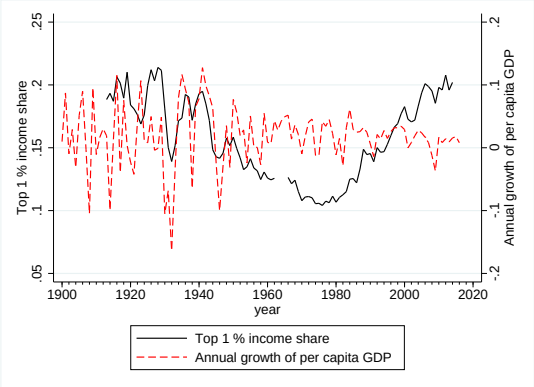
(c) France



(d) India



(e) Japan



(f) United States

FIGURE 4.3 Top 1 % income share (black, solid) and the growth of per capita GDP (red, dash)

Thanks to recent developments in the WID, a panel of 24 countries over the years 1981-2010 and a panel of 18 countries over the years 1981-2016 can be constructed. The composition of these panels will be discussed in Sections 4.4 and 4.5. Some additional data on consumption and investments for the long-run analysis are taken from the Jordà-Schularick-Taylor dataset (Jordà et al., 2017) while for Sections 4.4 and 4.5 the Penn World Table (Feenstra et al., 2015), version 9.1, is used to include information on investments and trade. Finally, Section 4.5 also uses the Barro-Lee dataset (Barro and Lee, 2013) for educational attainment.

4.3 Response of economic growth to falling and rising inequality

The empirical studies on the interplay between income inequality and economic growth have predominantly utilized panel data. This study takes a different route and makes use of the long time series freely available in the WID. By doing so, the empirical investigation can account for likely cross-country heterogeneity in the inequality-growth relationship and potentially shed light on the conflicting results obtained in the numerous panel studies. Moreover, the time series are likely more comparable over time within countries than across countries due to for example differences in household structures. The time series analysis adopted for this paper builds on recent developments on non-linear time series modelling. Namely, positive and negative changes in the income shares of the highest-earning percentile are distinguished from one another.

Although a large majority of the panel studies have focused on the Gini coefficient from survey-based data sets as a broad measure of income inequality, the tax-record-based top income shares have been used to analyze the inequality-growth question in some studies. Andrews et al. (2011) used standard panel regression techniques (pooled OLS, random effects, fixed effects) in a sample that covered 12 developed economies. They used both the top decile and the top percentile income share, and as the study pre-dates the WID or its predecessor the World Top Incomes Database, the data came from individual research papers. The average number of annual observations per country in their unbalanced panel was 68 for the top 1 % and 62 for the top 10 %. Their results suggest that during the latter half of the 20th century, the top 10 % income share was positively associated with subsequent growth. However, the reduced income share of the bottom 90 % will dominate the trickle-down mechanism at first and only after 13 years will the faster aggregate growth influence the mean income of the bottom 90 % positively.

Thewissen (2014) found support for the results of Andrews et al. (2011): a small positive association between top income shares and growth emerged. Herzer and Vollmer (2013) took a different approach and focused on the top income shares and *economic development*, i.e. the level of per capita GDP. Their cointegration analysis suggested that rising top income shares are bad for economic development. The cointegration approach is revisited in Section 4.4 of this study

while Section 4.5 places the WID data into a standard panel growth regression framework.

The fact that resorting to panel data may conceal wide-spread cross-country heterogeneity is a well-recognized issue in the literature. However, surprisingly little effort has been placed in studying whether income inequality supports or hurts growth in country-specific settings. The most likely reason for this is the perceived lack of data on income inequality over long time periods. Yet, for the United States for example, the top income shares have been available for a period 1913-1998 since the study by Piketty and Saez (2003). More recently, the WID has made it easy to access long time series for many countries. Thus, the use of panel data is likely driven by path-dependency (i.e. as we started with panel studies, the following literature builds on the existing one and produces more panel studies) and favoring survey-based data that cover some decades over time series that build on tax records and reach the early 20th century.

The WID data stretch all the way back to the 20th century for the six countries considered in this section. For Japan, as the extreme case, annual data on top 1 % income share extend until 1886. Thus, in terms of data coverage over time, the WID is far superior to other data sources on income inequality. However, the first half of the 20th century was a period of two World Wars and the Great Depression. The turmoil caused by these events shows clearly in Figure 4.3: the growth rates were highly volatile and the top income shares experienced massive shifts. Moreover, historical data on both GDP and the top income shares is likely more prone to mismeasurement. Consequently, as concerns over pronounced measurement error and abnormal nature of economic inter-dependencies arise, the analysis focuses on the period 1950-2010. For some countries, more recent data on the top income shares are available, but to ensure comparable samples, 2010 is chosen as the end point.

Some studies that use time series techniques to better understand the cross-country heterogeneity in the inequality-growth relationship do exist. Gobbin and Rayp (2008) and Risso et al. (2013) use a cointegrated VAR setting. The former considers Belgium, Finland and the United States while the latter focuses solely on Mexico. These studies differ from this paper not only in terms of the empirical approach but also regarding the economic emphasis. Gobbin and Rayp (2008) focuses on transposing the cross-sectional work by Perotti (1996) to a time series framework and Risso et al. (2013) end up analyzing how economic development affects the income distribution, whereas this study stresses the separation of positive and negative changes when the growth-consequences of inequality are examined. Herwartz and Walle (2020) take advantage of recent developments in identification of structural VAR modeling. The authors find that, in a sample of 12 OECD countries, a rise in the income share of the highest-earning percentile supports economic development on average, but there is considerable heterogeneity across countries.

In general, assuming that positive and negative changes in a given explanatory variable have symmetrical effects on the dependent variable may be too restrictive in many applications within social sciences. Recently, this has been

demonstrated to hold true empirically e.g. for unemployment & output and the dynamics of gasoline prices (Shin et al., 2014), exchange rate pass-through (Delatte and López-Villavicencio, 2012), and public debt & economic growth (Eberhardt and Presbitero, 2015). More specifically, in the interplay between inequality and growth, the underlying forces at play may well have different importance between eras of falling and rising inequality. If this indeed is the case, then allowing for asymmetry seems vital when consequences of inequality on economic growth are investigated.

This paper is not the first one to go down this specific avenue. In their panel study, Banerjee and Duflo (2003) found that changes in inequality in any direction are associated with lower subsequent growth rates. They provide a simple political economy model that combines some of the key arguments of the previous theoretical literature as a way to interpret their empirical finding. Going beyond the model of Banerjee and Duflo (2003), consider a set of potential transmission channels for the effect of inequality on economic growth:

1. income inequality is typically associated with high top incomes and if people see these positions attainable, income inequality promotes individual effort through economic incentives and eventually supports economic growth
2. through high savings rate of the top-earners, income inequality fosters savings, investments and economic growth (Kaldor, 1957; Bourguignon, 1981)
3. through socio-political instability, excessive income inequality hurts economic growth (Alesina and Perotti, 1996)
4. through redistribution and distortionary taxes, income inequality dampens economic growth (Alesina and Rodrik, 1994; Persson and Tabellini, 1994)
5. through insufficient accumulation of human capital at low income levels under credit constraints, income inequality is bad for economic growth (Galor and Zeira, 1993)

First, there is no guarantee that rising inequality induces an increase in individual effort to the same proportion as falling inequality decreases effort. Moreover, news about rising / falling inequality may have asymmetric discouraging / encouraging effects at low income levels. Second, a high-earning individual may cut their savings substantially if the top tax rates are increased or if some other negative income shock takes place, whereas an increase in a top income may not be translated into savings or finding investment opportunities may take time. Third, a large-scale unrest may take place after inequality reaches a certain threshold while a similar size decrease in inequality may not promote societal stability. Fourth, policy-makers are likely to respond differently to rising / falling inequality, which may create asymmetries to redistribution policies and tax systems as potential transmission channels. Fifth, it is not obvious that the educational decisions at low income levels respond symmetrically to income shocks. For example, the extra money may be invested elsewhere but saving from tuition fees is potentially more appealing than to save from food, housing or medical services.

Furthermore, it is unclear whether the potential mechanisms that transmit the changes in income distribution to overall economic activity possess asymmet-

ric nature both immediately after a shock and over time. Thus, separating short-run and long-run responses is an appealing feature for an econometric technique.

The arguments above, albeit informal and speculative, indicate that assuming symmetrical growth-responses to changes in income inequality may be too restrictive. The empirical approach, specified below, together with the long time span of the WID data for Australia, Canada, France, India, Japan and the United States makes it possible to disentangle positive and negative changes in income inequality in a way that allows for rich short-run and long-run dynamics and addresses cross-country heterogeneity beyond panel techniques. Moreover, the approach can be used to test for the appropriate functional form, which is highly valuable as the speculative discussion above does not conclusively rule out symmetrical structure.

4.3.1 The ARDL model and its non-linear extension

To examine the interplay between economic growth and top income shares within the six countries listed above, I adopt an autoregressive distributed lag approach (ARDL) popularised by Pesaran and Shin (1998) and Pesaran et al. (2001), whose work was extended by Schorderet et al. (2003) and Shin et al. (2014) to incorporate asymmetric responses. The ARDL models can accommodate both $I(0)$ and $I(1)$ variables, which is particularly attractive as the income shares of the highest-earning percentile show traces of non-stationarity. Specifically, different unit root tests show mixed results and, by definition, a bounded variable such as an income share cannot be characterized by pure unit root processes. Thus, it is not clear whether the top 1 % income share should be treated as $I(0)$ or $I(1)$. This demonstrates how the ARDL approach is more flexible than the regular cointegration techniques, where only $I(1)$ variables can enter the model. Based on unit root tests, the growth of per capita GDP is stationary in all six countries.

The symmetric (linear) ARDL(p,q) model can be written as

$$y_t = \sum_{j=1}^{p} \phi_j y_{t-j} + \sum_{j=0}^{q} \theta_j Log(Top1_{t-j}) + \varepsilon_t, \tag{4.1}$$

where $y_t = Log(PercapGDP_t) - Log(PercapGDP_{t-1})$. Equation (4.1) can be rewritten in an error correction form as

$$\begin{aligned} \Delta y_t &= \rho y_{t-1} + \theta Log(Top1_{t-1}) + \sum_{j=1}^{p-1} \gamma_j \Delta y_{t-j} + \sum_{j=0}^{q-1} \varphi_j' \Delta Log(Top1_{t-j}) + \varepsilon_t \\ &= \rho \xi_{t-1} + \sum_{j=1}^{p-1} \gamma_j \Delta y_{t-j} + \sum_{j=0}^{q-1} \varphi_j' \Delta Log(Top1_{t-j}) + \varepsilon_t, \end{aligned} \tag{4.2}$$

where $\rho = \sum_{j=1}^{p} \phi_j - 1$, $\gamma_j = -\sum_{i=j+1}^{p} \phi_i$ for $j = 1, \ldots, p-1$, $\theta = \sum_{j=0}^{q} \theta_j$, $\varphi_0 = \theta_0$, $\varphi_j = -\sum_{i=j+1}^{q} \theta_j$ for $j = 1, \ldots, q-1$, ε_t is the error term and $\xi_t = y_t - \beta' Log(Top1_t)$ is the error correction term where $\beta = -\theta/\rho$.

Short-run asymmetries can be introduced by replacing

$\varphi_j \Delta Log(Top1_{t-j})$ of equation (4.2)

with

$\Delta Log(Top1_{t-j})^+ \varphi_j^+ + \Delta Log(Top1_{t-j})^- \varphi_j^-$

while long-run asymmetries are incorporated by focusing on the error correction term (ξ). The non-linear ARDL (NARDL) error correction model, which corresponds to equation (2.7) in Shin et al. (2014), is

$$\begin{aligned} \Delta y_t = \rho \xi_{t-1} + \sum_{j=1}^{p-1} \gamma_j \Delta y_{t-j} + \sum_{j=0}^{q-1} (\Delta Log(Top1_{t-j})^+ \varphi_j^+ \\ + \Delta Log(Top1_{t-j})^- \varphi_j^-) + \varepsilon_t, \end{aligned} \tag{4.3}$$

where

- $\rho = \sum_{j=1}^{p} \phi_j - 1$
- $\xi_t = y_t - Log(Top1_t)^+ \beta^+ - Log(Top1_t)^- \beta^-$
- $\beta^+ = -\theta^+/\rho$ and $\beta^- = -\theta^-/\rho$
- $\theta^+ = \sum_{j=0}^{q} \theta_j^+$ and $\theta^- = \sum_{j=0}^{q} \theta_j^-$
- $\gamma_j = -\sum_{i=j+1}^{p} \phi_i$ for $j = 1, \ldots, p-1$
- $\varphi_0^+ = \theta_0^+$ and $\varphi_0^- = \theta_0^-$
- $\varphi_j^+ = -\sum_{i=j+1}^{q} \theta_j^+$ and $\varphi_j^- = -\sum_{i=j+1}^{q} \theta_j^-$ for $j = 1, \ldots, q-1$

The non-linear extension of ARDL modelling can be used to differentiate between four cases. First, sticking to the standard approach and assuming that the growth-responses to negative and positive changes in income inequality are symmetrical (equation (4.2)). Second, allowing for full asymmetry (equation(4.3)). Third and fourth, allowing for short-run asymmetry but assuming long-run symmetry and assuming short-run symmetry but allowing for long-run asymmetry, respectively. Moreover, Shin et al. (2014) show that both short-run and long-run symmetry can be tested using the Wald statistic following χ^2 distribution.

The lag order for the models is determined by moving from general to specific. Following Delatte and López-Villavicencio (2012) and Hovi and Laamanen (2017), I start from $p = 4$ and $q = 4$, test for the significance of γ_3, φ_3^+ and φ_3^-, drop the variables associated with insignificance at 10 % level and re-estimate the model. This is continued until the longest lags of γ_j, φ_j^+ and φ_j^- are statistically significant or until γ_1, φ_1^+ and φ_1^- are reached. This model selection procedure yields 9 possible (p,q) combinations: (4,4), (4,3), (4,2), (3,4), (2,4), (3,3), (3,2), (2,3) and (2,2). In all cases, where full asymmetry is allowed for, the most parsimonious NARDL(2,2) model is found to be the appropriate one.

The tests for long-run and short-run symmetry (Table 4.1) show that cross-country heterogeneity and asymmetry between positive and negative changes

TABLE 4.1 Testing for long-run and short-run symmetry

	AUS (1)	CAN (2)	FRA (3)	IND (4)	JPN (5)	USA (6)
Long-run	2.651	0.319	33.800	22.670	90.280	13.260
(p-value)	(0.110)	(0.575)	(<0.000)	(<0.000)	(<0.000)	(0.001)
Short-run	1.845	4.423	3.390	0.335	1.093	4.194
(p-value)	(0.180)	(0.040)	(0.071)	(0.566)	(0.301)	(0.046)

Notes: Wald F-statistics for long-run and short-run symmetry, H_0: symmetry, p-values in parantheses. Dependent variable: the growth of per capita GDP. The statistics are based on the econometric model specified in equation (4.3), i.e. full symmetry is allowed for. Sample: 1950-2010.

in income inequality are pervasive. The former implies that the use of panel techniques conceals wide-spread differences between countries while the latter supports the idea that it is important to distinguish between positive and negative changes in income inequality in all countries except one. Namely, in Australia, the growth-response is symmetrical. In India and Japan, the short-run response is symmetrical while asymmetry should be allowed for in the long-run, whereas in Canada, the tests show signs of short-run asymmetry and long-run symmetry. In France and in the United States, allowing for full asymmetry is needed.

TABLE 4.2 Critical values for the t_{BDM} and F_{PSS} tests

The left panel corresponds to t_{BDM} (Banerjee et al., 1998), the right one to F_{PSS} (Pesaran et al., 2001).

Critical values of the t-ratio error correction test with one or two regressors k (with an unrestricted intercept)					Asymptotic critical value bounds for the F-statistic to test for the existence of a levels relationship with one or two regressors k (with an unrestr. intercept)				
		Size					Size		
	T	0.10	0.05	0.01		I(0), I(1)	0.10	0.05	0.01
k=1	25	-2.95	-3.35	-4.12	k=1	I(0)	4.04	4.94	6.84
	50	-2.93	-3.28	-3.94		I(1)	4.78	5.73	7.84
	100	-2.94	-3.27	-3.92					
	500	-2.90	-3.23	-3.82					
	∞	-2.89	-3.19	-3.78					
k=2	25	-3.24	-3.64	-4.53	k=2	I(0)	3.17	3.79	5.15
	50	-3.20	-3.57	-4.29		I(1)	4.14	4.85	6.36
	100	-3.22	-3.56	-4.22					
	500	-3.10	-3.50	-4.11					
	∞	-3.19	-3.48	-4.06					

Shin et al. (2014) use two testing procedures to investigate whether there exists a long-run relationship between the variables of interest. The first (t-statistic, t_{BDM}) follows Banerjee et al. (1998) while the second (F-statistic, F_{PSS}) builds on Pesaran et al. (2001). In brief, both procedures test for the existence of error correcting mechanism: t_{BDM} tests $\rho = 0$ against $\rho < 0$ while F_{PSS} specifies a joint null $\rho = \theta^+ = \theta^- = 0$. As the asymptotic distributions for both of these tests are complicated to derive due to complex dependence structure between the partial sum decompositions of the regressors, Shin et al. (2014) recommend to use the

pragmatic bounds-test approach by Pesaran et al. (2001). This procedure allows for regressors that are $I(0)$, $I(1)$ or mutually cointegrated. For both procedures, the critical values tabulated in the original studies are summarized in Table 4.2.

Because of the partial sum decompositions, the exact number of regressors, k, for the critical values is unclear. In this study, where the relationship is given by y, $Log(Top1^{+}_{t-1})$ and $Log(Top1^{-}_{t-1})$ (France, India, Japan and the United States), the true value of k is between one and two. The authors expect that the tests are modestly undersized (oversized) for $k = 1(2)$. Using the undersized test is a conservative approach and will thus provide strong evidence if the null hypothesis of no cointegration is rejected. For Australia and Canada, where the long-run relationship is given by y and $Log(Top1_{t-1})$, $k = 1$. As argued by Shin et al. (2014), the error correction approach is likely to improve the small sample properties of the model in general, and especially, in terms of the power of the cointegration tests.

The long-run estimates for the association between the top 1 % income share and the growth of per capita GDP are presented in Table 4.3. The model selection in terms of asymmetries is based on the results of Table 4.1 while the lag structure is determined by moving from general to specific as specified above. For France and the United States, the estimated models are the same as above. For Australia, the lag structure is given by $p = 2$ and $q = 4$. Otherwise, the most parsimonious model is the preferred one.

The findings shown in Table 4.3 are threefold. First, in France and the United States, falling top income shares are associated with lower subsequent growth. The estimates associated with rising shares are positive but statistically insignificant and roughly a tenth of the size of the former ones. Second, in India, rising inequality shows a positive association with growth while the estimate of falling inequality is negative but small (a third of β^{+}) and insignificant. Thus, the evidence of asymmetric responses (above, Table 4.1) is translated into economically meaningful findings. Third, the growth of per capita GDP seems to be independent of the top income shares in Australia, Canada and Japan. The first two can be characterized by "symmetrical null results", whereas the point estimates for Japan suggest that any change in inequality is bad for growth similarly to the panel level findings of Banerjee and Duflo (2003). However, both β^{+} and β^{-} are insignificant although the latter is fairly large in magnitude relative to the results obtained for France, India and the Unites States.

The magnitudes of the estimates indicate the following. In the case of France, a fall in the income share of the highest-earning percentile from the median value to the 25th percentile is associated with 0.48 percentage point decrease in annual growth of per capita GDP. In the United States, the same example yields a decrease of 0.53 percentage points. In India, a rise from the median value to the 75th percentile is associated with 0.33 percentage point increase in economic growth. As the average annual growth rates of per capita GDP in France, the United States and India during the sample period have been 2.44 %, 2.05 % and 2.76 %, respectively, the found associations are not negligible. However, the estimates should not be overinterpreted. A shock in the top income shares is not exogenous but

TABLE 4.3 Long-run estimates of the inequality-growth relationship

Estimated association between the income share of the highest-earning percentile and annual growth of per capita GDP between 1950 and 2010. Dependent variable: annual growth of per capita GDP. The statistical model is given by equation (4.2) for Australia (None), by equation (4.3) for France and the United States (Both), for Canada, short-run asymmetry is allowed for (Short) and for India and Japan, long-run asymmetry is allowed for (Long). The coefficients β, β^+ and β^- are the long-run estimates for the top income share on growth and their construction as functions of $\theta^{(+,-)}$ and ρ are given below equations (4.2) and (4.3). The short-run coefficients are omitted.

	AUS	CAN	FRA	IND	JPN	USA
	(1)	(2)	(3)	(4)	(5)	(6)
Asymmetry	None	Short	Both	Long	Long	Both
β, symmetric	0.002	-0.013				
(p-value)	(0.834)	(0.464)				
β^+, positive change			0.005	0.033	-0.011	0.006
(p-value)			(0.761)	(0.001)	(0.634)	(0.691)
β^-, negative change			-0.040	-0.012	-0.034	-0.060
(p-value)			(0.010)	(0.288)	(0.170)	(0.023)
Observations	61	61	61	61	61	61
Cointegration tests						
t_{BDM}	-5.975	-6.090	-6.749	-7.160	-5.737	-5.987
F_{PSS}	17.851	18.594	15.509	17.111	12.341	15.865
Model diagnostics						
(p-value)						
Portmanteau	(0.015)	(0.863)	(0.526)	(0.430)	(0.709)	(0.840)
Breusch-Pagan	(0.052)	(0.384)	(0.734)	(0.370)	(0.219)	(0.648)
Ramsey RESET	(0.100)	(0.324)	(0.113)	(0.037)	(<0.000)	(0.071)
Jarque-Bera	(0.865)	(0.144)	(0.709)	(0.174)	(0.623)	(0.009)

Notes: For the cointegration tests, the null hypothesis is "no cointegration". The test statistics should be compared to the critical values of Table 4.2. The null for Portmanteau test is "no residual autocorrelation", the null for Breusch-Pagan test is "no heteroskedasticity", the null for Ramsey RESET is "no model misspecification" and the null for Jarque-Bera test is "normally distributed residuals".

rather caused by an underlying factor or a set of factors that also influence other growth determinants. Even though the bivariate NARDL model includes lagged levels and first-differences of the dependent variable as explanatory variables and offers tests for the existence of a long-run relationship, it probably cannot isolate the effect of income inequality on growth.

When compared to the critical values in Table 4.2, the cointegration tests (t_{BDM} and F_{PSS}) give strong evidence for the existence of a valid long-run relationship between economic growth and top income shares. All test statistics exceed the most conservative critical values -4.29 and 7.84 of t_{BDM} and F_{PSS}, respectively.

The four bottom rows of Table 4.3 offer tests for model diagnostics. Except for Australia, the models seem not to suffer from residual autocorrelation or heteroskedasticity (Portmanteau and Breusch-Pagan), which gives support for the NARDL model specifications. The models for India, Japan and the United States appear to lack some relevant explanatory variables (Ramsey RESET) while, based on the Jarque-Bera test, only the model for the United States suffers from non-normally distributed residuals.

4.3.2 Dynamic multiplier plots

An additional benefit of the NARDL model is the computationally simple method to construct graphical illustrations to track the short-run and long-run responses of economic growth to changes in the top income shares. These dynamic multiplier plots map the gradual movement of the growth process from the initial equilibrium to the new one.

Shin et al. (2014) rewrite the NARDL model (equation (4.3)) as

$$\phi(L)y_t = \theta^+(L)Log(Top1_t)^+ + \theta^-(L)Log(Top1_t)^- + e_t, \tag{4.4}$$

where $\phi(L) = 1 - \sum_{i=1}^{p-1} \phi_i L^i$, $\theta^+(L) = \sum_{i=0}^{q} \theta_i^+ L^i$ and $\theta^-(L) = \sum_{i=0}^{q} \theta_i^- L^i$. Multiplying equation (4.4) by $[\phi(L)]^{-1}$ gives

$$y_t = \lambda^+(L)Log(Top1_t)^+ + \lambda^-(L)Log(Top1_t)^- + [\phi(L)]^{-1}e_t, \tag{4.5}$$

where $\lambda^+(L) = \sum_{j=0}^{\infty} \lambda_j^+ = \phi L^{-1}\theta^+(L)$ and $\lambda^-(L) = \sum_{j=0}^{\infty} \lambda_j^- = \phi L^{-1}\theta^-(L)$. The cumulative dynamic multiplier plots can be constructed using the following:

$$m_h^+ = \sum_{j=0}^{h} \frac{\partial y_{t+j}}{\partial Log(Top1_t)^+}, m_h^- = \sum_{j=0}^{h} \frac{\partial y_{t+j}}{\partial Log(Top1_t)^-}, h = 0, 1, 2, \ldots, \tag{4.6}$$

where h is the number of periods (years below) for the dynamic adjustment. By construction, as $h \longrightarrow \infty$, $m_h^+ \longrightarrow \beta^+$ and $m_h^- \longrightarrow \beta^-$, i.e. the dynamic multipliers converge to the long-run coefficients reported in Table 4.3.

The dynamic multipliers are not only useful in exemplifying the short-run and long-run responses but in fact introduces an additional form of potential asymmetry: the adjustment asymmetry (labeled by the authors (Shin et al., 2014)). The adjustment asymmetry combines the long-run (reaction, $\beta^+ \neq \beta^-$) and short-run (impact, $\varphi_0^+ \neq \varphi_0^-$) responses with the error correction coefficient ρ. Obviously, the graphical illustrations are conditional on the model specification: for Australia, the adjustments to positive and negative changes in inequality are symmetrical, whereas for the five other countries, the movements toward the new equilibrium associated with positive and negative changes will not be mirror images of one another.

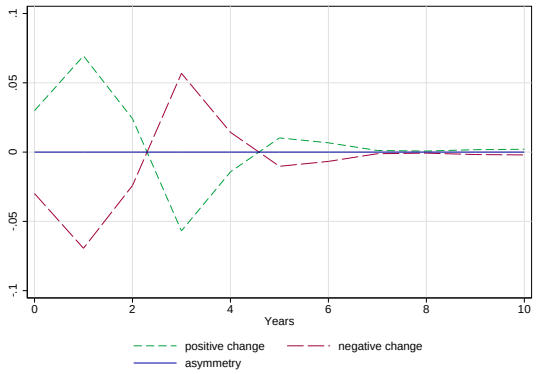
Conveniently for an empirical researcher, the 'nardl' routine of Stata by Marco Sunder includes a plotting option that can be used to construct difference lines, including bootstrapped confidence intervals, between the dynamic adjustments to positive and negative shocks. The multipliers are associated with unit changes in the log of top 1 % income share, i.e. percentage changes in the top income share.

Figure 4.4 shows the adjustments of per capita GDP growth to shocks in the top income shares. The illustrations are based on the models reported in Table 4.3 and the converged dynamic multipliers correspond to the coefficients β, β^+ and β^-. The green short-dash line corresponds to a positive change in the top income share, the red long-dash line to a negative change while the solid blue line depicts asymmetry as the difference between the dashed lines. The grey area around the solid line is the 95 % confidence interval for asymmetry and it is based on 500 bootstrap replications. The horizontal axis measures time in years after the inequality shock.

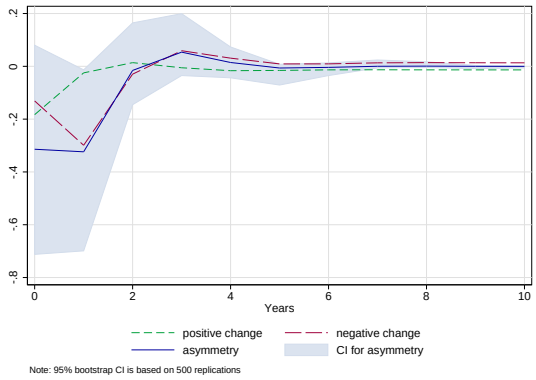
The first observation regarding the six individual plots is that the movement to new equilibrium takes place between two to seven years depending on the country. Thus, there are no large differences in the adjustment asymmetry between the countries. Moreover, it is unrealistic to assume that mechanisms related to human capital accumulation, legislation of redistributional policies or socio-political movements would be the ones that give rise to the patterns depicted in Figure 4.4. It seems evident that the ARDL model can capture growth responses that are transmitted through more direct economic mechanisms. This question is revisited below in more detail.

Based on the evidence of Table 4.1, the response in Australia is restricted to be symmetrical. At impact, rise (fall) in inequality supports growth, which is followed by a recoil and eventually the response dies out. In Canada, any change in inequality is bad for growth in the short-run but the cumulative association is minuscule.

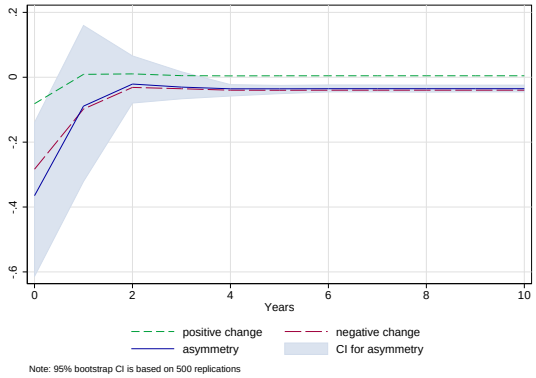
In France, the short-run impact is qualitatively similar to Canada, although the response to a negative shock is more pronounced. After the adjustment to the new equilibrium, the illustration portrays the findings discussed above: falling top income shares are associated with lower subsequent growth while the growth process seems to be independent of positive inequality shocks. The long-run case for the United States is similar to France and also already discussed above. In the



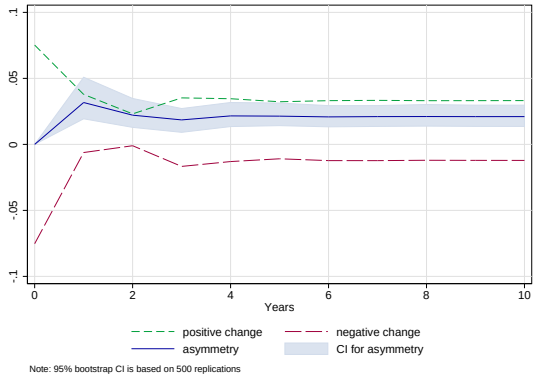
(a) Australia



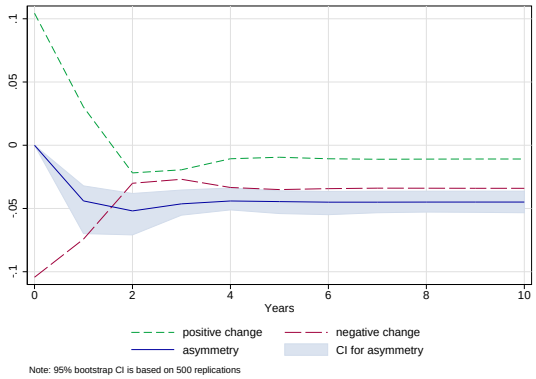
(b) Canada



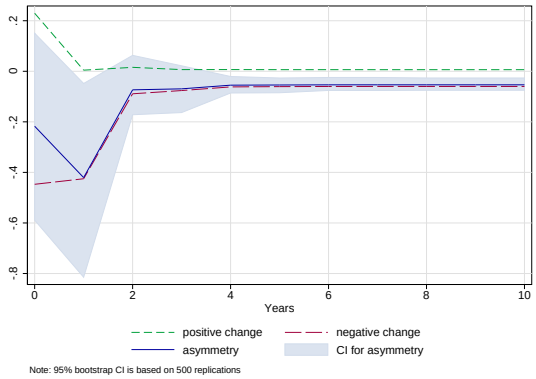
(c) France



(d) India



(e) Japan



(f) United States

FIGURE 4.4 Cumulative responses of per capita GDP growth to 1 % changes in the top income shares

short-run though, the asymmetry is not due to "any change is bad change" type of response. Rather, the negative growth-response to a negative inequality shock is larger in size than the positive response to a positive shock.

For India and Japan, short-run symmetry was imposed based on the results of Table 4.1. In both countries, rising (falling) inequality is associated with higher (lower) growth in the short-run. In India, both responses converge towards zero but the response remains higher in size for the positive shock as discussed above ($\beta^+ = 0.033, \beta^- = -0.012$), i.e. there is long-run asymmetry. In Japan, the positive response crosses the zero line during the adjustment process resulting in an asymmetric long-run response even though the coefficients β^+ (-0.011) and β^- (-0.034) are statistically insignificant.

4.3.3 Potential transmission channels

This section focuses on investigating whether additional data on potential transmission channels can help to explain the findings above. To reduce the dimensions of the analysis, the investigation is restricted to France and the United States for two reasons. First, the result that falling top income shares are associated with lower subsequent growth in both of these countries is intriguing and calls for further investigation. Second, the data for the potential mechanisms is easy to come by unlike for India, which was the third country that showed a combination of asymmetries and statistically significant relationship between the top income shares and growth.

As discussed above, the adjustment of the growth process to top income share shocks is fast suggesting that the NARDL model can capture associations transmitted through relatively direct economic mechanisms. The prime candidates are (i) economic incentives, (ii) consumption and (iii) savings and investments, which all can arguably be affected by changes in the distribution of income and also contribute to the overall economic activity. Distilling economic incentives into a single variable that can be used for time series analysis is a task next to impossible, but the first two candidates are suitable for empirical analysis. The variables used in the empirical specifications below are the the growth of physical investments and the growth of real per capita consumption. The data for both are easily accessible in the Jordà-Schularick-Taylor dataset (Jordà et al., 2017).

Following Kaldor (1957) and Bourguignon (1981), it is expected that top income shares are positively associated with investments through high savings rate of the top-earners. Furthermore, under credit frictions, setting up new firms or expanding existing ones may require sufficiently concentrated income or wealth for the entrepreneurs to cover the sunk costs associated with entrepreneurial activity. Contradicting the arguments that rely on convex savings function and investment indivisibilities discussed above, Aghion et al. (1999) note that under credit frictions, inequality may be negatively associated with investment opportunities. They argue that due to decreasing returns to individual capital investment, the marginal productivity of an investment made by the rich is lower than

an investment made by the poor.

Regarding the potential consumption channel, as the marginal propensity to consume is higher in the lower income brackets, the association between top income shares and aggregate consumption should be negative. However, this is not the only possible mechanisms at play because changes in inequality are not isolated economic events. For example, changes in the distribution of income in any direction may be associated with greater aggregate uncertainty about the future leading people to refrain both from consumption and investments and instead make precautionary savings.

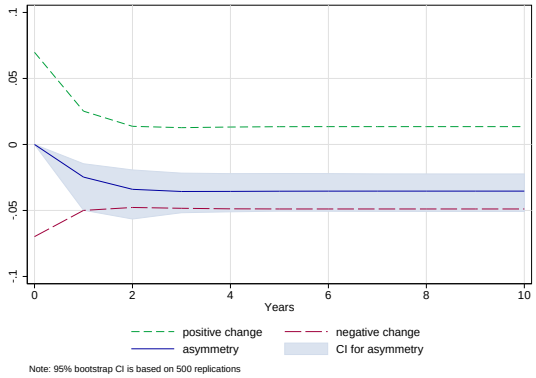
Consequently, because the relationships between inequality and investments and inequality and consumption are not clear-cut ones, single well-defined mechanisms based on theoretical predictions are not tested in this section. Rather, two obvious contributors to the growth process are taken to see whether they respond to changes in inequality like the growth of per capita GDP. Figure 4.5 illustrates the dynamic adjustments of consumption growth and investment growth to changes in the top 1 % income share. Based on the asymmetry tests, for consumption growth in France and for investment growth in the United States, the NARDL models are characterized by short-run symmetry and long-run asymmetry. Investment growth in France and consumption growth in the United States are characterized by full asymmetry.

The adjustment plots show that, in France, the association between consumption growth and the income share of the top 1 % is positive in the short-run. As the growth process converges to the new equilibrium, asymmetry emerges: the response to a negative shock is -0.049 (p-value: 0.014) while the response to a positive shock is 0.014 (0.501). Regarding the investment channel, changes in inequality in any direction are associated with lower investment growth in the short-run. Thus, both potential channels seem to contribute to the finding that a decrease in the top 1 % income share dampens growth of per capita GDP in France. The cumulative result persists for consumption, whereas the investment response is short-lived. For the United States, the conclusion is similar. Both channels contribute to the finding regarding per capita GDP growth in the short-run while neither persist when the new equilibrium is reached.

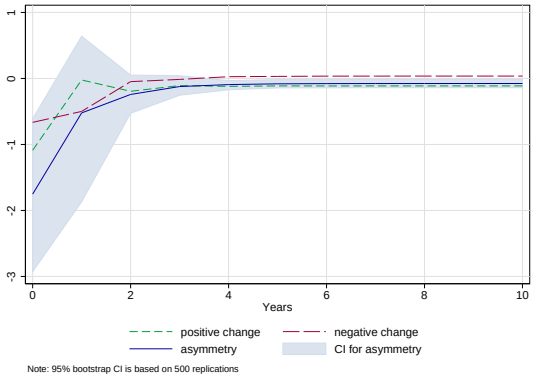
4.3.4 Japan over a very long-run

Above, the samples for each country are restricted to 1950-2010 due to the worry that the massive events during the first half of the 20th century may distort the results. However, it is still insightful to see whether the conclusions differ if a longer time frame is adopted. This is demonstrated in the case of Japan that offers the longest available annual time series, from 1886 to 2010. Only the observation from 1946 is missing and it is interpolated as an average of the 1945 and 1947 observations.

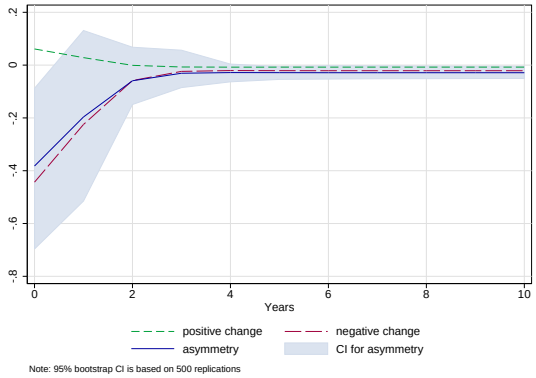
Working with the annual observations yields a total number of 123 observations for the preferred model that is a NARDL(2,2) with short-run asymmetries and long-run symmetry. The asymmetry structure is the opposite of the above



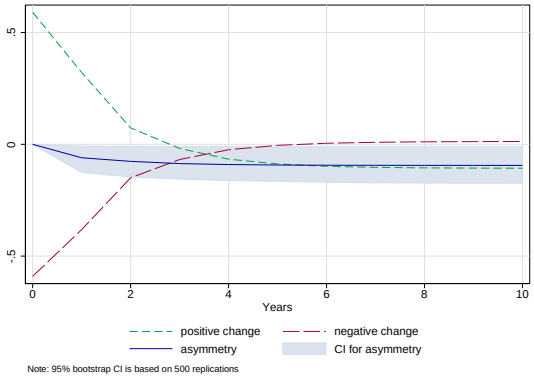
(a) France, consumption growth



(b) France, investment to GDP

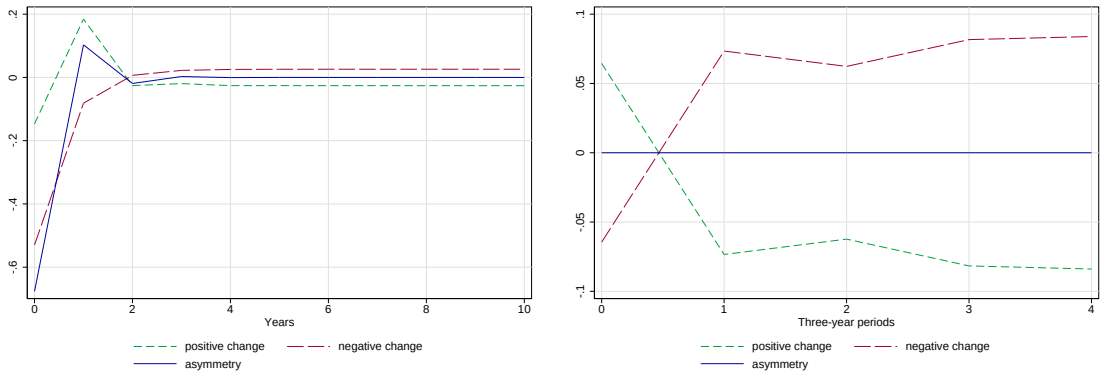


(c) United States, consumption growth



(d) United States, investment to GDP

FIGURE 4.5 Cumulative responses of consumption growth and investment growth to 1 % changes in the top income shares in France and the United States



(a) Annual observations (b) Three-year non-overlapping periods

FIGURE 4.6 Cumulative growth-responses to 1 % changes in the top income share in Japan 1886-2010

(Table 4.3, column (5)) and offers the first piece of evidence that the inclusion of data going back from 1950 changes the conclusions. In addition to annual data, three-year non-overlapping windows are considered. It is particularly interesting to see whether the speed of adjustment changes when the volatility of the annual observations is diluted by averaging over the three-year periods. This approach yields 40 available observations, which is not ideal for time series analysis and the results should be taken with a pinch of salt. The preferred model is a parsimonious ($p = q = 2$) one with full symmetry.

For the annual observations, the cointegration tests indicate the existence of a valid long-run relationship ($t_{BDM} = -8.27, F_{PSS} = 34.48$), whereas for the three-year windows, the evidence is not convincing ($t_{BDM} = -3.17, F_{PSS} = 5.03$). This finding gives support for the above conclusion that the ARDL framework captures the relatively direct economic mechanisms rather than the slow-moving transmission channels. The long-run coefficients, β, are -0.026 (p-value = 0.184) and -0.090 (p-value = 0.062), respectively for annual and averaged observations. Thus, the long-run relationship between the top income shares and economic growth seems to be symmetrical and negative over a very long-run in Japan.

The dynamic adjustments illustrated in Figure 4.6 suggest that the growth of per capita GDP adjusts quickly to an inequality shock. This is consistent with Figure 4.4 and holds for both the annual observations and the averaged ones. Panel a proposes that, on impact, "any change in inequality is bad change", whereas the long-run association is small. Panel b shows that, on impact, an increase (decrease) is good (bad) for growth while the long-run result is the opposite.

The findings of this section show that, for Japan at least, the results for the period 1950-2010 cannot be generalized to historical evolutions. Rather, the findings for the six developed countries should be viewed as evidence for the association between the top income shares and growth of per capita GDP during the latter part of the 20th century and the early years of the new millennium. This era was characterized by relatively steady growth rates and the absence of global crises, such as World Wars, and thus the main findings of this study help

to explain the interplay between the top income shares and growth during "good times". Analysing more volatile economic environments probably calls for a more nuanced approach.

4.4 Panel cointegration analysis

The key reference for this section is the study "Rising top incomes do not raise the tide" (Herzer and Vollmer, 2013, HV), where the authors applied panel cointegration methods in a panel of nine countries over 1961-1996. Their focus was on the highest-earning decile and the main finding was that the concentration of income reduces economic growth. Below, I investigate whether the result holds when the analysis is extended to the highest-earning percentile and larger samples of countries (24 countries 1981-2010, 18 countries 1981-2016). Furthermore, I examine the robustness of the results beyond the original study.

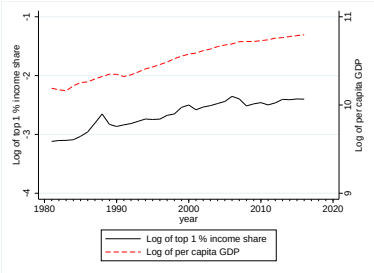
As a first step of any cointegration analysis, it is insightful to plot the variables of interest to see whether they appear to move in tandem over time. The logarithmic series of the top 1 % income share and per capita GDP are plotted in Figure 4.7. In general, both variables seem to be trending upwards between 1981 and 2016 and in some countries, such as Italy and the United States, the co-movements are remarkable. Thus, the visual evidence is promising for a central assumption that, in the long-run, permanent changes in the relative incomes of the highest-earning percentile are associated with permanent changes in economic activity. Obviously, as the top income shares are bounded between 1 % and 100 % and per capita GDP is not bounded from above, the co-movements depicted in Figure 4.7 can only take place in certain periods – not forever.

Closely related to boundedness, all variables entering a hypothesized cointegrating regression must be non-stationary. Although the stochastic processes for the top income shares cannot be characterized by pure unit root processes, they may act as unit root processes within a relevant range as argued by Jones (1995). Examining the time series properties of the data follows HV. First, the Im-Pesaran-Shin (IPS) (Im et al., 2003) panel unit root test is implemented, i.e. augmented Dickey-Fuller tests (ADF) (Dickey and Fuller, 1979) are run for all countries allowing for country-specific intercepts (and time trends):

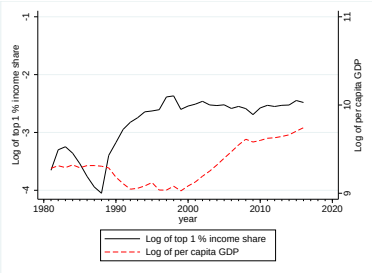
$$\Delta x_{it} = z'_{it}\gamma + \rho_i x_{it-1} + \sum_{j=1}^{k_i} \varphi \Delta x_{it-j} + \varepsilon_{it}, \tag{4.7}$$

where x_{it} is the variable tested for unit root, k_i is the lag order and z'_{it} represents country-specific deterministic terms.

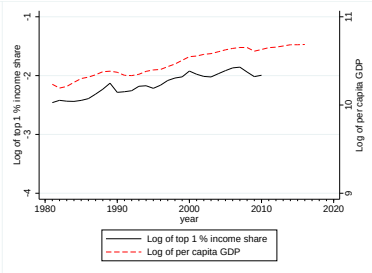
The null and alternative hypotheses are $H_0 : \rho_i = 0, \forall i = 1, 2, \ldots, N$ and $H_a : \rho_i < 0, i = 1, 2, \ldots, N_1; \rho_i = 0, i = N_1 + 1, N_1 + 2, \ldots, N$. The null of "unit root in all series" is tested against the alternative of "some stationary series" using the standardized t-bar statistic:



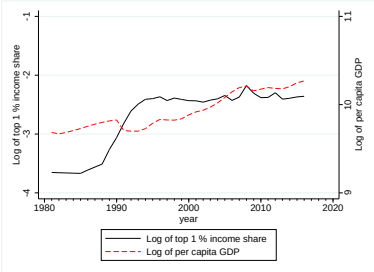
(a) Australia



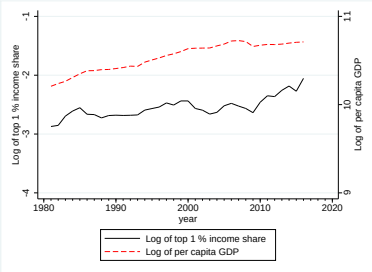
(b) Bulgaria



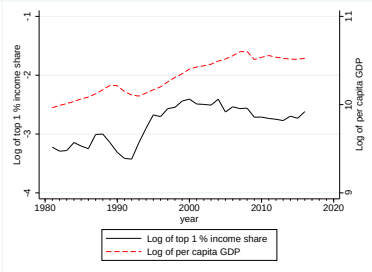
(c) Canada



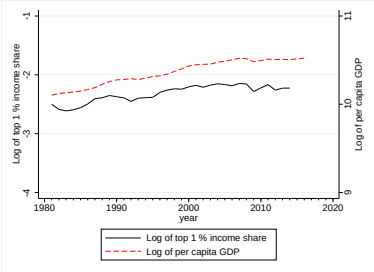
(d) Czech Republic



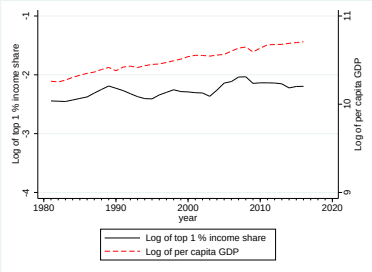
(e) Denmark



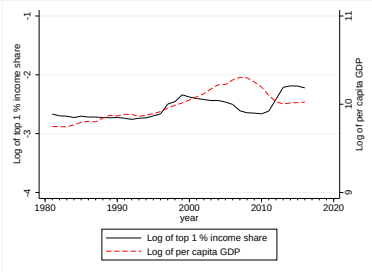
(f) Finland



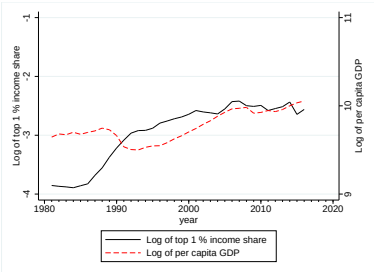
(g) France



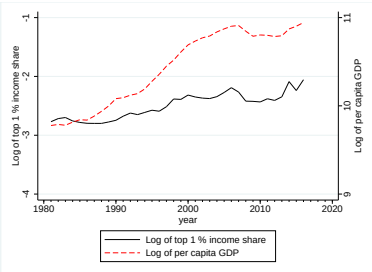
(h) Germany



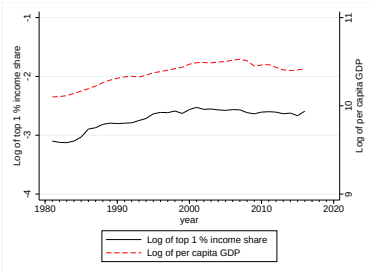
(i) Greece



(j) Hungary

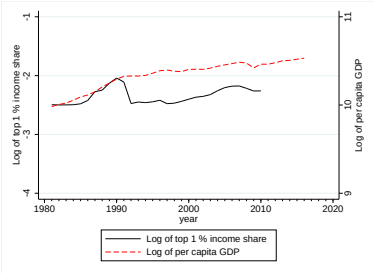


(k) Ireland

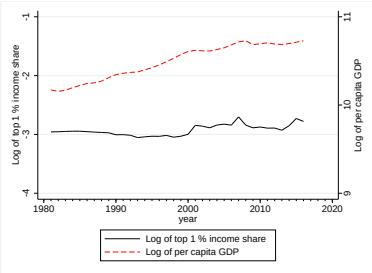


(l) Italy

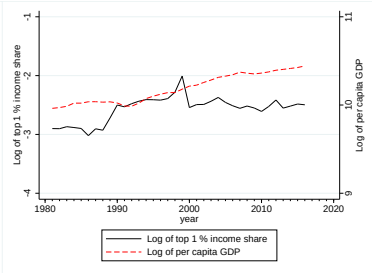
FIGURE 4.7 Top 1 % income share (black & solid) and per capita GDP (red & dash), logarithmic values



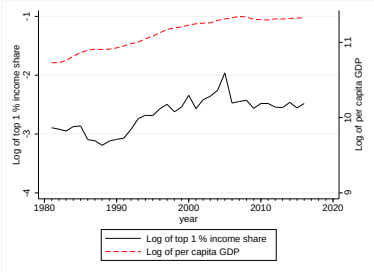
(m) Japan



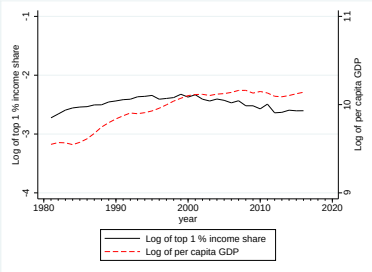
(n) Netherlands



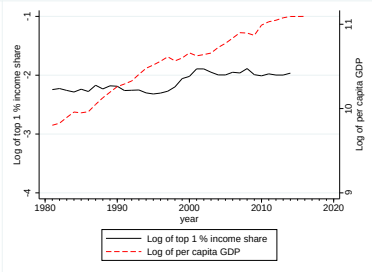
(o) New Zealand



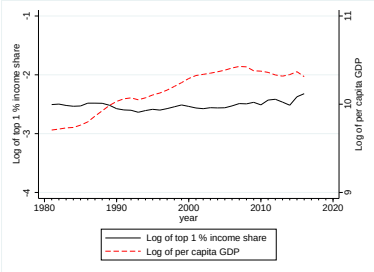
(p) Norway



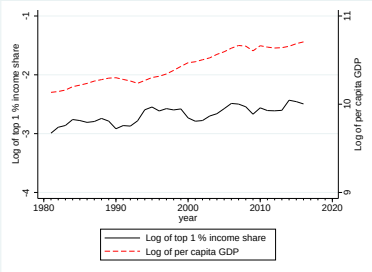
(q) Portugal



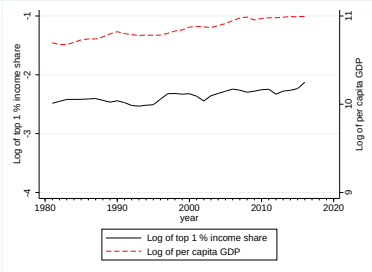
(r) Singapore



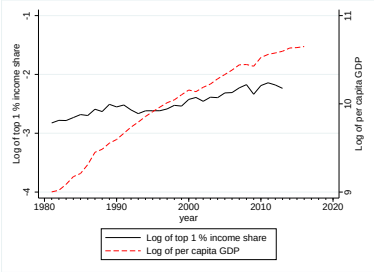
(s) Spain



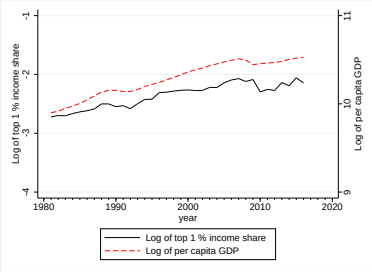
(t) Sweden



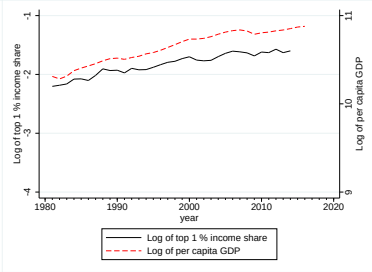
(u) Switzerland



(v) Taiwan



(w) United Kingdom



(x) United States

FIGURE 4.7 Top 1 % income share (black & solid) and per capita GDP (red & dash), logarithmic values

$$\Gamma_{\bar{t}} = \frac{\sqrt{N}[\bar{t}_{NT} - \mu]}{\sqrt{v}}, \tag{4.8}$$

where $\bar{t}_{NT}$ is the average of the (24 or 18) ADF t-statistics and μ and v are the mean and variance of the average of the individual t-statistics (tabulated in Im et al. (2003)), respectively.

If the errors ε_{it} are not independet across countries, IPS can lead to spurious statistical inference. Thus, HV also use the test proposed by Pesaran (2007) to filter out the likely cross-country dependency by augmenting the ADF (CADF) regression:

$$\Delta x_{it} = z'_{it}\gamma + \rho_i x_{it-1} + \sum_{j=1}^{k_i} \varphi \Delta x_{it-j} + \alpha_i \bar{x}_{t-1} + \sum_{j=0}^{k_i} \eta_{ij} \Delta \bar{x}_{t-j} + v_{it}, \tag{4.9}$$

where $\bar{x}_t$ is the cross-country mean of x_{it}. The cross-sectionally augmented IPS statistic (CIPS) is the average of the individual CADF statistics. The critical values are tabulated in Pesaran (2007).

The results for per capita GDP and the top 1 % income share in logs and in first differences are similar to HV: neither test rejects the null hypothesis for logs while the null is rejected for first differences (Table 4.8, Appendix 4.A.1). Thus, both series seem to be integrated of order 1. Based on three of the four tests, the inference is the same for trade volume to GDP, which was used as an additional variable in the HV study. IPS for the period 1981-2010 suggests that openness is stationary around a linear time trend as the null is not rejected if the trend is dropped from the deterministic terms.

To test for panel cointegration, I employ two residual-based procedures and one procedure that builds on a panel error correction model. For the residual-based Pedroni procedure (Pedroni, 1999, 2004), the hypothesized cointegrating regression is

$$Log(PercapGDP_{it}) = \alpha_i + \beta_i Log(Top1_{it}) + \varepsilon_{it}, \tag{4.10}$$

whereas in the approach suggested by Kao (1999), homogeneous cointegrating coefficients are assumed, i.e. β_i is replaced by β. First, regression (4.10) is estimated and second, the residuals $\hat{\varepsilon}_{it}$ are tested for unit roots: stationarity indicates cointegration.

Pedroni suggests four test, where the autoregressive coefficients are not allowed to vary across cross-sections and three tests that allow for heterogeneous autoregressive parameters. All five Kao tests impose homogeneous autoregressive coefficients. Differences in the tests arise from whether a simple Dickey-Fuller test or an ADF test is employed and whether the tests assume strict exogeneity of the regressors or not.

The tests proposed by Westerlund (2007) examine whether there exists error correction for individual cross-sections or for the full panel. In an error correction framework given by

$$\begin{aligned}\Delta Log(PercapGDP_{it}) &= c_i + \sum_{j=1}^{p} \rho_{1ij} \Delta Log(PercapGDP_{it-j}) \\ &+ \sum_{j=1}^{p} \rho_{2ij} \Delta Log(Top1_{it-j}) + \alpha_i (Log(PercapGDP_{it-1}) \\ &- \beta_i Log(Top1_{it-1})) + u_{it},\end{aligned} \tag{4.11}$$

a null hypothesis $H_0 : \alpha_i = 0, \forall i$ is tested against $H_{a1} : \alpha_i < 0$ for at least one i and $H_{a2} : \alpha_i < 0, \forall i$. Rejection of H_0 should therefore be taken as evidence for cointegration in at least one of the countries in the first case and as evidence for cointegration in the full panel in the second case.

The testing procedures above do not address potential cross-country dependence. Following Holly et al. (2010), equations (4.10) and (4.11) can be augmented with cross-country averages ($\overline{Log(PercapGDP_t)}$ and $\overline{Log(Top1_t)}$) to control for common unobserved factors. As an illustration, the augmented hypothesized cointegrating regression is

$$\begin{aligned}Log(PercapGDP_{it}) &= \alpha_i + \beta_i Log(Top1_{it}) \\ &+ g_{1i} \overline{Log(PercapGDP_t)} + g_{2i} \overline{Log(Top1_t)} + \xi_{it}\end{aligned} \tag{4.12}$$

In their study, HV were unable to find evidence for cointegration in a bivariate specification between per capita GDP and the income share of the highest-earning decile. Consequently, they augment the hypothesized cointegrating regression by the sum of imports and exports relative to GDP (Openness) and find evidence for a long-run relationship between the three variables. They argued that, since trade volume to GDP drives economic development but is not primarily determined by inequality, the relationship between the top income shares and per capita GDP can be estimated consistently under cointegration.

Tables 4.9 and 4.10 in Appendix 4.A.1 report the results of the panel cointegration tests for the bivariate and trivariate specifications, respectively. In brief, the evidence for both hypothesized cointegrating regressions is mixed. HV did not report the results for the bivariate case but instead stated that they "were unable to find a bivariate cointegrating relationship". Thus, it is not clear whether they reached similar mixed results as in Table 4.9 of this study or whether they were consistently unable to reject the null hypothesis of no cointegration. However, the trivariate results are clearly different between HV and this paper. They found strong evidence for cointegration, whereas the picture paint by Table 4.10 is ambiguous. Nevertheless, since a majority of the tests in both cases (bivariate, trivariate) of this study show evidence for cointegration, it is meaningful to proceed and find estimates for the cointegrating relationships.

Following HV, the cointegrating vectors are estimated using the group-mean panel fully modified OLS (FMOLS) and dynamic OLS (DOLS) estimators of Pedroni (2001). Essentially, the point estimates are mean values of the country-specific cointegrating vectors, i.e. cross-country heterogeneity is allowed for. The FMOLS estimator aims to eliminate endogeneity bias by introducing a non-parametric correction, whereas the DOLS augments a hypothesized cointegrating regression by including leads, lags and contemporaneous values of the $I(1)$ regressors. The bivariate panel DOLS model can be written as

$$Log(PercapGDP_{it}) = \alpha_i + \beta_i Log(Top1_{it}) + \sum_{j=-k_i}^{k_i} \Phi_{ij} \Delta Log(Top1_{it-j}) + \nu_{it} \quad (4.13)$$

while the trivariate model can be constructed by including terms $Log(Openness_{it})$ and $\Delta Log(Openness_{it-j})$ with the corresponding parameter estimates and the sum operator. In their study, HV found estimates -0.598 and -0.552, using FMOLS and DOLS respectively. Economically, one percent increase in the top 10 % income share is associated with decrease in per capita GDP of about 0.6 %.

The results of this study, gathered in Table 4.4, contradict the findings of HV: all coefficient for the top income shares on economic development are positive. The spread for the estimates is wide (0.2753-0.9000), which, together with the cointegration tests, questions if the long-run relationship between the two focal variables really exists for the periods 1981-2010 or 1981-2016. Irrespective of whether the cointegrating relationship does not exist or whether the nature of the association has changed from negative to positive, the HV results do not generalize beyond their sample and to the top 1 % income share.

TABLE 4.4 FMOLS and DOLS, panel results

Mean-group panel estimates of the long-run relationship between top 1 % income shares and per capita GDP, dependent variable: Log(Per cap GDP). Sample 1981-2010 includes all countries of Figure 4.7. For sample 1981-2016, Canada, Taiwan, France, Japan, Singapore and United States are dropped due to missing observations between 2011 and 2016. The trivariate regressions exclude Czech Republic due to missing observations for Log(Openness)

Cointegrating regression: $Log(PercapGDP_{it}) = \alpha_i + \beta_i Log(Top1_{it}) + \varepsilon_{it}$				
	1981-2010, 24 countries		1981-2016, 18 countries	
	FMOLS	DOLS	FMOLS	DOLS
Log(Top 1)	0.9000*** (67.66)	0.8892*** (57.91)	0.7450*** (45.11)	0.7706*** (37.79)
Cointegrating regression: $Log(PercapGDP_{it}) = \alpha_i + \beta_{1i} Log(Openness_{it}) + \beta_{2i} Log(Top1_{it}) + \varepsilon_{it}$				
	1981-2010, 23 countries		1981-2016, 17 countries	
	FMOLS	DOLS	FMOLS	DOLS
Log(Openness)	0.5643*** (72.11)	0.6517*** (63.70)	0.5800*** (73.95)	0.6265*** (66.69)
Log(Top 1)	0.4822*** (47.10)	0.3891*** (34.06)	0.2753*** (33.63)	0.1829*** (23.01)

Notes: t-statistics in paranthesis, *** indicate statistical significance at the 1% level

Because the group-mean estimates are, plain and simple, averages over the country-specific cointegrating vectors, it is easy to examine whether the panel estimates conceal subgroups of countries that pull in different directions. Bluntly, they do not. In the bivariate specification, there are negative estimates only for

Bulgaria and Spain for the period 1981-2010. Otherwise, all estimates of the country-specific cointegrating vectors are positive (Appendix 4.A.2).

I also investigate if the HV results can be reproduced when I adopt their data sources and their sample to make sure that the differences in results are not stemming from the implementation of the panel cointegration techniques. Since the very same estimates (-0.598 and -0.552) emerge and the same techniques are applied for the sample of this study, the results are not driven by technical implementation. Interestingly, if up-to-date revised data on per capita GDP is taken to the HV analysis, the DOLS estimate show substantial sensitivity: the estimate for the income share of the richest decile on per capita GDP turns from highly significant into a non-significant, the magnitude being one third of the original one. As the correlations between the original time series and the updated ones are close to one, but not exactly one, this finding is further evidence for the sensitivity of the techniques to small changes in the underlying data.

To summarize, the findings of HV seem not to generalize beyond their sample. First, in this study, there is only weak evidence for cointegration between economic development and the top income shares as opposed to the original study, where the support for a trivariate cointegrating regression was strong. Second, contradicting the finding that "rising top incomes do not raise the tide" by HV, the panel FMOLS and DOLS estimates for the top income shares on economic development are consistently positive in this study.

4.5 Panel regressions

The bulk of the empirical literature on the relationship between income inequality and economic growth has focused on survey-based data together with either cross-country investigation or panel growth regressions. The data sources have included a wide variety of primary sources and secondary data sets while the estimation techniques span from least squares to standard panel estimators and different variations of generalized method of moments (GMM). Typically, the studies have focused on growth inside five-year non-overlapping windows, the measure of income inequality and level of per capita GDP ("convergence term") are observed before the growth window commences and a varying set of other growth determinants are included as control variables. The time span has typically reached the 1970s or 1990s, depending on the country. Due to data availability, the research has predominantly focused on developed economies although recent evolutions in data coverage have made it possible to analyze developing countries as well.

As a next step of this paper, the WID series on the top 1 % income shares are used to form a panel of 24 countries (same as above) that relies on five-year intervals. This is now possible because the available data on top income shares have increased substantially over the recent years. The panel constitutes of six growth windows for each country resulting in 144 total observations per regres-

sion, i.e. the panel is completely balanced. On average in the sample, the annualized growth of per capita GDP inside a five-year window was 1.6 % and the highest-earning percentile earned roughly 8.2 % of the total national income before taxes and transfers. As the graphical illustrations above (Figures 4.1 and 4.7) portray, the top income shares show wide-spread variation both over time and especially across countries. In the sample, lowest and highest shares were 2.1 % and 19.5 %, respectively. Due to lack of observations for some of the control variables for Czech Republic, the specifications with control variables are estimated using a balanced panel of 23 countries (138 total observations).

The baseline panel growth regression follows a standard convention in the literature, where the growth of per capita GDP is assumed to depend on the level of economic development (Log(Per cap GDP)), a set of standard growth determinants as control variables ($\boldsymbol{X}_{it}$) and income inequality (Log(Top 1)):

$$Log(PercapGDP_{it+4}) - (Log(PercapGDP_{it}) = \rho(\frac{1}{5}\sum_{j=0}^{4} Log(PercapGDP_{it-5+j}))$$
$$+ \delta'(\frac{1}{5}\sum_{j=0}^{4} \boldsymbol{X}_{it-5+j}) + \beta(\frac{1}{5}\sum_{j=0}^{4} Log(Top1_{it-5+j})) + \alpha_i + \eta_t + \varepsilon_{it}, \tag{4.14}$$

where α_i and η_t are the vectors of fixed country and year effects and ε_{it} is the overall error term. I include gross capital formation to GDP (Investments), average years of secondary education (Education) and the sum of imports and exports to GDP (Openness) as the control variables. The inclusion of these three is appealing in two ways: they contribute to economic growth and data are easy to come by. I also augment the baseline regression (4.14) by

(i) including (in two separate regressions)

$\beta^{int}(\frac{1}{5}\sum_{j=0}^{4} Log(Top1_{it-5+j}) \times Log(PercapGDP_{it-5+j}))$ to analyze dependency on the level of economic development,

$\beta^{sq}(\frac{1}{5}\sum_{j=0}^{4} Log(Top1_{it-5+j})^2)$ to analyze dependency on the level of inequality, and by

(ii) replacing (in a separate regression)

$\beta(\frac{1}{5}\sum_{j=0}^{4} Log(Top1_{it-5+j}))$ with

$\beta^{top25}(\frac{1}{5}\sum_{j=0}^{4} Log(Top1_{it-5+j})^{top25})$ and $\beta^{bottom75}(\frac{1}{5}\sum_{j=0}^{4} Log(Top1_{it-5+j})^{bottom75})$ to analyze dependency on the level of inequality.

The above models are estimated using standard panel estimation techniques (pooled OLS, fixed effects, random effects) and GMM estimators that aim to control for endogeneity of the regressors (Arellano and Bond, 1991; Arellano and Bover, 1995; Blundell and Bond, 1998). The simplest estimator, POLS, ignores the country-specific fixed effects. FE, as the name suggests, removes the fixed

effects by time-demeaning the data and thus effectively relies on time variation. RE makes the assumption that the individual effect does not correlate with the regressors.

The dGMM uses suitably lagged values of the regressors as instruments for the first-differenced transformation of equation (4.14) and like FE does not make use of the cross-country variation. The sGMM estimates equation (4.14) and its first-difference as a system using suitably lagged values of the regressors as instrument variables for the first-differenced equation and lagged variables of first-differences as instruments for the level equation. The estimator can therefore exploit both variation in time and across individuals since the individual-specific characteristics are not removed from the equation in levels. A large evolving literature on the properties of these GMM estimators exists. Here, it is only noted that the estimates are typically associated with wide weak-instrument robust confidence intervals meaning that the a causal interpretation for the point estimates is not warranted. For further details, see Bazzi and Clemens (2013) and Kraay (2015).

The results of Table 4.5 suggest that the association between top 1 % income shares and subsequent growth of per capita GDP is positive. The estimates between different techniques vary in a distinctive manner: the ones that rely only on variation within countries (FE and dGMM) are higher than the ones that use both variation in time and across countries. However, contrary to the findings of for example Berg et al. (2018), the signs of the estimates do not vary depending on the estimator. Using survey-based data tends to find positive estimates when only time variation is considered (FE and dGMM), whereas using both variation in time and across countries typically yields negative estimates. Now, when the WID data are considered, the magnitude of the estimate – not the sign – is conditional on the utilized variation.

The least conservative estimate of Table 4.5 (column (8)) together with the standard deviation of Log(Top 1) contributes 0.66 percentage points to annual growth of per capita GDP. If the conservative sGMM estimate (column (10)) is taken instead, the contribution is 0.006. Although Table 4.6 shows some traces of non-linearity, the results do not verify that the inequality-growth relationship is dependent on the level of economic development or the level of inequality.

Overall, the results are in line with recent studies that used similar data and estimated panel growth regressions (Andrews et al., 2011; Thewissen, 2014): a small positive association between top income shares and growth emerges. Recent studies that have used survey-based data on broader measures of inequality, such as the Gini coefficient, have typically found a negative association. Thus, different income concepts paint different pictures of the inequality-growth nexus when panel growth regressions are applied.

TABLE 4.5 Panel growth regressions, linear form

The panel regression is given in equation (4.14). Dependent variable: growth of per capita GDP inside a five-year window. Regressors observed during the previous window. Estimation techniques: pooled least squares (POLS), fixed effects (FE), random effects (RE), difference GMM (dGMM) and system GMM (sGMM). Czech Republic dropped when the controls are used due to lack of observations for some controls.

	POLS		FE		RE		dGMM		sGMM	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Log(Per cap GDP)	-0.0785***	-0.1051***	-0.2638***	-0.2362***	-0.1171***	-0.1219***	-0.2922***	-0.3099***	-0.2332***	-0.2880***
	(0.0218)	(0.0241)	(0.0203)	(0.0271)	(0.0311)	(0.0325)	(0.0257)	(0.0562)	(0.0241)	(0.0360)
Log(Top 1)	0.0478**	0.0284	0.1084***	0.0953***	0.0585*	0.0311	0.1381***	0.1572***	0.1011***	0.0014
	(0.0234)	(0.0229)	(0.0206)	(0.0323)	(0.0307)	(0.0285)	(0.0252)	(0.0362)	(0.0209)	(0.0531)
Log(Investments)		0.0342***		0.0390***		0.0385***		0.0607***		0.0699***
		(0.0097)		(0.0126)		(0.0061)		(0.0175)		(0.0122)
Log(Education)		-0.0276		-0.0165		-0.0410		0.1039		0.1396*
		(0.0319)		(0.0591)		(0.0302)		(0.0848)		(0.0785)
Log(Openness)		0.0220**		-0.0129		0.0192*		-0.0633*		0.0470**
		(0.0100)		(0.0340)		(0.0113)		(0.0344)		(0.0222)
Constant	0.9899***	1.3340***	3.0444***	2.8161***	1.4134***	1.5458***	omitted	omitted	2.7109***	2.8471***
	(0.2533)	(0.2456)	(0.2369)	(0.2453)	(0.3505)	(0.3505)			(0.2705)	(0.2959)
Observations	144	138	144	138	144	138	120	115	144	138
Countries	24	23	24	23	24	23	24	23	24	23
Instruments							19	22	24	27
AR1 test (p values)							0.003	0.004	0.003	0.011
AR2 test (p values)							0.106	0.197	0.077	0.135
Hansen test of joint instrument validity (p-value)							0.219	0.197	0.365	0.449

Robust standard errors in parantheses. *, ** and *** indicate statistical significance at 10 %, 5 % and 1 % levels, respectively.

TABLE 4.6 Panel growth regressions, non-linearity through interactions

The panel regressions are given in equation (4.14) with augmentations specified below. Dependent variable: growth of per capita GDP inside a five-year window. Regressors observed during the previous window. Estimation techniques: pooled least squares (POLS), fixed effects (FE), random effects (RE), difference GMM (dGMM) and system GMM (sGMM). Controls and intercept omitted from the table, Czech Republic dropped due to lack of observations for some controls.

	POLS	FE	RE	dGMM	sGMM
	(1)	(2)	(3)	(4)	(5)
Dependency on economic development, i.e. Log(Per cap GDP) × Log(Top1) introduced					
Log(Per cap GDP)	-0.2590**	-0.2724***	-0.2781***	-0.0742	-0.3960*
	(0.1233)	(0.0675)	(0.0859)	(0.2061)	(0.2247)
Log(Top 1)	0.6487	0.2587	0.6697	-0.6381	0.7894
	(0.5104)	(0.3197)	(0.4341)	(0.9706)	(1.0703)
Log(Per cap GDP) × Log(Top 1)	-0.0606	-0.0163	-0.0627	0.0816	-0.0802
	(0.0492)	(0.0330)	(0.0434)	(0.0987)	(0.1075)
Controls	yes	yes	yes	yes	yes
Observations	138	138	138	115	138
Countries	23	23	23	23	23
Joint signif. of Log(Top 1) and Log(Per cap GDP) × Log(Top 1) (p-value)	0.276	0.007	0.052	<0.000	0.743
Instruments				23	28
AR1 test (p values)				0.006	0.008
AR2 test (p values)				0.211	0.079
Hansen test of joint instrument validity (p-value)				0.227	0.484
Dependency on inequality, i.e. Log(Top1)^2 introduced					
Log(Per cap GDP)	-0.1036***	-0.2498***	-0.1197***	-0.3838***	-0.2557***
	(0.0241)	(0.0334)	(0.0341)	(0.0650)	(0.0369)
Log(Top 1)	-0.0704	0.2395*	-0.0803	0.9808*	-0.0479
	(0.1517)	(0.1308)	(0.1696)	(0.5242)	(0.3375)
Log(Top 1)^2	-0.0185	0.0249	-0.0206	0.1401*	-0.0094
	(0.0301)	(0.0212)	(0.0306)	(0.0851)	(0.0596)
Controls	yes	yes	yes	yes	yes
Observations	138	138	138	115	138
Countries	23	23	23	23	23
Joint signif. of Log(Top 1) and Log(Top 1)^2 (p-value)	0.449	0.024	0.388	0.010	0.982
Instruments				27	32
AR1 test (p values)				0.004	0.010
AR2 test (p values)				0.199	0.109
Hansen test of joint instrument validity (p-value)				0.477	0.798

Robust standard errors in parantheses. *, ** and *** indicate statistical significance at 10 %, 5 % and 1 % levels, respectively.

TABLE 4.7 Panel growth regressions, piece-wise

The panel regression is given by equation (4.14), where $\beta(\frac{1}{5}\sum_{j=0}^{4} Log(Top1_{it-5+j}))$ is replaced with $\beta^{top25}(\frac{1}{5}\sum_{j=0}^{4} Log(Top1_{it-5+j})^{top25}) + \beta^{bottom75}(\frac{1}{5}\sum_{j=0}^{4} Log(Top1_{it-5+j})^{bottom75})$. Dependent variable: growth of per capita GDP inside a five-year window. Regressors observed during the previous window. Estimation techniques: pooled least squares (POLS), fixed effects (FE), random effects (RE), difference GMM (dGMM) and system GMM (sGMM). Controls and intercept omitted from the table, Czech Republic dropped due to lack of observations for some controls.

	POLS	FE	RE	dGMM	sGMM
	(1)	(2)	(3)	(4)	(5)
Log(Per cap GDP)	-0.1052***	-0.2384***	-0.1228***	-0.3153***	-0.2580***
	(0.0242)	(0.0268)	(0.0331)	(0.0678)	(0.0718)
Log(Top 1)^{top25}	0.0244	0.0877**	0.0270	0.1335***	-0.0004
	(0.0370)	(0.0361)	(0.0345)	(0.0331)	(0.0699)
Log(Top 1)^{bottom75}	0.0259	0.0920**	0.0288	0.1504***	-0.0026
	(0.0310)	(0.0338)	(0.0314)	(0.0330)	(0.0644)
Controls	yes	yes	yes	yes	yes
Observations	138	138	138	115	138
Countries	23	23	23	23	23
Test of equality btw Log(Top 1)^{t25} and Log(Top 1)^{b75} (p-value)	0.844	0.393	0.776	0.265	0.839
Instruments				27	32
AR1 test (p values)				0.004	0.009
AR2 test (p values)				0.146	0.112
Hansen test of joint instrument validity (p-value)				0.463	0.762

Robust standard errors in parantheses. *, ** and *** indicate statistical significance at 10 %, 5 % and 1 % levels, respectively.

4.6 Conclusion

This study examined how the growth of per capita GDP responded to falling and rising top income shares in the period 1950-2010. Data on the top income shares were retrieved from the World Inequality Database with a focus on a heterogeneous group of six countries: Australia, Canada, France, India, Japan and the United States. The positive and negative changes in income inequality were disentangled by adopting a flexible autoregressive distributed lag model that makes use of partial sum decompositions. Two previously used panel estimation approaches were also briefly revisited.

In France and the United States, a fall in the top income shares was associated with lower subsequent growth of per capita GDP. In India, the association between rising inequality and growth was positive. Thus, the inequality-growth nexus seems to be characterized by cross-country heterogeneity and asymmetries. Based on the fast adjustment process to changes in the top income shares in all countries, the results are transmitted through relatively direct economic mechanisms instead of slow-moving long-run factors.

In general, empirical studies on the interplay between inequality and growth

suffer from two major limitations. First, it has proven to be impossible to establish a causal interpretation for the effect of income inequality on growth. Second, a large majority of the cumulative evidence is based on panel studies. If the results effectively correspond to averages in a sample of 30 or 100 countries, what should people interested in individual countries make of the parameter estimates? The findings of this study, albeit not causal, correspond to individual countries thus making it possible to analyze the inequality-growth relationship within entities, where the policy-makers operate. As the data coverage is constantly improving, the approach of this study will lend itself to a larger group of countries effortlessly in the future.

4.A Appendix

4.A.1 Pre-tests for panel cointegration techniques

TABLE 4.8 Panel unit root tests

H_0: All series contain unit roots, H_a: Some series are stationary. Sample 1981-2010 includes all countries of Figure 4.7. For sample 1981-2016, Canada, Taiwan, France, Japan, Singapore and United States are dropped due to missing observations 2011-2016. Missing observations for trade volume to GDP (Openness) in Czech Republic and thus, Log(Openness) and ΔLog(Openness) are tested in panels of 23 and 17 countries for periods 1981-2010 and 1981-2016, respectively.

		1981-2010, 24 (23) countries		1981-2016, 18 (17) countries	
Variables	Determ. terms	IPS statistic	CIPS statistic	IPS statistic	CIPS statistic
Levels					
Log(Per cap GDP)	constant, trend	1.567	-1.043	2.175	-1.075
Log(Top 1)	constant, trend	0.693	-2.066	0.428	-2.245
Log(Openness)	constant, trend	-4.011***	-2.055	-0.641	-2.334
First differences					
ΔLog(Per cap GDP)	constant	-10.271***	-3.759***	-9.205***	-4.050***
ΔLog(Top 1)	constant	-14.553***	-4.321***	-16.569***	-4.982***
ΔLog(Openness)	constant	-29.784***	-4.969***	-25.881***	-5.418***

Notes: constant (trend) indicates that I allow for different intercepts (and time trends) for each country. To adjust for autocorrelation, Bayesian information criterion (BIC) with maximum of 5 lags was used to determine the lag order for IPS. For CIPS, an iterative process from 0 to 5 lags was adopted. The relevant 1% (5%, 10%) critical value for CIPS is -2.85 (-2.71, -2.63). *, ** and *** denote statistical significance at the 10%, 5% and 1% levels, respectively.

TABLE 4.9 Panel cointegration tests, bivariate regression

Hypothesized cointegrating regression: $Log(PercapGDP_{it}) = \alpha_i + \beta_i Log(Top1_{it}) + \varepsilon_{it}$
H_0: no cointegration, test statistics (and p-values) reported
Sample 1981-2010 includes all countries of Figure 4.7. For sample 1981-2016, Canada, Taiwan, France, Japan, Singapore and United States are dropped due to missing observations between 2011 and 2016.

	1981-2010, 24 countries		1981-2016, 18 countries	
	Cross-country independence assumed	Cross-country dependency allowed	Cross-country independence assumed	Cross-country dependency allowed
Pedroni, heterogeneous autoregressive parameters				
Modified Phillips-Perron t-statistic	1.844 (0.033)	3.704 (<0.000)	1.358 (0.087)	3.812 (<0.000)
Phillips-Perron t-statistic	1.455 (0.073)	3.507 (<0.000)	0.825 (0.205)	3.348 (<0.000)
ADF t-statistic	1.663 (0.048)	4.794 (<0.000)	0.316 (0.376)	3.055 (<0.000)
Pedroni, homogeneous autoregressive parameters				
Modified variance ratio statistic	-4.572 (<0.000)	-3.711 (<0.000)	-3.818 (<0.000)	-1.870 (0.031)
Modified Phillips-Perron t-statistic	1.147 (0.126)	3.238 (0.001)	0.778 (0.218)	2.520 (0.006)
Phillips-Perron t-statistic	0.400 (0.345)	3.349 (<0.000)	0.211 (0.416)	2.321 (0.010)
ADF t-statistic	0.384 (0.351)	3.928 (<0.000)	-0.096 (0.462)	1.933 (0.027)
Kao				
Modified Dickey-Fuller t-statistic	1.459 (0.072)	1.535 (0.062)	0.280 (0.390)	1.265 (0.103)
DF t-statistic	-0.295 (0.384)	-0.264 (0.396)	-1.026 (0.152)	0.602 (0.274)
ADF t-statistic	-1.186 (0.118)	-1.030 (0.152)	-2.661 (0.004)	-1.545 (0.061)
Unadjusted modified DF t-statistic	2.285 (0.011)	2.211 (0.014)	1.483 (0.069)	2.188 (0.014)
Unadjusted DF t-statistic	0.507 (0.306)	0.397 (0.346)	-0.104 (0.459)	1.574 (0.058)
Westerlund				
H_a: cointegration in some countries	2.256 (0.012)	2.208 (0.014)	2.253 (0.012)	1.307 (0.096)
H_a: cointegration in all countries	1.166 (0.122)	3.806 (<0.000)	1.214 (0.112)	1.664 (0.048)

TABLE 4.10 Panel cointegration tests, trivariate regression

Hypothesized cointegrating regression: $Log(PercapGDP_{it}) = \alpha_i + \beta_{1i}Log(Openness_{it}) + \beta_{2i}Log(Top1_{it}) + \varepsilon_{it}$
H_0: no cointegration, test statistics (and p-values) reported
Sample 1981-2010 includes all countries of Figure 4.7 except Czech Republic due to missing observations for trade volume to GDP (Openness). For sample 1981-2016, Canada, Taiwan, France, Japan, Singapore and United States are dropped due to missing observations between 2011 and 2016.

	1981-2010, 23 countries		1981-2016, 17 countries	
	Cross-country independence assumed	Cross-country dependency allowed	Cross-country independence assumed	Cross-country dependency allowed
Pedroni, heterogeneous autoregressive parameters				
Modified Phillips-Perron t-statistic	-1.155 (0.124)	3.296 (0.001)	-1.032 (0.151)	4.214 (<0.000)
Phillips-Perron t-statistic	-4.080 (<0.000)	2.439 (0.007)	-2.333 (0.010)	3.726 (<0.000)
ADF t-statistic	-4.246 (<0.000)	2.402 (0.008)	-2.381 (0.009)	3.880 (<0.000)
Pedroni, homogeneous autoregressive parameters				
Modified variance ratio statistic	-4.181 (<0.000)	-3.654 (<0.000)	-2.626 (0.004)	-2.543 (0.006)
Modified Phillips-Perron t-statistic	-1.641 (0.050)	1.792 (0.037)	-2.389 (0.008)	3.108 (0.001)
Phillips-Perron t-statistic	-3.491 (<0.000)	1.115 (0.132)	-2.771 (0.003)	3.219 (0.001)
ADF t-statistic	-4.363 (<0.000)	0.421 (0.337)	-2.936 (0.002)	2.912 (0.002)
Kao				
Modified Dickey-Fuller t-statistic	0.996 (0.160)	1.272 (0.102)	0.468 (0.320)	1.353 (0.089)
DF t-statistic	-1.016 (0.155)	-0.144 (0.443)	-1.116 (0.132)	0.857 (0.196)
ADF t-statistic	-1.292 (0.098)	-2.080 (0.019)	-2.300 (0.011)	-1.870 (0.031)
Unadjusted modified DF t-statistic	2.296 (0.011)	2.207 (0.014)	1.644 (0.050)	2.339 (0.010)
Unadjusted DF t-statistic	0.114 (0.455)	0.751 (0.226)	-0.189 (0.425)	1.962 (0.025)
Westerlund				
H_a: cointegration in some countries	-1.270 (0.102)	2.171 (0.015)	-1.311 (0.095)	1.388 (0.083)
H_a: cointegration in all countries	-0.855 (0.196)	0.755 (0.225)	-1.124 (0.108)	0.268 (0.394)

4.A.2 Country-specific FMOLS and DOLS results

TABLE 4.11 FMOLS and DOLS estimates by country

Unbundling the mean-group panel estimates of the long-run relationship between top 1 % income shares and per capita GDP, bivariate cointegrating regression: $Log(PercapGDP_{it}) = \alpha_i + \beta_i Log(Top1_{it}) + \varepsilon_{it}$

	Australia	Bulgaria	Canada	Czech Rep.	Denmark	Finland	France	Germany
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
FMOLS 1981-2010								
Log(Top 1)	0.8378***	-0.0383	0.7505***	0.2062***	1.5045***	0.4924***	0.9102***	1.0043***
	(0.0554)	(0.0553)	(0.0419)	(0.0466)	(0.3630)	(0.0782)	(0.0545)	(0.2606)
Constant	12.7374***	9.1534***	12.0594***	10.4552***	14.4470***	11.7001***	12.4654***	12.7576***
	(0.1499)	(0.1617)	(0.0899)	(0.1310)	(0.9440)	(0.2240)	(0.1271)	(0.5955)
Observations	29	29	29	29	29	29	29	29
FMOLS 1981-2016								
Log(Top 1)	0.9006***	0.1428		0.2754***	0.8547***	0.5685***		1.0764***
	(0.0635)	(0.1568)		(0.0726)	(0.2395)	(0.1140)		(0.2029)
Constant	12.9172***	9.7871***		10.6958***	12.7314***	11.9531***		12.9475***
	(0.1689)	(0.4480)		(0.1990)	(0.6093)	(0.3238)		(0.4597)
Observations	35	35		35	35	35		35
DOLS 1981-2010								
Log(Top 1)	0.9290***	-0.0914***	0.7315***	0.2575***	1.6327***	0.4634***	0.9019***	1.2991***
	(0.0240)	(0.0310)	(0.0544)	(0.0477)	(0.1709)	(0.0407)	(0.0043)	(0.1806)
Constant	12.9462***	8.9898***	12.0129***	10.5707***	14.7768***	11.6308***	12.4526***	13.4550***
	(0.0621)	(0.0853)	(0.1109)	(0.1182)	(0.4433)	(0.1161)	(0.0097)	(0.4167)
Observations	23	23	23	23	23	23	23	23
DOLS 1981-2016								
Log(Top 1)	0.9863***	0.0573		0.2885***	1.3249***	0.5100***		1.1508***
	(0.0408)	(0.1590)		(0.0083)	(0.2879)	(0.0708)		(0.0524)
Constant	13.1234***	9.4930***		10.7304***	13.9825***	11.7926***		13.1132***
	(0.1029)	(0.4278)		(0.0204)	(0.7467)	(0.1980)		(0.1183)
Observations	29	29		29	29	29		29

Table 4.11 continues

	Greece (9)	Hungary (10)	Ireland (11)	Italy (12)	Japan (13)	Netherlands (14)	New Zealand (15)	Norway (16)
FMOLS 1981-2010								
Log(Top 1)	0.9739***	0.1238***	2.1699***	0.6872***	0.5671	1.4773**	0.3136**	0.6355***
	(0.3006)	(0.0458)	(0.1347)	(0.0477)	(0.3485)	(0.6771)	(0.1547)	(0.0884)
Constant	12.5320***	10.1017***	15.8861***	12.2469***	11.6515***	14.7981***	10.9778***	12.7987***
	(0.7854)	(0.1391)	(0.3430)	(0.1303)	(0.8164)	(1.9929)	(0.3989)	(0.2388)
Observations	29	29	29	29	29	29	29	29
FMOLS 1981-2016								
Log(Top 1)	0.5875**	0.1779***	2.0225***	0.6756***		1.4238***	0.3865*	0.6960***
	(0.2525)	(0.0497)	(0.1652)	(0.0460)		(0.3705)	(0.2098)	(0.0987)
Constant	11.5127***	10.2971***	15.4978***	12.2110***		14.6676***	11.1975***	12.9808***
	(0.6474)	(0.1470)	(0.4129)	(0.1248)		(1.0846)	(0.5382)	(0.2634)
Observations	35	35	35	35		35	35	35
DOLS 1981-2010								
Log(Top 1)	1.2653***	0.2453***	2.0701***	0.5012***	0.2155	1.0185	0.2001***	0.5946***
	(0.0928)	(0.0805)	(0.0273)	(0.0131)	(1.1574)	(0.9002)	(0.0710)	(0.0160)
Constant	13.2930***	10.4303***	15.6455***	11.7782***	10.8529***	13.4460***	10.6873***	12.7059***
	(0.2423)	(0.2029)	(0.0704)	(0.0337)	(2.7134)	(2.6741)	(0.1783)	(0.0441)
Observations	23	23	23	23	23	23	23	23
DOLS 1981-2016								
Log(Top 1)	1.3009***	0.1282	2.0968***	0.5366***		1.7547***	0.2065	0.6391***
	(0.0910)	(0.1072)	(0.0262)	(0.0345)		(0.5321)	(0.3656)	(0.0246)
Constant	13.3953***	10.2037***	15.7315***	11.8618***		15.6545***	10.7473***	12.8422***
	(0.2353)	(0.2751)	(0.0653)	(0.0899)		(1.5628)	(0.9169)	(0.0648)
Observations	29	29	29	29		29	29	29

Table 4.11 continues

	Portugal (17)	Singapore (18)	Spain (19)	Sweden (20)	Switzerland (21)	Taiwan (22)	UK (23)	US (24)
FMOLS 1981-2010								
Log(Top 1)	1.2964***	2.0085***	-0.9161	1.3069***	1.0249***	2.5100***	0.9149***	0.9829***
	(0.3128)	(0.4816)	(1.7356)	(0.3482)	(0.2356)	(0.2298)	(0.0297)	(0.0334)
Constant	13.1190***	14.7076***	7.8004*	13.9347***	13.2743***	16.1793***	12.4364***	12.4310***
	(0.7671)	(1.0290)	(4.4131)	(0.9419)	(0.5627)	(0.5786)	(0.0710)	(0.0620)
Observations	29	29	29	29	29	29	29	29
FMOLS 1981-2016								
Log(Top 1)	0.2144		0.1165	1.2542***	1.0795***		0.9609***	
	(0.3101)		(1.1829)	(0.2473)	(0.1882)		(0.0412)	
Constant	10.5210***		10.4217***	13.7993***	13.4044***		12.5571***	
	(0.7682)		(2.9837)	(0.6619)	(0.4449)		(0.0972)	
Observations	35		35	35	35		35	
DOLS 1981-2010								
Log(Top 1)	1.0219***	1.8783***	-0.6876	1.4675***	0.9716***	2.8296***	0.9038***	1.0501***
	(0.1198)	(0.1367)	(2.7372)	(0.2539)	(0.0570)	(0.2418)	(0.0161)	(0.0256)
Constant	12.4654***	14.4797***	8.4013	14.3676***	13.1596***	17.1031***	12.4540***	12.5482***
	(0.2893)	(0.2952)	(6.9856)	(0.6883)	(0.1375)	(0.6218)	(0.0381)	(0.0438)
Observations	23	23	23	23	23	23	23	23
DOLS 1981-2016								
Log(Top 1)	0.6732***		0.0778	1.5846***	1.0490***		0.8910***	
	(0.0786)		(0.9778)	(0.1572)	(0.0613)		(0.0306)	
Constant	11.6347***		10.3648***	14.6894***	13.3484***		12.4083***	
	(0.1928)		(2.4823)	(0.4208)	(0.1463)		(0.0690)	
Observations	29		29	29	29		29	

Notes: standard errors in parentheses, *, ** and *** indicate statistical significance at 10 %, 5 % and 1 % levels, respectively.

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5 INTEGRATED CAPITAL SHARES

Abstract*
In empirical macroeconomics, cross-country inter-dependencies are often analyzed by using standard cross-country correlations or by investigating time series graphically. This study shows that applying an alternative methodological approach, which builds on identifying the latent common factors for national capital shares of total income, indicates a stronger cross-country integration of national functional income distributions than the simple standard methods. The primary driving factor seems to be the same, irrespective of the set of countries and time period. Furthermore, in most of the countries, this factor is strongly correlated with both trade openness and total factor productivity, which have been suggested to be the key drivers behind changes in national functional income distributions.

Keywords: Functional income distribution, Cross-country integration, Principal component analysis

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5.1 Introduction

Recent economic literature has found that the share of national income paid to workers started to decline in the early 1980s. The suggested drivers of this evolution span from declining relative prices of investment goods (Karabarbounis and Neiman, 2013) and the rise of superstar firms (Autor et al., 2017) to the "$r > g$ dynamics" introduced by Piketty (2015). Dao et al. (2017) document the roles of technological improvement and participation in global value chains. The findings are against the traditional view of a stable share, which has been one of the building blocks in many macroeconomic growth models. Furthermore, since capital income tends to be more unevenly distributed than labor income, falling labor share of income is potentially positively associated with rising levels of income inequality[1]. Thus, the dynamics of the functional income distribution, i.e. the division between labor and capital income, is a topic worth studying.

This paper complements the existing literature by examining the potential inter-dependencies across capital income shares in 19 countries. The cross-country panel data set used in this study comes from a study by Bengtsson and Waldenström (2018) and covers 19 countries over the 20th century. The structure of this study is the following: the next section presents the data and methodological approach, Section 5.3 shows the results and discusses their implications and Section 5.4 concludes the findings.

5.2 Data and methodology

Without going specifically into details on how the factor shares are estimated, two issues deserve to be discussed. First, the method for estimating the labor income of self-employed workers affects the estimates of functional income distribution. Bengtsson and Waldenström (2018) assume that one third of the self-employed incomes are capital income while the rest is assigned to labor income[2]. Second, for the estimation of the net capital shares, capital depreciation rates need to be estimated[3], which adds an additional layer of measurement uncertainty into the estimates. For comparability of the capital shares across countries and since Bengtsson and Waldenström (2018) provide both gross and net capital shares, this study focuses on the gross shares that are free from measurement concerns related to capital depreciation. The larger sample relative to net shares is also a well-welcomed feature.

1 This line of thinking is at the core of the analysis by Piketty (2015)

2 See e.g. Gollin (2002) and (Elsby et al., 2013) for a detailed discussion

3 As a specific challenge, factors such as taxation incentives may bring about volatility, non-fundamental to the distinction between gross and net capital shares, in the rates of capital depreciation.

FIGURE 5.1 Gross capital shares over the 20th century in 19 countries (Bengtsson and Waldenström, 2018)

Figure 5.1 shows that for many countries the time series are characterized by a decreasing trend in the first half of the 20th century, whereas in the latter half of the sample, the capital shares rose in many countries. This does not hold universally across the countries, but on aggregate, sample mean in year 2000 has reverted back to its initial level at the early decades of the sample after a dip during the mid-decades of the last century. Since the variable of interest is defined as a share of total income, raw levels series are commensurable across countries and have a clear economic interpretation.

By construction, capital share of income is restricted to vary between 0 % and 100 % and thus the time series are treated as stationary, which makes the approach relying on the correlation matrices meaningful. The standard cross-sectional correlations summarized in Tables 5.1 and 5.2 show that the pairwise correlation coefficients are predominantly positive and statistically different from zero although clear exceptions, e.g. Argentina, exist. Still, it is a demanding task to infer integration among the capital shares based on the correlations because the number of combinations is very large. More fundamentally, assuming that the potential integration is driven by a set of common global factors and allowing the country-specific capital shares to respond heterogeneously, simple correlations are unlikely to provide a comprehensive view on the inter-dependencies.

Improving on the simple correlation analysis, Pukthuanthong and Roll (2009) introduce a three-stage approach to identify global financial integration. First, the driving factors are identified by running a principal component analysis on either the covariance or correlation matrix. Second, a set of principal components is retained as proxies for driving factors and are used as regressors in least squares regressions, where the country-specific index returns, or capital shares in this paper, are the dependent variables. Pukthuanthong and Roll (2009) take the first 10 principal components, which in their framework capture roughly 90 % of the cumulative eigenvalues, i.e. 90 % of the total volatility in the covariance matrix. Finally, the R^2 values of each individual regression are collected and interpreted as the measure of integration.

Following the ideas in the analytical framework of Pukthuanthong and Roll (2009), let the integration between two countries, A and B, depend on two factors, technological change (τ) and globalization (γ). Each country's capital share of income, y, is given by

$$y_{i,t} = \alpha_i + \beta_{i,\tau} f(\tau)_t + \beta_{i,\gamma} f(\gamma)_t + \epsilon_{i,t}, \tag{5.1}$$

where $i = A, B$; t refers to year, $\beta_{i,\tau}$ and $\beta_{i,\gamma}$ correspond to sensitivity parameters and $f(\tau)$ and $f(\gamma)$ are the factors driving the capital share. The main point of Pukthuanthong and Roll (2009) is that even under complete integration, defined as $\epsilon_{A,t} = \epsilon_{B,t} = 0$ for all t, the correlation between $y_{A,t}$ and $y_{B,t}$ is smaller than one if $\beta_{A,\tau} \neq k\beta_{B,\tau}$ or $\beta_{A,\gamma} \neq k\beta_{B,\tau}$ for some positive scalar k. In other words, perfect integration, as defined above, does not imply perfect correlation.

TABLE 5.1 Standard cross-country correlations in the sample 1960-2000

	ARG	AUS	AUT	BEL	BRA	CAN	DNK	FIN	FRA	DEU	IRL	JPN	NLD	NZL	NOR	ESP	SWE	GBR	USA
ARG	1.00																		
AUS	-0.40	1.00																	
AUT	-0.40	0.84	1.00																
BEL	-0.42	-0.21	-0.14	1.00															
BRA	0.23	0.47	0.38	-0.86	1.00														
CAN	0.17	0.04	0.08	-0.57	0.43	1.00													
DNK	-0.54	0.26	0.38	0.50	-0.49	-0.25	1.00												
FIN	-0.44	0.57	0.70	-0.17	0.29	0.34	0.32	1.00											
FRA	-0.37	0.92	0.83	-0.23	0.56	-0.07	0.18	0.53	1.00										
DEU	-0.38	0.88	0.86	-0.26	0.50	0.12	0.27	0.62	0.86	1.00									
IRL	-0.22	0.80	0.81	-0.43	0.63	0.24	0.23	0.68	0.81	0.90	1.00								
JPN	-0.33	0.00	0.00	0.84	-0.62	-0.63	0.28	-0.12	-0.02	-0.16	-0.31	1.00							
NLD	-0.50	0.66	0.82	0.19	-0.03	-0.06	0.66	0.50	0.63	0.71	0.55	0.18	1.00						
NZL	-0.71	0.76	0.69	0.16	0.04	-0.06	0.59	0.64	0.67	0.72	0.63	0.21	0.68	1.00					
NOR	-0.36	0.68	0.73	-0.35	0.34	0.35	0.38	0.57	0.53	0.68	0.65	-0.26	0.67	0.60	1.00				
ESP	-0.20	0.80	0.89	-0.45	0.58	0.28	0.25	0.68	0.82	0.84	0.86	-0.33	0.70	0.55	0.74	1.00			
SWE	-0.44	0.78	0.79	-0.24	0.31	0.25	0.40	0.60	0.71	0.73	0.62	-0.19	0.74	0.65	0.77	0.81	1.00		
GBR	-0.49	0.73	0.84	0.01	0.20	0.26	0.41	0.71	0.68	0.81	0.73	0.02	0.78	0.75	0.59	0.76	0.74	1.00	
USA	-0.38	0.68	0.65	-0.14	0.16	0.12	0.52	0.37	0.55	0.78	0.67	-0.22	0.70	0.64	0.70	0.66	0.73	0.71	1.00

TABLE 5.2 Standard cross-country correlations in the sample 1929-2000

	ARG	AUS	BRA	CAN	DNK	FIN	FRA	ESP	SWE	GBR	USA
ARG	1.00										
AUS	-0.32	1.00									
BRA	0.43	0.39	1.00								
CAN	0.29	-0.19	0.25	1.00							
DNK	-0.59	0.48	-0.45	-0.27	1.00						
FIN	-0.09	0.76	0.45	-0.10	0.40	1.00					
FRA	-0.15	0.67	0.54	-0.04	0.12	0.64	1.00				
ESP	-0.41	0.02	-0.21	-0.06	0.22	-0.28	-0.01	1.00			
SWE	-0.54	0.68	-0.08	0.00	0.76	0.44	0.32	0.43	1.00		
GBR	-0.58	0.56	0.01	0.02	0.52	0.44	0.53	0.50	0.70	1.00	
USA	-0.12	-0.01	0.03	0.30	0.08	-0.10	0.13	0.40	0.28	0.46	1.00

To illustrate how the principal component analysis works, suppose that there are N countries and $K \leq N$ factors. Let y_t ($N \times 1$) depend on a constant α ($N \times 1$) and a set of factors f_t ($N \times 1$) with corresponding sensitivities β ($N \times K$):

$$y_t = \alpha + \beta f_t + \epsilon_t, \tag{5.2}$$

where the factors f_t and disturbances ϵ_t ($N \times 1$) have the following properties:

$E[\epsilon_t] = 0, E[\epsilon_t \epsilon_t'] = \Omega$
$E[f_t] = 0, E[f_t f_t'] = I$
$E[f_t \epsilon_t'] = 0$

The variances of the capital shares for $i = 1, 2, \cdots, N$ countries $\{y_{1t}, y_{2t}, \cdots, y_{Nt}\}$, i.e. the diagonal elements of $Cov(y_t)$, are

$$\begin{pmatrix} Var(y_{1t}) \\ Var(y_{2t}) \\ \vdots \\ Var(y_{Nt}) \end{pmatrix} = \lambda_1 \begin{pmatrix} P_{1,1}^2 \\ P_{2,1}^2 \\ \vdots \\ P_{N,1}^2 \end{pmatrix} + \lambda_2 \begin{pmatrix} P_{1,2}^2 \\ P_{2,2}^2 \\ \vdots \\ P_{N,2}^2 \end{pmatrix} + \cdots + \lambda_N \begin{pmatrix} P_{1,N}^2 \\ P_{2,N}^2 \\ \vdots \\ P_{N,N}^2 \end{pmatrix} \tag{5.3}$$

The eigenvectors P_i are normalized so that $P_i' P_i = 1$ and the overall variance is equal to the sum of the eigenvalues λ_1. If the correlation matrix is used instead of the covariance matrix, the eigenvalues sum up to the number of countries, i.e. $\sum_{i=1}^{N} \lambda_i = N$. Adopting the "90 % rule" of Pukthuanthong and Roll (2009) and using the correlation matrix, means that the number of factors (K) included in the least squares regressions is equal to the number of eigenvalues required to reach a cumulative value of $0.9N$, where N is either 19 or 11 depending on the sample.

5.3 Results

This chapter presents the results of the principal component analysis and the subsequent measures of integration, which are based on sets of least squares regressions, where the country-specific capital shares are regressed on the principal components that capture just over 90 % of the cumulative eigenvalues. In

both of the samples, 19 and 11 countries, six principal components is sufficient to reach this threshold (Figure 5.2). In the larger set of countries that covers the period 1960-2000, the first factor captures more than half of the cumulative value, whereas in the smaller set that covers the period 1929-2000, the relative importance of the factors 3-6 is higher.

The lack of a firm economic interpretation is not a fundamental issue for this study since the aim of the empirical analysis is not to explicitly identify the mechanisms that influence the functional income distribution unlike the studies briefly reviewed in Section 5.1. Rather, this paper demonstrates how techniques used in financial literature can improve the analysis of macroeconomic inter-dependencies with a special focus on the capital shares of total national income. Nevertheless, one possible way to find economic meaning for the factors extracted from the data generating processes of the capital shares is to compare the factors to some candidate driving factors. Considering the trade openness measure of Fouquin and Hugot (2016), the sum of imports and exports relative to GDP, and the measure of technological progress of the Penn World Table (Feenstra et al., 2015), total factor productivity, reveals that the first factor is positively correlated with these two potential drivers of the functional income distribution in many countries.

The estimated six factors for the two samples, (i) 19 countries in a period 1960-2000 and (ii) 11 countries in a period 1929-2000, are presented in Figure 5.3. The first factors of the two samples that capture 54 % and 38 % of the cumulative eigenvalues, respectively, seem to follow one another very closely in the overlapping period 1960-2000. A correlation coefficient of 0.96 implies that the primary driving factor is the same irrespective of the sample. The same is not true for the five other factors as the pairwise correlations between the ordered factors are -0.86, -0.22, 0.13, 0.29 and 0.24. The first factor, which follows the suggested actual drivers in many countries as discussed above, seems to stand out from the others throughout the empirical analysis. Since in the forthcoming least squares regressions the six factors enter as regressors and the objective is to collect the country-specific R^2 values, multicollinearity is a potential issue. Beneficially, the correlations between the factors are minuscule irrespective of the sample.

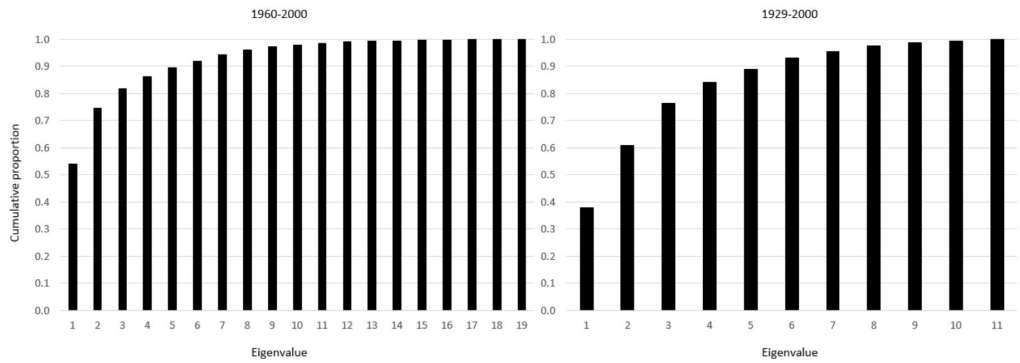

FIGURE 5.2 Cumulative percentage of variance explained by sorted eigenvalues

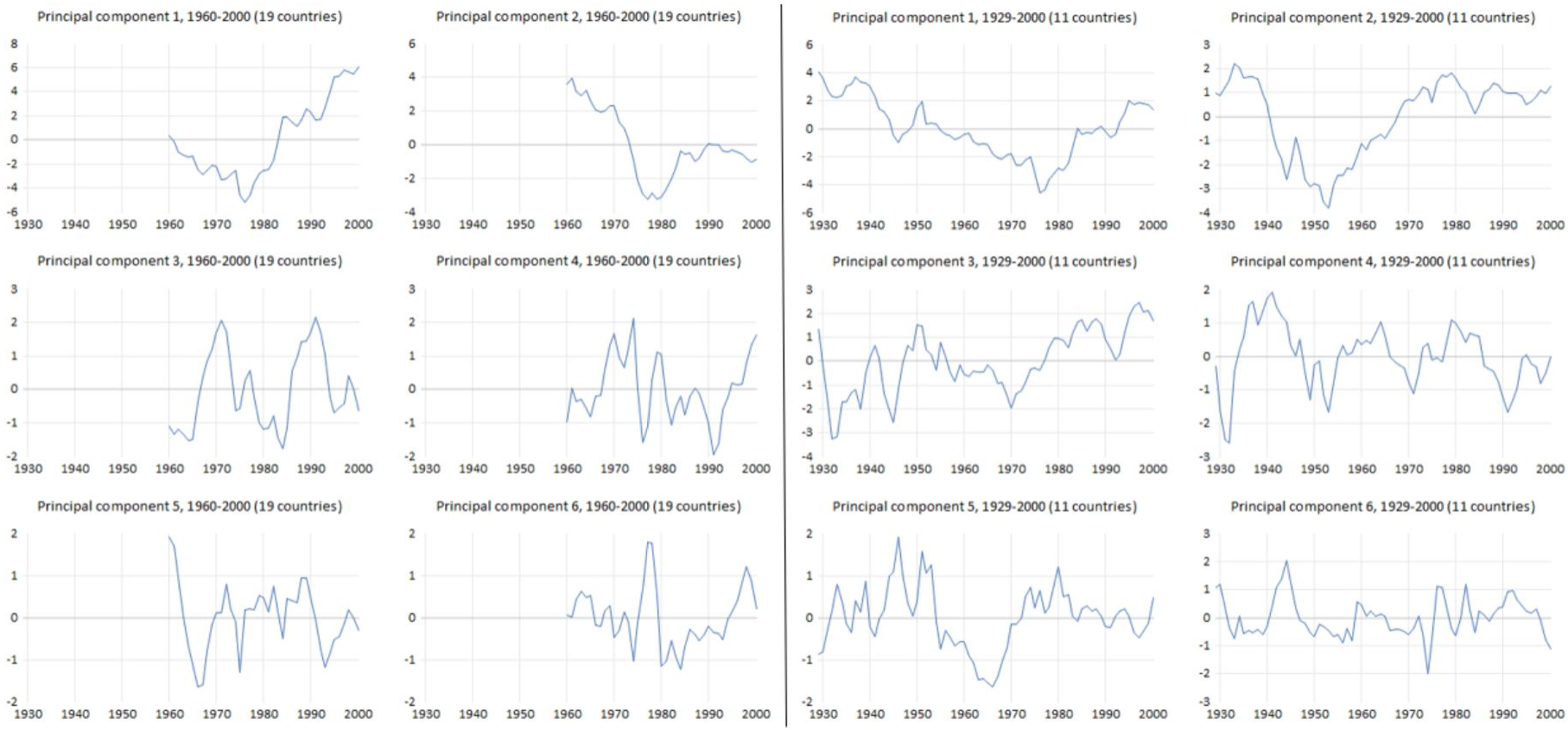

FIGURE 5.3 The principal components

Figure 5.4 summarizes the evidence of integration across the country-specific capital shares. The R^2 values are predominantly 0.9 or higher while the lowest value is 0.85. Narrowing the sample of 11 countries to cover the period 1929-1970 reveals that the main result remains unaltered. Since the two samples produce 30 individual least squares regressions and the number of specifications rises with additional robustness checks, only the R^2 values are reported. The detailed regression outputs can be produced from the data and software codes that are available upon a request.

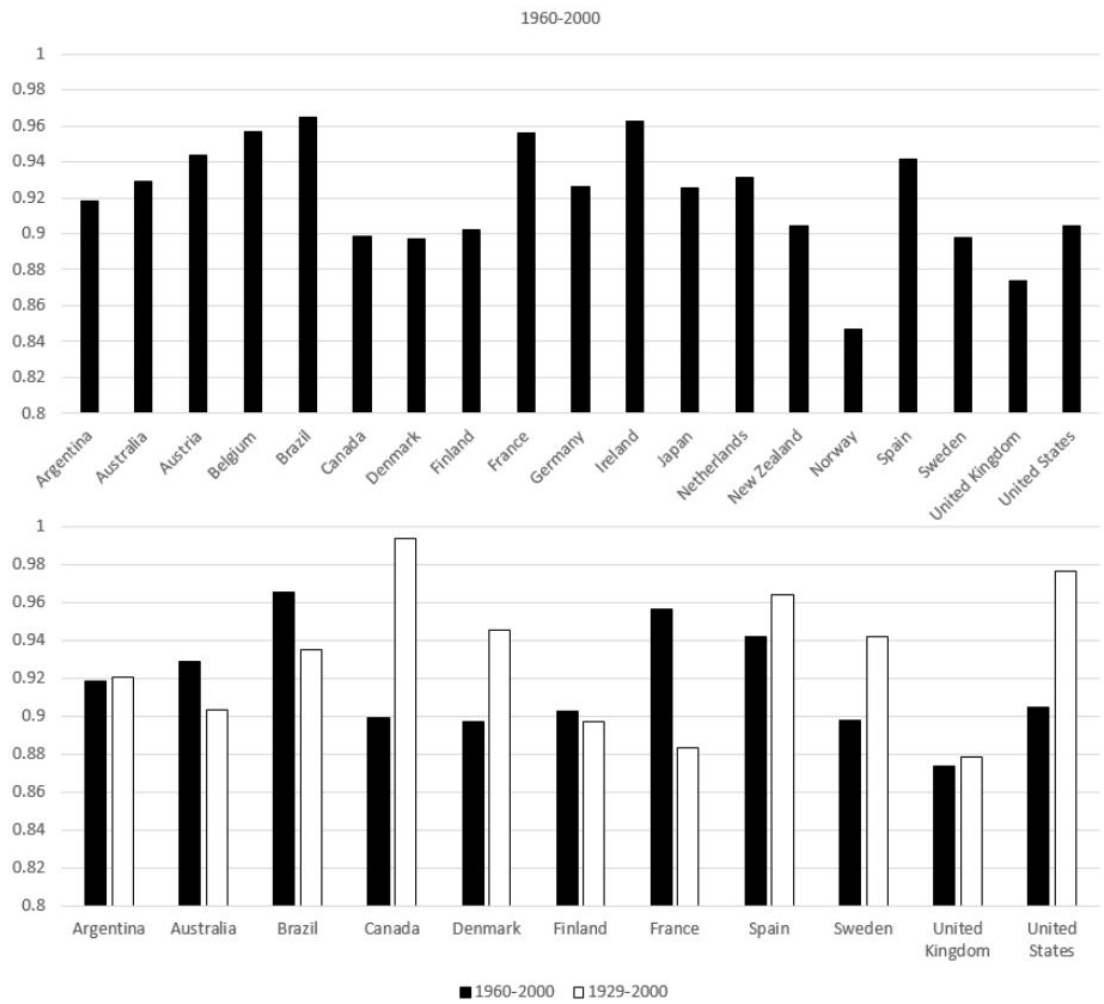

FIGURE 5.4 Pukthuanthong and Roll (2009) measures of integration

As discussed in Pukthuanthong and Roll (2009), the multi-factor R^2 measure of integration may have some weaknesses beyond the interpretation of factors. First, and not limited to this specific technique, the countries that Bengtsson and Waldenström (2018) had data on are likely to be more integrated to the global economic system than many countries for which there is no data on capital shares. In other words, there may be a selection issue and thus claiming that the results of this study imply a global integration of functional income distribution may be an exaggerated statement. Perhaps, integration among developed countries

is an apt depiction of the main finding. Second, the derived factors may well be country-specific instead of "global" even if the R^2 values for individual countries were large. As a simple example, Pukthuanthong and Roll (2009) consider two countries and two estimated global factors. If the exposures to the factors are (1,0) for country A, and (0,1) for country B, the integration measure may indicate complete integration even though, in reality, the countries are completely non-integrated as they respond to disparate global shocks.

In the sample of 19 countries, the first factor as a sole regressor yields an R^2 higher than 0.5 for 13 countries and a value higher than 0.8 for four countries. The countries whose capital shares seem to have been driven by other factors are Argentina ($R^2 = 0.23$), Belgium (0.06), Brazil (0.18), Canada (0.04), Denmark (0.18) and Japan (0.02). Argentina and Brazil are clear exceptions from the rest in terms of the level of economic development, Japan experienced economic stagnation during the final decade of the sample and is the only Asian economy in the sample, whereas Belgium, Canada and Denmark are not apparently different from for example Netherlands, the other Anglo-American countries and the Nordic welfare states, respectively. As a speculative conclusion, these countries may possess some nation-specific institutional traits that partly detach them from evolutions driven by e.g. the expansion of trade and technological progress. The number of countries for which the R^2 rises over 0.5 drops to four in a single-factor model for the period 1929-2000. This suggests that the role of the first factor as a determinant of integration of the capital shares has increased over time. In Australia, Sweden and the United Kingdom, the role of the first factor seems to be particularly strong irrespective of the time period as the single-factor R^2 is roughly 0.7.

5.4 Conclusion

This study has investigated the cross-country inter-dependencies of functional income distributions in 19 countries that are mostly developed OECD member states. The methodological approach relies on principal component analysis to evaluate how well unobservable common latent factors can explain the national capital shares of total national income. A set of six factors can capture more than 90 % of the total volatility in the correlation matrix of the country-specific capital shares. Using the factors as regressors for the national capital shares in least squares regressions yields high R^2 values, which indicates that common factors are driving the national functional income distributions. Under strong integration, policy actions pursuing to influence national functional income distributions are potentially less effective than under country-specific dynamics. The high level of integration seems not to exist if the scope is narrowed to standard correlations and graphical analysis on the country-specific time series.

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6 WHEN AIYAGARI MEETS PIKETTY: GROWTH, INEQUALITY AND CAPITAL SHARES

Abstract*
We incorporate the division of income between capital and labor into an analysis of the relationship between inequality and growth. Using historical data, we document that changes in the top 1 % income shares are positively associated with the subsequent growth of per capita GDP when the capital share of income is low, whereas under high capital share, the association is negative. We show that these findings are compatible with a theoretical analysis that emphasizes how changes in the distribution of income translate into capital accumulation and overall economic activity through the interplay between precautionary saving motives and consumption smoothing. We also investigate how accounting for financial frictions affects our main findings.

Keywords: Economic growth, Inequality, Top income shares, Capital shares

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6.1 Introduction

The interplay between overall economic activity, the distribution of personal income and the division of total national income between factors of production has fascinated economists since the early days of the discipline. During the past 30 years, many theoretical studies have suggested channels through which economic inequality affects economic growth, and to accompany the theoretical work on the subject, numerous empirical papers using cross-country datasets have emerged. While numerous theoretical studies have challenged the traditional views that inequality enhances growth through economic incentives and higher savings rate of the rich[1], empirical evidence remains inconclusive.

In this study, we contribute to the vast literature that has examined how economic growth depends on economic inequality. We show both theoretically and empirically that the association between growth and income inequality is conditional on the division of income between capital and labor, i.e. the functional income distribution. Although the linkages between personal and functional income distributions have been widely-studied, we are unaware of any previous theoretical or empirical studies that would have examined whether the complex nature of the inequality-growth relationship can be better understood by incorporating functional income distribution into the analysis.

Our theoretical analysis builds on the seminal study by Aiyagari (1994). We adopt Aiyagari's (1994) model and follow the original model specification and parameterization to innovatively examine the responses of economic growth to an inequality shock conditional on the level of capital share of total income. Our main theoretical prediction is that an increase in income inequality is associated with higher subsequent economic growth when labor is the dominant factor of production in the economy. On the contrary, when the capital share of income is large, an increase in inequality is related with lower growth. This prediction holds when credit constraint is sufficiently low.

In terms of mechanisms, our theoretical analysis stresses the accumulation of physical capital in a simple capital market equilibrium. The dependency of the inequality-growth relationship to functional income distribution stems from the interplay between precautionary motives and consumption smoothing. For low capital shares, the former dominates, and as a result, an increase in income inequality leads into higher capital supply and higher per capita growth. For high capital shares, the latter dominates resulting in a negative link between increasing inequality and capital supply, which eventually hurts growth in our Aiyagari (1994) type economy. The previous holds when credit constraint is low, whereas if the households cannot borrow as easily, precautionary motives dominate con-

[1] Most notable studies on the growth-dampening effects of inequality include Galor and Zeira (1993), Alesina and Rodrik (1994), Persson and Tabellini (1994), Alesina and Perotti (1996) and Galor and Moav (2004). See Kaldor (1957) and Bourguignon (1981) on convex savings function ("the rich save more"). In Section 6.2, we present the main feature of these studies, and also review the previous empirical literature on the topic.

sumption smoothing for all values of capital share. Consequently, under high credit constraint, our model predicts that income inequality is positively associated with growth irrespective of the distribution of income between capital and labor.

Our empirical findings align with the theoretical predictions. Focusing on all available data at our disposal reveals that the association between changes in the top 1 % income share and subsequent growth rates is i) positive when the capital share of income is low, and ii) negative when the capital share of income is high. Furthermore, based on various measures of financial development, we seek to build a bridge between theory's credit constraint and measurable evolutions. Namely, we show that, like in the full sample, the inequality-growth relationship depends on the capital share under eras of high financial development, whereas this dependency is not present in the data under low financial development.

We obtain these empirical results by relying on panel data from 13 developed countries that span over the period 1895-2014. The data come from a study by Bengtsson and Waldenström (2018), whose work is closely related to the influential book by Piketty (2014). For financial development, we resort to Rajan and Zingales (2003). Our panel regressions focus on five-year non-overlapping windows, which has been a typical approach in previous studies, to investigate how the growth of per capita GDP depends on the top income shares and the capital share of total national income while controlling for the level of economic development and fixed country and year effects. Our results are robust to numerous robustness checks.

Our contribution to the existing literature is threefold. First, using historical data on distributional measures and per capita GDP, we reveal a previously undiscovered robust association between personal and functional income distributions and per capita growth. Second, we introduce a novel theoretical link between the distribution of income, capital accumulation and growth. Furthermore, the focal results of our theoretical and empirical analysis are in line with one another. Third, we demonstrate the role of financial frictions as an underlying determinant for the nature of the relationship between the distribution of income – both personal and functional – and economic growth.

The structure of the study is the following. In Section 6.2, we provide the central previous literature from the perspective of our theoretical model and empirical approach. We present our theoretical model in Section 6.3, dedicate Section 6.4 for the empirical analysis and, finally, conclude our findings in Section 6.5.

6.2 Literature review

Our study contributes to several branches of previous economic literature on income distribution and real growth, and in particular the interplay of the two. First, in Section 6.3, we illustrate the dependency of the inequality-growth nexus to functional income distribution by adopting the seminal theoretical model by

Aiyagari (1994). In an Aiyagari economy the aggregate capital demand is given by a representative firm and the aggregate capital supply is endogenously determined by the saving decisions of households (Aiyagari, 1994; Bewley, 1983). In the steady state capital market equilibrium, the marginal productivity of capital gives the slope for the demand curve for the real productive capital, whereas the supply of capital is determined subject to precautionary motives and borrowing constraints of households (Aiyagari, 1994; Huggett, 1993).

In early studies, Sibley (1975) and Miller (1975) showed that under a concave periodic utility function a mean-preserving spread in the income distribution increases the savings of each households in long horizons. In Aiyagari's model, this can be interpreted as an increased income uncertainty, which increases precautionary motives. However, it is not clear whether the precautionary savings will increase the aggregate capital supply, due to the assumed stationary distribution of total resources. In our theoretical analysis, we exploit this curiosity in the determination of the capital market equilibrium to investigate how the relationship between income inequality and growth is conditional on the marginal productivity of capital and the capital share.[2]

The inequality-growth relationship has been previously analyzed using theoretical frameworks other than the one discussed above. Next, we present the main features of some notable studies on the topic. The conventional view is that inequality enhances economic incentives and consequently promotes economic growth. Another traditional argument states that because the savings rate of the rich is larger than that of the poor (i.e. the savings function is convex), economies with more unequal income distribution tend to save more and experience faster economic growth (Kaldor, 1957; Bourguignon, 1981). Furthermore, in the absence of sufficiently developed financial markets and institutions, some level of inequality may be needed for entrepreneurial individuals to cover the set-up costs for a new firm (Aghion et al., 1999). Thus, according to this argument too, inequality fosters growth.

As pointed out by Aghion et al. (1999), development economists have long presented informal counterarguments to the views that inequality enhances growth. Starting from the 1990s, numerous authors have developed these arguments into theoretical models. One of the most influential models was constructed by Galor and Zeira (1993): under credit frictions, individual level investment in human capital is determined by inherited wealth, and consequently, inequality dampens the aggregate level human capital accumulation and economic growth. More recently, Galor and Moav (2004) developed a model, where human capital replaces physical capital as a prime growth engine during the process of economic development. In the early stages of development, when the accumulation of physical capital drives growth, the convex savings function mechanism dominates and inequality is growth-enhancing. Later on, the human capital channel takes the dominant role and inequality is bound to dampen growth.

Two additional channels through which inequality may hurt growth in-

[2] See Quadrini et al. (1997) and Benhabib and Bisin (2018) for detailed overview of the theoretical studies on the distribution of wealth.

volve the leaky bucket metaphor and sociopolitical instability. In brief, the former states that, due to the need of redistribution, higher inequality leads to higher taxation and lower economic growth. The idea of a leaky bucket was introduced by Okun (1975): "The money must be carried from the rich to the poor in a leaky bucket. Some of it will simply disappear in transit, so the poor will not receive all the money that is taken from the rich". The concept was further developed by Alesina and Rodrik (1994) and Persson and Tabellini (1994). The role of sociopolitical instability was formalized by Alesina and Perotti (1996), who argue that, by fueling social discontent, inequality induces instability that is harmful for investments and overall economic activity.

Datawise, we anchor ourselves firmly to the bestselling book *Capital in the Twenty-First Century* by Piketty (2014) and to the work by dozens of other scholars, whose pioneering effort is gathered in the World Inequality Database.[3] As illustrated in Figures 6.4 and 6.5 in Section 6.4.1 of this study, the top income shares and capital shares declined from the early twentieth century to the 1970s, whereas during the past 40 years, the shares have risen in many countries.[4]

Finally, by adopting a standard panel regression approach for the empirical analysis in Section 6.4, our study contributes to the empirical reduced-form studies that have examined whether income inequality enhances or dampens economic growth. In their meta-analysis, Neves et al. (2016) review 28 studies that were published between 1994 and 2014. The first wave of studies relied on

[3] See https://wid.world/methodology/ for an extensive list of studies.

[4] Analyzing the drivers of inequality, the changes in the functional income distribution or the link between the two are beyond the scope of this study. Seminal work on inequality include, among many others, Kuznets (1955) on inequality during economic development, Goldin and Katz (2009) on the supply and demand of educated workers and technological progress, Piketty (2014) on the difference between the return on capital and economic growth ($r - g$), and Milanovic (2016a) on the so-called Kuznets waves. Furthermore and interestingly for us, who use data on top income shares, Piketty and Saez (2003) found that the rising top income shares in the United States were largely driven by wage income in the late twentieth century, whereas during the twenty-first century, the role of capital income has strengthened (Piketty et al., 2018). Smith et al. (2019) documented that top earners in the US tend to derive their income mostly from human – rather than financial – capital. The recent increases in capital shares have been suggested to stem e.g. from the declining relative prices of investment goods (Karabarbounis and Neiman, 2013), technological progress and automation (Acemoglu and Restrepo, 2018), the loss of labor unions' bargaining power (Stansbury and Summers, 2020) and the rise of superstar firms (Autor et al., 2020). Piketty (2014) sees the connection between personal and functional income distributions straightforwardly and argues that since capital income tends to be more unevenly distributed than labor income, rising capital share (or falling labor share) of income is positively associated with income inequality. Bengtsson and Waldenström (2018), whose data we use in this study, found long run evidence on this positive linkage, Atkinson (2009) discussed the relevance of studying factor shares and offers an analytical framework to assess the association between functional income distribution and personal income inequality while Milanovic (2016b) derived the conditions for the positive association to prevail. Further empirical evidence on the positive association between functional income distribution and income inequality was provided by Daudey and García-Peñalosa (2007) and by Checchi and García-Peñalosa (2010) while Civardi and Lenti (2018) link the two in a framework that follows the work of Atkinson (2009).

a cross-sectional data structure. More recently, researchers have predominantly used panel data and started to apply techniques (variants of generalized method of moments, GMM[5]) that aim to separate causation from correlation. Perhaps the most interesting finding of the meta-analysis is evidence for publication bias, i.e. statistically significant results are more willingly reported and published. Also, positive and negative estimates tend to be cyclically reported. Furthermore, the findings suggest that the estimation technique, data quality and the specification choice for the growth regression are not significant drivers of the varying estimates. Rather, cross-sectional analyses tend to find a stronger negative association than panel studies, the negative association is stronger in less developed countries, the inclusion of regional dummies soak up much of the previous finding and the concept of inequality significantly affects the results.

Even though the number of empirical studies is vast, a few have made a particularly strong impact. The cross-sectional studies by Alesina and Rodrik (1994) and Perotti (1996) found evidence for growth-hurting inequality. Barro's (2000) findings suggested that the association between inequality and growth is negative for low levels of economic development and positive for high ones. Banerjee and Duflo (2003) showed that changes in inequality in any direction are associated with lower subsequent growth rates. Voitchovsky (2005) found that inequality at the top end of the income distribution supports economic activity while inequality at the bottom dampens growth. Halter et al. (2014) focused on the time dimension and found that inequality supports growth in the short-run but is harmful for economic performance farther in the future. Ostry et al. (2014) and Berg et al. (2018) take both inequality and redistribution. Their results suggest that inequality is bad for growth when redistribution is controlled for, whereas redistribution seems not to dampen growth.

Measure-wise, the Gini coefficient is by far the most used one in the empirical studies. However, the most extensively discussed inequality patterns are based on the top income shares (Piketty, 2014) rather than the broader measures such as the Gini.[6] Some of the few studies that analyze the relationship between the top income shares and growth are by Barro (2000), who investigated whether his results hold between different measures; by Andrews et al. (2011), whose findings suggested that during the latter half of the twentieth century, the top 10 % income share was positively associated with subsequent growth, while focusing on the entire century revealed no systematic pattern between top income shares and growth; by Herzer and Vollmer (2013), who focused on the level of per capita GDP and found that rising top income shares are bad for economic development;

5 See Bazzi and Clemens (2013) and Kraay (2015) for critique on the weakness of the instrument variables when the popular system GMM estimator is used.

6 Moreover, it is not clear that the Gini is the best available measure to distill the income distribution into a single number. Cobham et al. (2013) document that in countries at different income levels, the deciles 5–9 tend to capture roughly half of national income, whereas the shares going to the top 10 % and bottom 40 % vary considerably both in time and especially across countries. Thus, the authors suggest that the Palma ratio – defined as the ratio between the income share of the top 10 % and the income share of the bottom 40 % – would be a more relevant indicator than the Gini, which places a high weight on the middle incomes.

and by Thewissen (2014), whose results are similar to those of Andrews et al. (2011). To summarize, it is safe to say that no clear consensus emerges from the numerous empirical studies.

6.3 Theoretical model

This section of the study presents our theoretical analysis, which builds on the seminal study by Aiyagari (1994). First, we summarize the key features of Aiyagari (1994) with respect to our study. Second, we describe the modelling details and present the findings of our theoretical analysis.

In brief, we closely follow the model specification and parameterization by Aiyagari (1994). Our innovation is to analyze growth-responses to an inequality shock conditional on the division of income between capital and labor. Furthermore, we address the role of credit constraint in terms of the predictions of our model.

6.3.1 Aiyagari (1994)

We use Aiyagari's (1994) model to study the effects of an exogenous inequality shock on output and capital. In Aiyagari (1994), wealth inequality is endogenously determined by exogenously given labor endowment states and their transition probabilities. In our model, an exogenous inequality shock refers to a change in the labor endowment state space in the following way.

We increase, first, the expected value, and second, the variance of the labor endowment. Regarding the former, we increase the labor state for the top income brackets relatively more than for the poor, which is associated with increased productivity at the aggregate level. We label the effects related to the increased expected value of the labor endowment as *consumption smoothing effects*. Increasing the variance of the labor endowment generates an uncertainty shock, which makes the population more divergent. We call these effects as *precautionary savings effects*. It turns out that the two class of effects can be modeled only by changing the variance of the idiosyncratic labor endowment, and consequently, we compare the stationary equilibrium outcomes before and after an exogenous shock to labor endowment states.

Assume that there is a unit mass of infinitely lived households. Let c_t, a_t, and ℓ_t be a single household's consumption, assets, and labor endowment in period t. The labor endowment shocks are random and independent and identically distributed (i.i.d) over time with the cumulative probability distribution F and support $[\ell_{min}, \ell_{max}]$ where $0 < \ell_{min} < \ell_{max} < \infty$. The utility in each period is given by $u(c_t)$ and it is discounted by $\beta = \frac{1}{1+\lambda} \in (0,1)$, where λ is the rate of time preference. The utility function $u : \mathbb{R}_+ \to \mathbb{R}$ is continuously differentiable and bounded with derivatives $u'(c_t) > 0$, $u''(c_t) < 0$, $\lim_{c_t \to 0} u'(c_t) = \infty$, and $\lim_{c_t \to \infty} u'(c_t) = 0$. The household receives return r on assets and wage $w \cdot \ell$

having labor endowment ℓ. There is a borrowing limit $\underline{a}$ that makes the capital market incomplete.

All households are ex-ante symmetric and each of them solves the following recursive problem

$$V(a_t, \ell_t) = \max_{c_t, a_{t+1}} \left\{ u(c_t) + \beta \int_{\ell_{min}}^{\ell_{max}} V(a_{t+1}, \ell_{t+1}) dF(\ell_{t+1}) \right\} \tag{6.1}$$

subject to

$$a_{t+1} + c_t = (1 + r_t)a_t + w_t \ell_t, \tag{6.2}$$

$$a_t \geq \underline{a}, \qquad \text{almost surely} \tag{6.3}$$

$$c_t \geq 0, \tag{6.4}$$

$$c_0, k_0 \text{ given}, \tag{6.5}$$

where $V(a_t, \ell_t)$ is the value function in state (a_t, ℓ_t). The solution to this problem will include an optimal savings policy $a_{t+1} = g(a_t, \ell_t)$, an optimal consumption policy $c(a_t, \ell_t)$, and the value function $V(a_t, \ell_t)$.

A representative firm has a constant-returns-to-scale production technology $y_t = f(k_t, n_t)$, where y_t is per-capita output, k_t per-capita capital, and n_t per-capita labor force. The equilibrium interest rate and wage level are given by the sufficient and necessary conditions of the firm's maximization problem

$$r_t = f_k(k_t, n_t) - \delta, \tag{6.6}$$

$$w_t = f_n(k_t, n_t). \tag{6.7}$$

The partial equilibria of the households' problems and the firm's problem constitute the general equilibrium of the model together with the total resource constraint $y_t = c_t + i_t$, where i_t is investments per capita. Let us denote $\lambda_t(a_t, \ell_t)$ as the distribution of households over the state variables in period t – that is, the mass of households in state (a_t, ℓ_t) in period t is given by $\lambda_t(a_t, \ell_t)$.

The stationary equilibrium consists of the policy functions $g(a_t, \ell_t)$ and $c(a_t, \ell_t)$ that solve the household's problem and a stationary distribution $\lambda(a_t, \ell_t)$ for all a_{t+1} and all ℓ_{t+1}. Moreover, prices r and w solve the firm's problem, and the aggregate resource constraint $y = k + i$ is satisfied, where y is aggregate per-capita output, k aggregate per-capita capital, and i aggregate per-capita investments.

6.3.2 Model Specification, Parameterization, and Computation

With model specification and parameterization we closely follow the original study by Aiyagari (1994). We assume that the period utility function is $u(c_t) = \frac{c_t^{1-\mu}-1}{1-\mu}$ with the relative risk aversion coefficient $\mu = 3$. The discount factor β is set to 0.97 for one year period.

We model the labor endowment shocks with $s = 7$ states. By choosing $s = 7$ we follow Aiyagari's original estimations. The state space for ℓ is denoted by

$\mathcal{L} = \{L_1, L_2, \ldots, L_s\}$. For discretizing a continuous stochastic process we use the Rouwenhorst method for the following AR(1) process:

$$\log(\ell_t) = \rho \log(\ell_{t-1}) + \sigma\sqrt{(1-\rho^2)}\varepsilon_t, \tag{6.8}$$

where $\varepsilon_t \sim N(0,1)$. For simplicity, we set the serial correlation parameter $\rho = 0$. In other words, we assume that the income of the population is distributed log-normally.

We use two different coefficients of variation $\sigma \in \{0.29, 0.3\}$. A jump in σ represents an exogenous shock in inequality. We simulate our results first with $\sigma = 0.29$ and then change it to 0.3. After that we compare the results.[7]

Changing σ from 0.29 to 0.3 has the desired two effects: an increase in the expected value and an increase in the variance of the labor endowment shocks. To be more precise, the expected values with different σ are $\mathbb{E}(\ell|\sigma = 0.29) = 1.0428$ and $\mathbb{E}(\ell|\sigma = 0.3) = 1.0459$, whereas the variances are $(\ell|\sigma = 0.29) = 0.0938$ and $(\ell|\sigma = 0.3) = 0.1012$. That is, our generated inequality shock has relatively greater effect on the variance of the labor endowment rather than the expected value. The change is depicted in Figure 6.1.

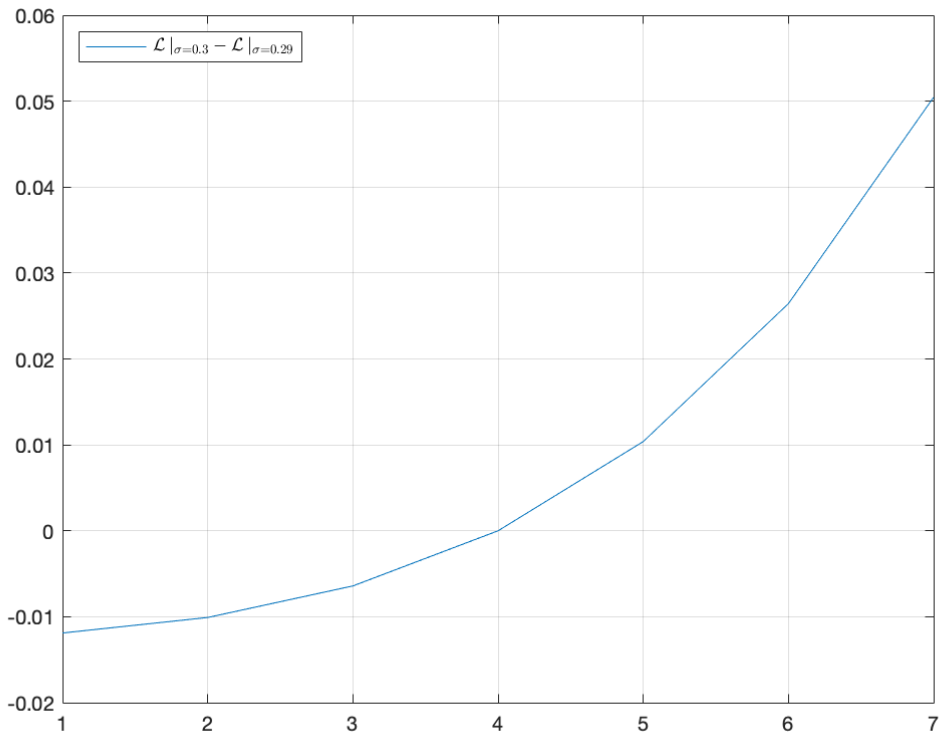


FIGURE 6.1 Change in labor endowment for states $1, 2, \ldots, 7$ after an inequality shock

Our aim is to find out how the aggregate output and capital are affected by a change in σ with different capital shares of income. In order to do so, we use the

[7] More description about the Markov chain approximation and discussion about the labor endowment shock can be found from Aiyagari (1994).

Cobb-Douglas production function $f(k_t, n_t)$ with the capital share parameter α. For simplicity we normalize the labor force to unity and assume it constant over time. We hence need to study only the changes in the aggregate capital to get the reactions of the output as well. Results are reported for five different values of $\alpha \in \{0.1, 0.2, 0.3, 0.4, 0.5\}$. The capital depreciates at rate $\delta = 0.08$.

The asset grid is discrete $\mathcal{A} = \{A_1, A_2, \ldots, A_n\}$ with $A_1 \in \{0, 0.5, 1.0, 1.5, 2.0\}$, $A_n = 50$, and $n = 500$. We thus compare the results with five different credit constraints.

The stationary distribution λ solves

$$\lambda_{t+1}(a_{t+1}, \ell_{t+1}) = \sum_{\ell_t \in \mathcal{L}} \sum_{\{a_t : a_{t+1} = g(a_t, \ell_t)\}} \lambda_t(a_t, \ell_t) P(\ell_t, \ell_{t+1}) \tag{6.9}$$

for all $a_{t+1} \in \mathcal{A}$ and all $\ell_{t+1} \in \mathcal{L}$, where $P(\ell_t, \ell_{t+1})$ is the transition probability from labor endowment ℓ_t to ℓ_{t+1} given by the Rouwenhorst method. The stocks of aggregate capital and consumption are given by

$$k = \sum_{i=1}^{n} \sum_{j=1}^{s} \lambda(A_i, L_j) g(A_i, L_j) \tag{6.10}$$

$$c = \sum_{i=1}^{n} \sum_{j=1}^{s} \lambda(A_i, L_j) c(A_i, L_j). \tag{6.11}$$

The firm's first-order condition gives us the (inverse) demand curve for capital r = $D_\alpha(k) = \alpha k^{\alpha-1} - \delta$. This is s decreasing function in capital and increasing in α since

$$\frac{\partial}{\partial k} D_\alpha(k) = \alpha(\alpha - 1) k^{\alpha-2} < 0 \qquad \text{for all } \alpha \in (0, 1) \tag{6.12}$$

$$\frac{\partial}{\partial \alpha} D_\alpha(k) = k^{\alpha-1}(1 + \alpha \log(k)) > 0 \qquad \text{for all } \alpha \in (0, 1) \text{ and } k > 1. \tag{6.13}$$

The inverse demand curve approach infinity as k goes to zero, and tends to $-\delta$ as k goes to ∞.

The aggregate capital is given by $k = \sum_{i=1}^{n} \sum_{j=1}^{s} \lambda(A_i, L_j) g(A_i, L_j)$, where $g(A_i, L_j)$ is a function of r and w – so the optimal decision of tomorrow's capital depends on the real interest rate and the wage level. We write the (inverse) capital supply as $r = S_\alpha(k)$ which is given by the aggregate capital equation.[8] This is the same curve as Aiyagari's (1994) curve $\mathbb{E}a(r)$ given by the $\mathbb{E}a_w = \mathbb{E}\{g(a, \ell)\}$, where $\mathbb{E}\{\cdot\}$ denotes the expectation with respect to the stationary distribution. It can be shown that $\mathbb{E}a(r)$ is a continuous function of r but not necessary monotone (see Bewley (1984) and Clarida (1990)). Moreover, $\mathbb{E}a(r)$ approaches to infinity as the interest rate goes towards the rate of time preference λ. That is, $S_\alpha(k)$ is a continuous function such that $\lim_{k \to \infty} S_\alpha(k) = \lambda$. In words, if the interest rate exceeds the rate of time preference, then the households would not consume at all and accumulate an infinite amount of assets which would explode the aggregate supply as well.

[8] Note that S is also affected by α since r and w are functions of α.

Aiyagari (1994) points out an important feature of $S_\alpha(k)$ for our purposes: $S_\alpha(k)$ is always lower under uncertainty than if earnings were certain. This is due to the borrowing constraint and the infinite-horizon maximization of households. However, and interestingly, the capital supply does not decrease monotonically everywhere with uncertainty. It might be the case that an increase in the variance of the labor endowment (an increase in the income uncertainty and so an increase in income inequality) decreases $S(k)$, but also makes it more steep. This can make the original and the shifted capital supply curves to intersect at some point. This can give a rise to the opposite reactions of equilibrium capital with different capital shares of income α. This phenomenon is depicted in Figure 6.2. On the left-hand side figure a positive shock in the variance of income increases the equilibrium capital, and vice versa on the right-hand side figure.

Why and when this could be the case? First, since the households do precautionary savings, increasing the variance of the labor endowment increases the savings in each asset level. However, due to the increase in the expectations of the income, there is also a consumption smoothing effect: in the aggregate level households consume more and invest less.

It turns out that with low interest rate the precautionary savings effect dominates the consumption smoothing effect. Savings yield less with low interest rate and the households must save relatively much for the bad times. An increase in uncertainty then makes the households even more precautionary. In this case the capital supply increases and consequently the equilibrium capital is greater after an inequality shock than before. This appears as a shift in the supply curve $S_\alpha(k)$ to the right in Figure 6.2.

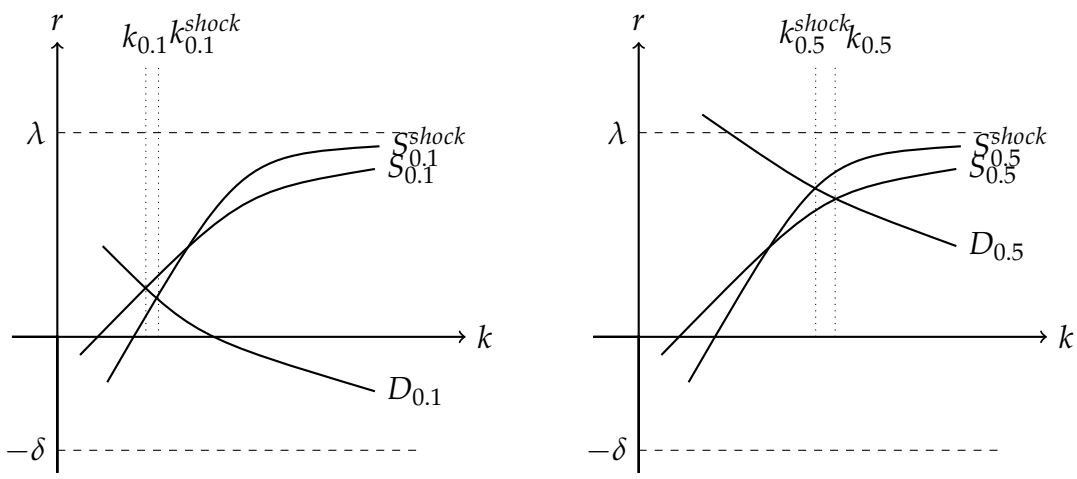


FIGURE 6.2 Equilibria in Capital Market with $\alpha \in \{0.1, 0.5\}$.

As for high interest rates, the consumption smoothing effect dominates the precautionary motives. This is due to the fact that now the assets yield good returns and a lower increase in savings compensate easily the increased uncertainty. Then the increased expectations about the future income makes the households to consume more rather than save. Consequently, the aggregate capital supply decreases with high interest rates.

Putting these two stories together, an inequality shock shifts the capital supply curve to the left and makes it more inelastic. Since this has no impact on the capital demand, we observe different equilibrium outcomes with different production functions after an inequality shock.

Consider first a case in which the capital share of income is high (e.g. α = 0.5). Now the capital is efficient in production and the demand of it is high. Then a positive inequality shock has a negative effect on the equilibrium capital level since the consumption smoothing effect is dominant. However, with a small capital share of income (e.g. $\alpha = 0.1$) this effect is positive. This is due to the fact that the precautionary savings effects are dominating. This exact possible scenario is illustrated in Figure 6.2.

The aggregate output is given based on the aggregate capital by the production function as $y = k^{\alpha}$, and consequently, reacts to the same direction as capital. We simulate the effects of the inequality shock on the output. The results are given for five different credit constraints $A_1 \in \{0, 0.5, 1.0, 1.5, 2.0\}$.

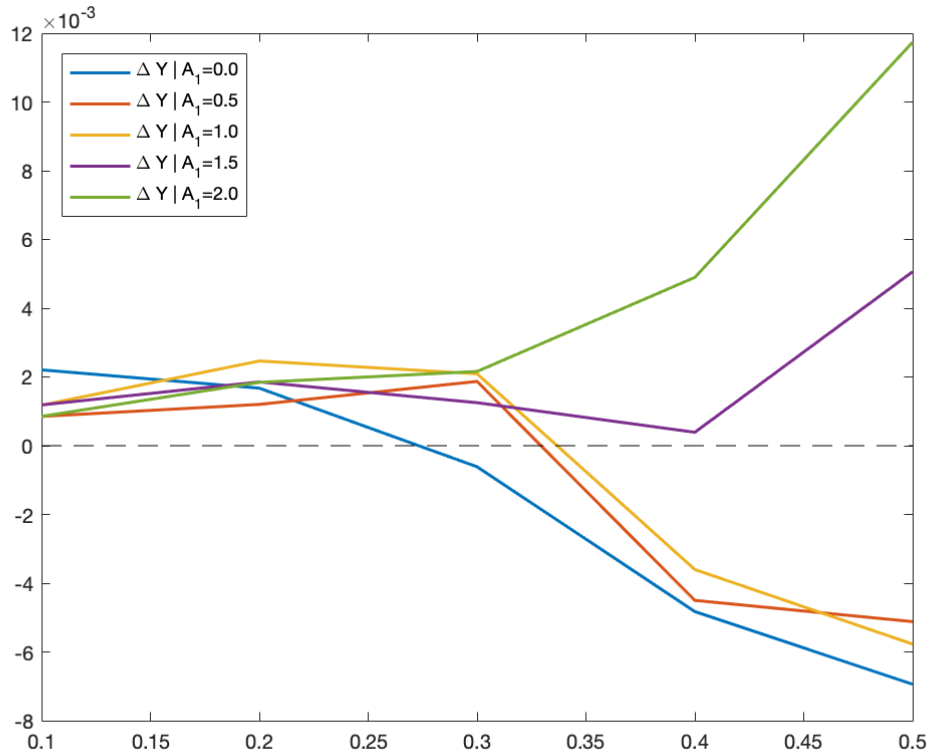


FIGURE 6.3 Simulated reaction of the aggregate output on a positive inequality shock with $\sigma \in \{0.29, 0.30\}$, $A_1 \in \{0, 0.5, 1.0, 1.5, 2.0\}$.

Figure 6.3 depicts the results of simulations by showing the difference between the equilibrium output (y) with $\sigma = 0.29$ and $\sigma = 0.30$. We observe that once we increase the credit constraint the negative change in output disappears. This is due to the fact that the greater the credit constraint, the weaker the consumption smoothing effect; the households cannot utilize the increased

income in consumption because of the binding credit constraint. Consequently, the precautionary savings effect dominates. This results in a situation where a positive inequality shock has *always* a positive impact on output for all $\alpha \in \{0.1, 0.2, 0.3, 0.4, 0.5\}$.

The equilibrium outcomes with $\sigma \in \{0.29, 0.30\}$ are reported in Appendix 6.A.1 in Tables 6.2 and 6.3. From there we observe that the income Gini coefficient is 0.159 with $\sigma = 0.29$ and 0.165 with $\sigma = 0.3$. The wealth Gini coefficients increase in α and are greater than the income coefficients. For instance, with $\alpha = 0.5$ and $\sigma = 0.29$ the wealth Gini coefficient is 0.307, whereas with $\sigma = 0.29$ it is 0.311. The model is thus qualitatively consistent with the income and wealth distributions: the wealth distribution is more dispersed than the income distribution, and the Gini coefficient is significantly higher for wealth than for income. However, which is a well-known feature of Aiyagari (1994) model, it does not generate empirically plausible relative degrees of inequality.

6.4 Empirical analysis

In this section, we present the results from our empirical analysis. Based on our theoretical model, we have two empirically testable hypotheses. First, we investigate whether the association between changes in income inequality and subsequent economic growth is i) positive when the capital share of total national income is low, and ii) negative when the capital share is high. Second, given that we find empirical support for the first hypothesis, we examine whether it fails to hold during eras of low financial development, i.e. when the credit constraint is binding, using the language of our theoretical model.

When drawing comparisons between our theoretical and empirical results, it is noteworthy that an Aiyagari (1994) type economy is a closed one while the countries in our sample have allowed for capital flows across national borders. However, domestic investment and savings tend to be highly correlated (see Feldstein and Horioka (1979) for seminal work on the topic), and consequently, we feel comfortable using our theoretical and empirical analyses as complements to one another.

Our analysis builds on a database compiled by Bengtsson and Waldenström (2018) and we adopt a standard panel growth regression approach (data and empirical approach presented in Section 6.4.1). To complement our baseline specification (reported in Section 6.4.2), we experiment with various alternative specifications to ensure the robustness of our findings (Section 6.4.3), and address the role of credit constraint (Section 6.4.4). As we discussed in the derivation of our theoretical model, we seek to explain how economic growth relates to income inequality conditional on the functional income distribution. Rather than examining the drivers of inequality, we make use of the variation in the distributional measures in a set-up that follows the previous empirical inequality-growth studies.

6.4.1 Data and empirical approach

For data on functional income distributions and income inequality, we resort to a study by Bengtsson and Waldenström (2018), who build on the work of Piketty and Zucman (2014). The authors not only provide lengthy time series for 21 countries but also examine the correlation between capital shares of total national income and the income shares of the top earners in a subset of 16 countries. Using the same data, Bengtsson et al. (2020) studied the association between capital shares and political and institutional changes. The data set, in which the coverage varies across countries (see Table 6.4, Appendix 6.A.2), contains capital shares both gross and net of capital depreciation and the top income shares for the highest-earning top 10 %, top 1% and top 0.1 %.

We focus on a group of 13 developed countries instead of the 16 that Bengtsson and Waldenström (2018) analyzed. The reasons for this are, first, that the process of economic development in Argentina was substantially different from the other countries during the twentieth century and thus, we feel more comfortable pooling the data when Argentina is excluded. Second, for Ireland and Spain, the data coverage is remarkably worse than for the remaining 13 countries. Consequently, the countries included are Australia, Canada, Denmark, Finland, France, Germany, Japan, Netherlands, New Zealand, Norway, Sweden, the United Kingdom and the United States.

In our analysis, we prefer the capital shares net of capital depreciation over the gross shares. Bengtsson and Waldenström (2018) point out that even though the net share is the appropriate "who gets what" measure, the capital depreciation rates need to be estimated, which adds an additional layer of uncertainty to the data. We also experiment with the gross shares to ensure that the results are not driven by patterns in depreciation rates.

Another measurement issue is the estimation of labor income of self-employed workers, whose income is not decomposed into labor and capital compensation in national income accounts and is therefore not directly observable. Bengtsson and Waldenström (2018) assume that one third of the self-employed incomes are capital income while the rest is assigned to labor income, which has been a typical solution for the issue.[9]

Data on the income shares of total national income come from the World Inequality Database (previously the World Top Incomes Database). The data are constantly improving on both quality and coverage and are freely available on-

[9] Gollin (2002) finds that as the labor income of the self-employed was often treated as capital income, the variation in the labor income shares between rich and poor countries seemed to be an artifact of misleading statistical procedures. More careful approach on the self-employed workersâ incomes results in labor shares ranging between 0.65 and 0.80, whereas the naïve shares lie between 0.05 and 0.80. In the US, the headline measure of the labor share has relied on the assumption of equal wages for self-employed and payroll-employed. However, the data on recent evolution between the wages of these two groups reveals that the assumption is violated and roughly one third of the fall in the labor shares can be attributed to the dubious baseline measure (Elsby et al., 2013).

line.[10] The top 1 % income shares outperform the top 10 % and the top 0.1 % in coverage and since the highest-earning percentile has been "the income bracket" in public debate and previous studies on income inequality, it rightfully earns its place as the preferred variable in this study. However, we also make use of the the top 10 % and the top 0.1 % to investigate the sensitivity of our results to alternative definitions of the top income shares. The income shares are calculated before taxes and transfers, and they are based on annual tax returns and the methods to construct the income shares emphasize long-run comparability. To our understanding, no other data source would enable us to better analyze the 13 countries in our sample over the twentieth century.

The use of the top income shares has some disadvantages. First, these data only focus on the right tail of the income distribution. However, Bengtsson and Waldenström (2018) found that population-wide measures – such as the Gini coefficient – have substantially worse country-time coverage over their sample period. The top income shares are also found to track the broader measures (Leigh, 2007), which suggests that the top income shares are useful in the absence of information on the full income distribution. Moreover, it is not evident that the Gini, for example, would be the "best measure of income inequality" as it places more weight in the middle of the distribution thus effectively undervaluing the variation in the tails. Second, income inequality before taxes and transfers is different from the disposable income inequality. As our consumption, savings and investments decisions are based on the income we actually get, disposable income shares would perhaps be more suitable – or at least offer a meaningful comparison to our data – when analyzing the consequences of inequality on economic activity. Unfortunately, data that would adequately capture inequality in disposable income are not available for the same coverage as the data used in this study.

The data on per capita GDP come from the Maddison Project Dataset (Bolt et al., 2018). The time series stretch to the 19th century for many countries, and even to the Middle Ages for some, thus making it possible to evaluate economic activity in a cross-country basis over a very long run.

Following a standard convention in the previous literature, we focus on the growth of per capita GDP inside five-year non-overlapping windows. By doing so, we aim to (i) move away from a short-run scope influenced by business cycles; and (ii) mitigate the issues of missing observations and noisiness stemming from potential measurement errors in the top income share and capital share time series. The estimation sample consists of 230 total observations and includes 13–21 growth windows per country. The detailed composition is reported in Table 6.5 (Appendix 6.A.2).

Figures 6.4 and 6.5 show the evolutions of the income shares of the highest-earning percentile and capital shares when the data are averaged over the five-year windows. The variables are expressed in decimals: the sample mean for top 1 % income share, 0.104, implies that on average the highest-earning percentile received 10.4 % of the total pre-tax & pre-transfer national income; and the sam-

[10] See https://wid.world/

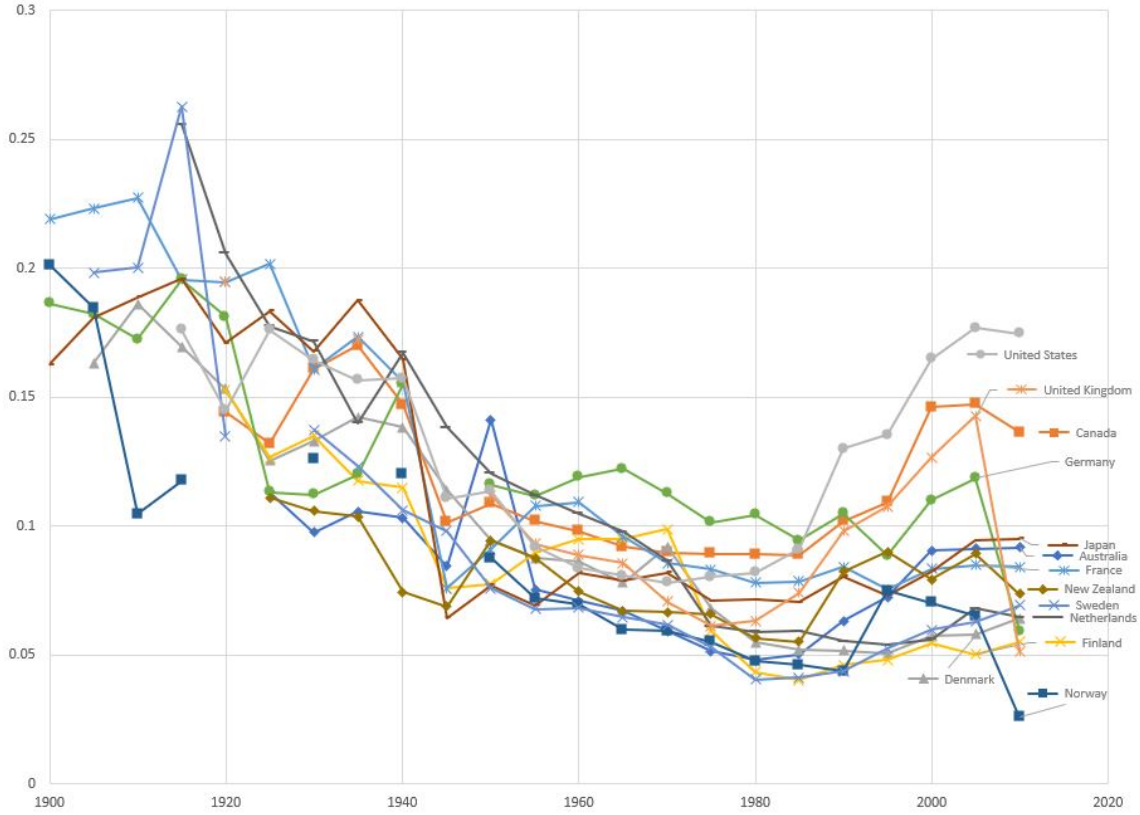


FIGURE 6.4 Top 1 % income share, five-year non-overlapping windows

ple mean for capital share, 0.261, indicates that the capital income on average constituted 26.1 % of the total national income, while 73.9 % was labor income.

Both figures depict a U-shape, which is more distinctive for the top income shares. The relative incomes of the best-paid individuals declined in all countries between the early twentieth century and 1950, whereas since the 1980s, countries such as Canada, the United Kingdom and especially the United States have experienced substantial increases in the top income shares. Among the rest of the countries, the shares have remained at low levels or risen less dramatically. Although there is a noticeable dip in the capital shares roughly between 1960 and 1980 in many countries, the evolutions of functional income distribution show more cross-country heterogeneity than the ones of personal income distribution. Thus, categorization of countries or identifying common time trends is not as evident as for the top income shares.

The descriptive statistics on growth of per capita GDP and the distributional measures are summarized in Table 6.6 (Appendix 6.A.2). Our sample countries experienced the highest average rates of economic growth during the decades after the Second World War (1950–1980 in Table 6.6). During this 30-year period, none of the economies we analyze shrunk during any five-year growth window. The smallest and largest window-to-window growth rates were experienced during the turmoil of the first of half of the twentieth century.[11] For the distributional

[11] Note that we investigated also the sensitivity of our results to these extreme values by dropping them from the analysis as one of our robustness checks.

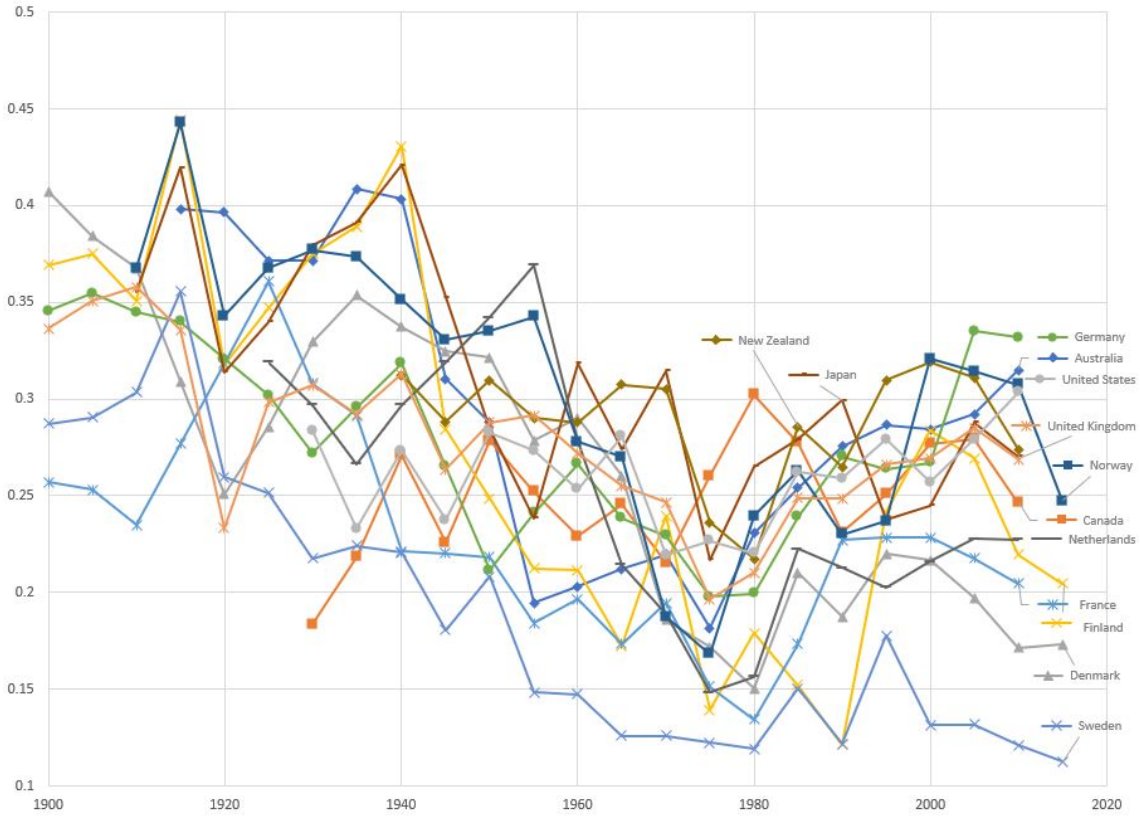


FIGURE 6.5 Capital share, five-year non-overlapping windows

measures, Table 6.6 depicts similar evolutions as Figures 6.4 and 6.5. Interestingly, in average terms, the top 1 % shares were at lower levels during the period 1985–2010 than during the post-WWII decades despite the recent substantial increases in the top income shares in some of the countries in our sample (namely Canada, the UK and the US).

As the first step to examine the relationship between economic growth, top income shares and capital shares, we plot the observations in a three-dimensional illustration (Figure 6.8, Appendix 6.A.2). We also fit a regression plane to the data based an a pooled least squares regression, where the growth of per capita GDP is regressed on contemporaneous income share of the top 1 % income and capital shares. Clearly, the simple correlation between economic growth and top 1 % income share is negative as the plane is down-ward sloping towards high values of top income share. The most obvious source of bias is that poorer countries tend to be more unequal and simultaneously, due to growth convergence, have higher growth rates of per capita GDP. The plane also tilts slightly towards high values of capital share indicating that the contemporaneous correlation between growth and capital share is modestly negative.

Our main results are based on the following panel growth regressions. Namely, we regress per capita growth on income inequality ($Top1$) and functional income distribution (α, we adopt the notation from the theoretical model):

$$\frac{1}{4}(lnY_{i,t+4} - lnY_{i,t}) = \beta_1(\frac{1}{5}\sum_{j=0}^{4} lnY_{i,t-5+j}) + \beta_2(\frac{1}{5}\sum_{j=0}^{4} Top1_{i,t-5+j}) \\ + \beta_3(\frac{1}{5}\sum_{j=0}^{4} \alpha_{i,t-5+j}) + \beta_4(\frac{1}{5}\sum_{j=0}^{4} (Top1 \times \alpha)_{i,t-5+j}) + \omega_i + \eta_t + \varepsilon_{i,t}, \tag{6.14}$$

where ω_i and η_t are the vectors of fixed country and year effects and $\varepsilon_{i,t}$ is the overall error term. $Y_{i,t}$ stands for the expenditure-side based measure of real per capita GDP in country i in year t. The inclusion of country fixed effects is motivated by cross-country comparability of the adopted data, namely, Bengtsson and Waldenström (2018) state that "most of the time series are consistent within countries, whereas the comparability across countries is lower". Thus, the empirical approach effectively relies on the variation within countries. By including the year fixed effects, we aim to control for omitted variable bias stemming from unobserved variables that have evolved over the sample period but that have been constant across countries, such as shared trends in educational attainment, openness to trade and technological change.

The logarithmic difference in $Y_{i,t}$ between two time periods corresponds to growth rate, which is annualised by $\frac{1}{4}$ when observations that are five years apart are considered. The income share of the highest-earning percentile and capital share are observed during the preceding five-year window, as is also the level of economic development. As less-developed countries tend to have higher growth rates than the developed ones, we expect that the coefficient for the "convergence term" (β_1) is negative. Consequently, the statistical specification of equation (6.14) allows us to examine whether the association between inequality and growth is dependent on the level of capital share when we control for country and year fixed effects, growth convergence and the potential direct role that functional income distribution plays in the growth process.

We have chosen the parsimonious growth regression, equation (6.14), for three reasons. First, we are unsure what other growth determinants to include in our panel regression as we do not know what the "true" regression is. As Sala-i Martin (1997) states, "A good theorist [. . .] could make almost any variable look like an important theoretical determinant of the rate of economic growth". Second, the exclusion of additional control variables is not likely to deteriorate the credibility of our results. We can capture a partial correlation rather than a causal estimate irrespective of whether we include some of the dozens of suggested growth determinants. Rather, we interpret the empirical results in terms of the model presented in Section 6.3. Third, high-quality data covering the 13 countries of the study on the potential control variables over the twentieth century are difficult to come by.

Nevertheless, to ensure that our results are not sensitive to the exclusion of widely-used control variables in growth regressions, we experiment with alternative specifications. If we include only population growth (Bolt et al., 2018) and educational attainment (Barro and Lee, 2013), we do not lose any observations.

The data on investment per GDP (Jordà et al., 2017) do not cover New Zealand and five individual windows from other countries, and consequently, the number of observations drops from 230 to 212. Proceeding sequentially, the inclusion of public debt per GDP (Jordà et al., 2017) and the sum of exports and imports per GDP (Fouquin et al., 2016), reduces the sample to 199 observations.

6.4.2 Main results

In Table 6.1, we introduce the explanatory variables of equation (6.14) sequentially. In all models, we include the level of economic development, a constant term and both country and year fixed effects. The first regression includes the log of per capita GDP inside the previous five-year period as the only explanatory variable for the growth of per capita GDP inside a five-year window (column (1)). As expected, this estimate is negative in all specifications. Column (2) presents the simple inequality-growth regression, column (3) reports the association between functional income distribution and growth, column (4) has both the top 1 % income share and capital share while column (5) matches equation (6.14) as it introduces the interaction term $Top1 \times \alpha$.

Columns (2)–(4) show that the associations between income inequality and growth and capital shares and growth are very weak in a linear form. The result of column (2) accords with Andrews et al. (2011), who found no systematic relationship between the top income shares and growth over the twentieth century. Allowing for interaction between the income share of the highest-earning percentile and capital share (column (5)) shows evidence for a richer story. The coefficients are individually and jointly statistically significant suggesting that the association between growth and top 1 % income share is positive under low capital share. Compatible with the predictions of our theoretical analysis, the positive association becomes smaller as capital share increases and turns negative after capital share reaches a value 0.281 (28.1 %)

To illustrate the magnitude of our main finding (Table 6.1, column (5)), let us consider capital share at the first and third quartile in our sample, 0.217 and 0.302, respectively.[12] At the first quartile, one percentage point (pp) increase in the top 1 % income share during a given five-year period is associated with 0.14 pp higher annual growth of per capita GDP during the following five-year window. At the third quartile, the same increase in the top 1 % share is associated with 0.04 pp lower annual economic growth. Using a standard deviation change in the top 1 % (0.043 or 4.3 % as a percentage share) corresponds to 0.59 pp higher annual growth at the first quartile and 0.19 pp lower annual growth at the third quartile. Given that the average annual growth rate in our sample over the full period was roughly 2 %, the empirical association we discover is sizable.

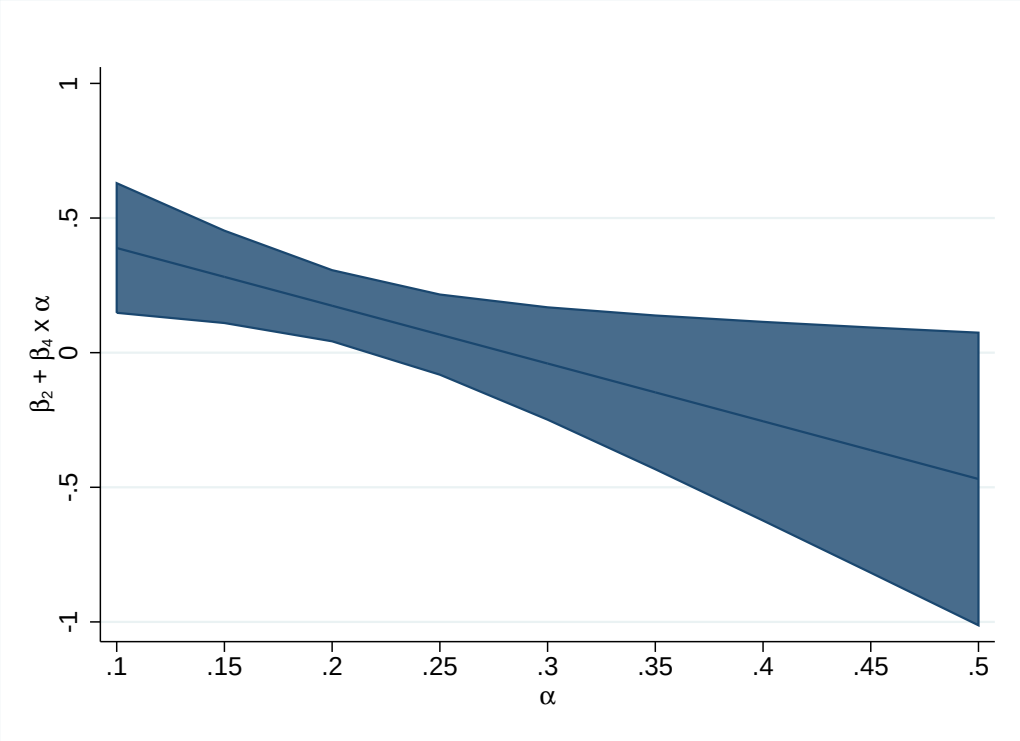
[12] To clarify, 25 % of the sample values are below 0.217, whereas 25 % of the sample values are above 0.302.

TABLE 6.1 Top 1 % income share, capital share and the subsequent growth of per capita GDP

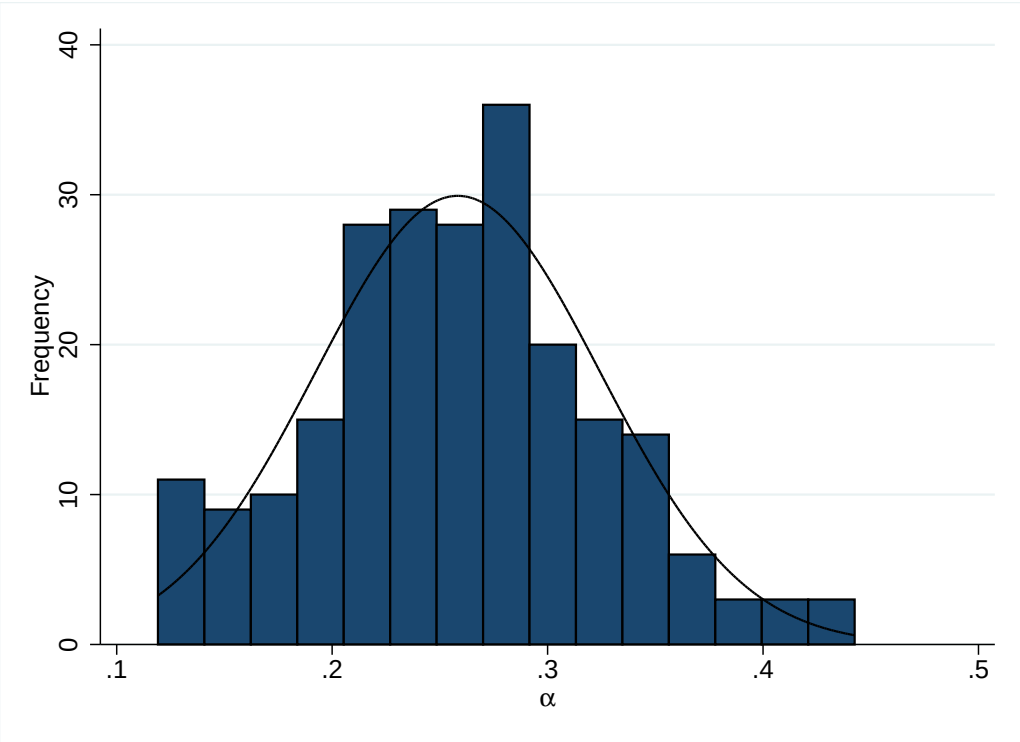
Fixed effects panel regression, column (5) corresponds to equation (6.14). Growth of per capita GDP inside a five-year non-overlapping window as the dependent variable, explanatory variables observed during the previous window. Year fixed effects included. Null hypotheses for tests of joint significance: the coefficients are not jointly significant.

	(1)	(2)	(3)	(4)	(5)
Initial lnY (β_1)	-0.0359***	-0.0360***	-0.0371***	-0.0370***	-0.0387***
	(0.0080)	(0.0079)	(0.0087)	(0.0085)	(0.0064)
$Top1$ (β_2)		-0.0217		0.0112	0.6032**
		(0.1044)		(0.1101)	(0.2073)
α (β_3)			-0.0797*	-0.0808*	0.1554
			(0.0402)	(0.0429)	(0.1034)
$Top1 \times \alpha$ (β_4)					-2.1448**
					(0.9307)
Constant	0.3291***	0.3334***	0.3641***	0.3623***	0.3169***
	(0.0684)	(0.0654)	(0.0803)	(0.0747)	(0.0629)
Joint significance of $Top1$ and α (p-value)				0.1818	
Joint significance of $Top1$ and $Top1 \times \alpha$ (p-value)					0.0233
Joint significance of α and $Top1 \times \alpha$ (p-value)					0.0390
Joint significance of $Top1$, α and $Top1 \times \alpha$ (p-value)					0.0488
R-squared	0.3387	0.3390	0.3521	0.3521	0.3869
Observations	230	230	230	230	230
Number of countries	13	13	13	13	13

Robust standard errors in parantheses. *, ** and *** indicate statistical significance at 10 %, 5 % and 1 % levels, respectively



(a) The association between growth of per capita GDP and top 1 % income share conditional on capital share (point estimate and 95 % confidence interval), β_2 and β_4 correspond to equation (6.14)



(b) Distribution of capital share in the estimation sample

FIGURE 6.6 Top 1 % income share, capital share and the subsequent growth of per capita GDP

Although Table 6.1 suggests that the association between the top income shares and subsequent growth of per capita GDP depends on how total national income is divided between capital and labor, the result is difficult to interpret in terms of different capital share values. To improve on the interpretation, we introduce a graphical illustration, where the reduced-form estimate for the top 1 % income share on growth ($\beta_2 + \beta_4 \times \alpha$) is on the vertical axis and values of the capital share (α) are on the horizontal axis (Figure 6.6a). In addition to the point estimate, 95 % confidence interval is included. This enables us to draw statistical inference on the interactive part of our specification far better than using regression tables. Furthermore, as the distribution of the conditioning variable is essential for the interpretation, we include a histogram for the sample values of capital share below the interaction plot (Figure 6.6b).

The interaction plot illustrates the main findings of Table 6.1, column (5): a down-ward sloping profile emerges as a function of β_2, β_4 and α. Moreover, the association between the top 1 % income share and growth is positive and statistically significant under low values of capital shares. As the histogram shows, the results are meaningful in terms of sample values. The point estimate line crosses zero (0.281) remarkably close to the sample mean of capital share (0.261) and roughly one quarter of the capital share values are below the cut-off, where the lower bound of the confidence interval starts to take positive values in Figure 6.6a.

The main empirical finding, i.e. the down-ward sloping line in Figure 6.6a, is compatible with the theoretical analysis of Section 6.3. Thus, we have shown the conditionality of the inequality-growth nexus to functional income distribution i) in a simple conceptual framework of capital market equilibria, ii) by simulating our theoretical model, and iii) empirically. It is worth emphasizing that i) and ii) stem from the seminal study by Aiyagari (1994): we simply adopt a novel perspective to the model in our analysis.

More precisely, the link between Figure 6.6a and the theoretical predictions holds when the credit constraint is small, i.e. when A_1 is equal to or smaller than 1.0. In words while still in terms of the theoretical predictions, the credit constraint seems not to have been excessively binding when we pool the data across the 13 countries over the twentieth century. We acknowledge that the empirical counterpart to the credit constraint of our theoretical model was not constant over the sample. Thus, although data that correspond to the credit constraint of the theoretical model are difficult to come by for our sample period, below in Section 6.4.4 we do our best to investigate how variation in the credit constraint, i.e. financial development, affects our empirical results. We believe that this is important since our theoretical results stress the importance of parameter A_1.

6.4.3 Robustness

Next, we estimate a number of different econometric specifications to verify the robustness of our results. These analyses are reported in Appendix 6.A.3 via interaction plots in a similar spirit to Figure 6.6a.

Potential dependency to the level of inequality rather than to capital income share. The linkages between functional and personal income distributions have been widely-studied (see Section 6.2), and previous studies clearly indicate that capital shares and top income shares tend to move together over time. Thus, our first robustness check relates to the notion that perhaps we are capturing the dependency of the inequality-growth relationship to the level of total income inequality rather than to the division of income between capital and labor. We investigate this by introducing the following panel regression:

$$\begin{aligned}\frac{1}{4}(lnY_{i,t+4} - lnY_{i,t}) = \beta_1(\frac{1}{5}\sum_{j=0}^{4} lnY_{i,t-5+j}) + \beta_2(\frac{1}{5}\sum_{j=0}^{4} Top1_{i,t-5+j}) \\ + \beta_3(\frac{1}{5}\sum_{j=0}^{4} Top1^2_{i,t-5+j}) + \omega_i + \eta_t + \varepsilon_{i,t},\end{aligned} \tag{6.15}$$

where we let the association between the top 1 % total income share and growth of per capita GDP to depend on the level of top 1 % share. Otherwise, the notation follows equation (6.14) and there are no changes in the sample. Figure 6.9 clearly shows that our main findings cannot be explained by dependency to the level of inequality. This result further strengthens our main finding about the role of functional income distribution for the inequality-growth relationship.

The inclusion of additional variables as controls. The inclusion of control variables is not straightforward as, with the distributional measures already narrowing the coverage, we have a small sample for our empirical analysis. Consequently, we prefer not to narrow the data and present results corresponding to equation (6.14), Table 6.1 and Figure 6.6a as our main findings. Yet, Figure 6.10 shows that our finding remains when we include a set of additional variables, for which we have data for, into our regression.[13]

Excluding the extreme growth rates of per capita GDP. Our sample period includes the turmoil of the early twentieth century, the Great Depression and the two World Wars. These periods were characterized by volatile growth rates of per capita GDP even if we focus on five-year non-overlapping windows (Table 6.6),

[13] For the model that corresponds to Figure 6.10a, the data on population growth is obtained from the Maddison project dataset (Bolt et al., 2018) and it is measured as an average over the preceding growth window, whereas the data source for average total years of education contains observations for every five years (Barro and Lee, 2013), and consequently, educational attainment is observed at $t-5$. For Figure 6.10b, we have the two previous variables and investment per GDP ratio (measured as an average over the preceding growth window) taken from Jordà et al. (2017). Finally, for Figure 6.10b, we further introduce two additional controls, which are both measured as averages over the preceding growth window: public debt to GDP ratio is taken from Jordà et al. (2017) while the data on the ratio of trade to GDP come from Fouquin et al. (2016). The underlying model for Figure 6.10a relies on the same sample as our previous analysis (230 total observations), whereas the models for Figures 6.10b and 6.10c are estimated using 212 and 199 observations, respectively.

which might obscure our results. To evaluate whether our results are driven by this exceptional variation, we re-estimate our model by excluding these extreme growth rates (bottom and top 5 % of the observed growth rates are dropped for Figure 6.11a, whereas Figure 6.11b excludes the 10 % tails). The slopes of the profiles now become slightly more gradual than the slope in Figure 6.6a and the confidence intervals are much tighter around the point estimate lines. We conclude that the main result is not sensitive to whether we include the extreme observations or not.

Top 10 % and top 0.1 %. Our next robustness check utilizes alternative top income shares. The data compiled by Bengtsson and Waldenström (2018) enables us to use the top decile and top 0.1 percentile in addition to the top percentile with the costs of using only slightly smaller sample size. For top 10 %, we lose 13 observations from Finland and some from Australia, Canada, Germany and Japan. For top 0.1 %, we lose all observations from Finland and some from Germany, Netherlands, New Zealand, Norway and the United Kingdom. To ensure a meaningful comparison, we use a sample of 12 countries & 187 observations that includes information of all three measures. Moreover, to facilitate comparison, we use log transformations of the top income shares.

Figure 6.12 shows that the main result is qualitatively similar between the different definitions for top income shares. However, the slopes of the profiles differ: it is relatively steep for top 10 % (Figure 6.12a), moderate for top 1 % (6.12b) and gradual for top 0.1 % (6.12c). Thus, it seems that the magnitude of the mechanism uncovered in this study depends on how close we zoom to the right tail of the income distribution.

The role that the division of income between capital and labor plays on the growth-consequences of inequality seems to loose its importance at the very high-end of the income distribution. In other words, functional income distribution becomes less important for the inequality-growth relationship. In terms of our theoretical analysis, the mechanism driven by precautionary saving motives decreases the higher we zoom into the income distribution.

Capital shares gross of capital depreciation. We also have information on capital shares gross of capital depreciation (Bengtsson and Waldenström, 2018). The sample remains identical to the main analysis (Table 6.1 and Figure 6.6), and the similarity between Figures 6.6a and 6.13a shows that our findings are not sensitive to how capital depreciation is addressed.

Addressing dependency to both the extent of inequality and capital share. Next, we examine the sensitivity of our results to the extent of inequality by allowing for different coefficients at the top ($t50$) and bottom half ($b50$) of the distribution for the top 1 % income share:

$$\frac{1}{4}(lnY_{i,t+4} - lnY_{i,t}) = \beta_1(\frac{1}{5}\sum_{j=0}^{4} Y_{i,t-5+j}) + \beta_2^{t50}(\frac{1}{5}\sum_{j=0}^{4} Top1_{i,t-5+j}^{t50})$$
$$+ \beta_2^{b50}(\frac{1}{5}\sum_{j=0}^{4} Top1_{i,t-5+j}^{b50}) + \beta_3(\frac{1}{5}\sum_{j=0}^{4} \alpha_{i,t-5+j}) + \beta_4^{t50}(\frac{1}{5}\sum_{j=0}^{4}(Top1^{t50} \times \alpha)_{i,t-5+j})$$
$$+ \beta_4^{b50}(\frac{1}{5}\sum_{j=0}^{4}(Top1^{b50} \times \alpha)_{i,t-5+j}) + \omega_i + \eta_t + \varepsilon_{i,t}, \tag{6.16}$$

where the notation follows equation (6.14) again. In all specifications, we fail to reject the null hypothesis of equality of coefficients between the top-half and bottom-half data. The interaction plots (Figure 6.14) also show that our main results are independent of the top-bottom distinction.

Average annual growth instead of annualized growth. In equation (6.14), the growth of per capita GDP is defined as the growth from year t to year $t+4$ after which the growth rate is annualized. To examine the sensitivity of our results to the definition of growth rates, we replicate our analysis by using average annual growth rates inside the corresponding five-year window. Since we do not wish to mix information from different windows[14], we use annual rates from $t+1$ to $t+4$. The resulting growth rates are unsurprisingly more volatile than the preferred ones. Despite the added variation, our main findings hold. In fact, the confidence intervals around the familiar down-ward sloping profiles become slightly narrower especially for high values of α (Figure 6.15).

Different panel estimators. In addition to the fixed effects estimator, we also consider two other standard panel estimators, the random effects (RE) and the pooled OLS (POLS). RE and POLS do not control for the time invariant country-specific unobserved characteristics. Consequently, they make use of variation both in time and between countries. Figure 6.16 verifies our original results. Moreover, we also estimated the FE, RE and POLS models without the year dummies and / or the linear capital share term ($\beta_3(\frac{1}{5}\sum_{j=0}^{4}\alpha_{i,t-5+j})$), and the main finding holds.

Nowadays, the reduced-form panel studies typically rely on GMM estimates, which are used to control for the bias in dynamic panels with relatively few observations (Nickell bias), reverse causality and omitted variables. For our panel, this class of estimators are ill-suited as they tend to run into over-identification issues when the number of countries is small relative to the number of time periods. Moreover, the dynamic panel bias diminishes with the number of time periods.

[14] The growth rate at year t would not be independent of $t-1$ because the rate is calculated as $lnY_{i,t} - lnY_{i,t-1}$.

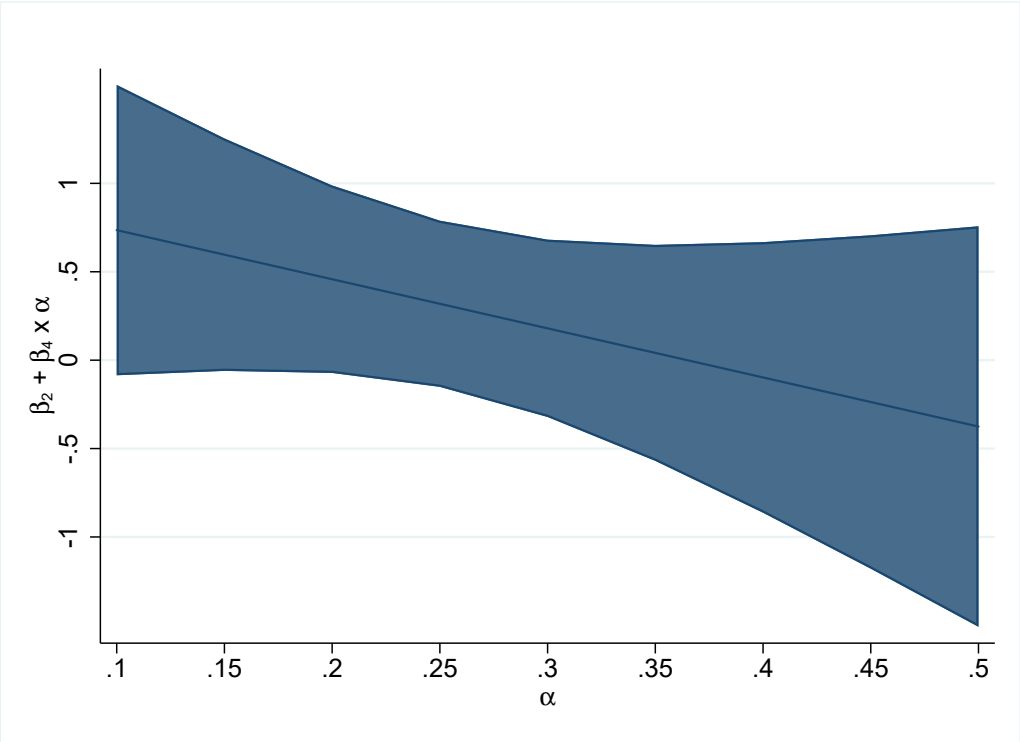
6.4.4 The role of financial development

Our baseline empirical model, equation (6.14), enables us to trace how accounting for functional income distribution affects the inequality-growth relationship. Yet, our theoretical analysis not only emphasizes the role of capital income share, α, but also shows that the results are conditional on the credit constraint, A_1. Ideally, we would investigate the role of credit constraint by augmenting our empirical specification with a proxy for credit constraint as a threshold variable, or more simply, by dividing our sample into eras or country groups characterized by "more binding" and "less binding" credit constraints. Neither of the alternatives are easy to conduct due to limited data on the measures of financial development, which are typically used as empirical counterparts to a theoretical concept of a credit constraint, due to limited sample size of our analysis in general, and due to non-homogeneous timing of changes in financial conditions.

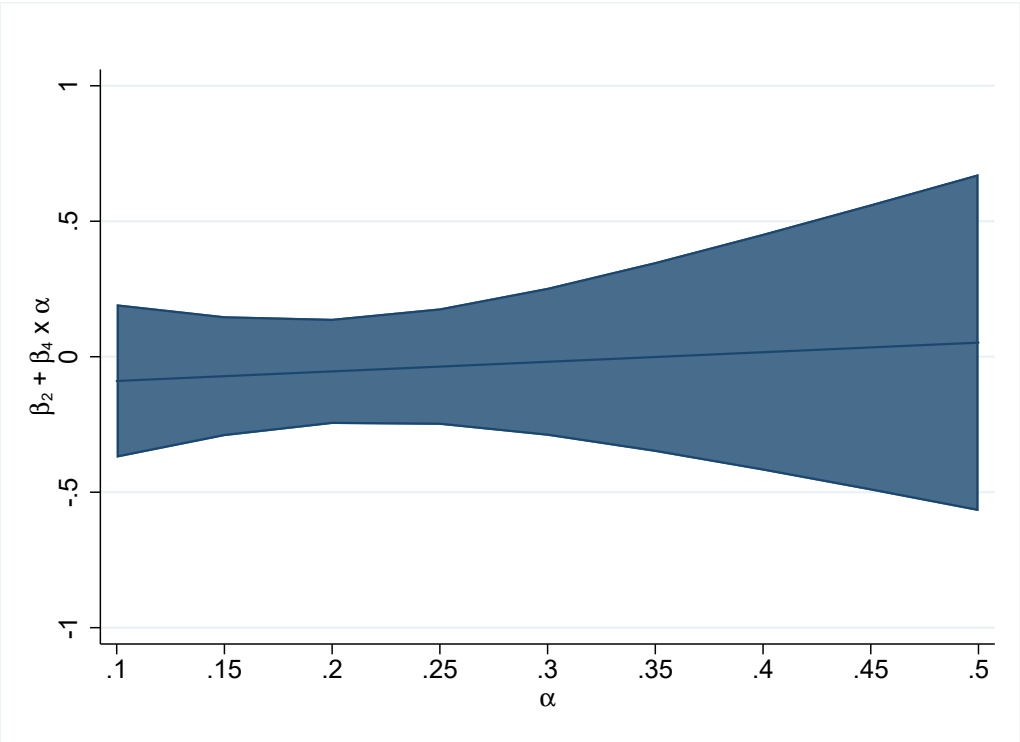
In the absence of data that would match the coverage of the time series compiled by Bengtsson and Waldenström (2018), we rely on lower frequency data from the study by Rajan and Zingales (2003), who analyze the determinants of financial development over the twentieth century. The pieces of information relevant to our study are gathered in Table 6.7 and Figure 6.17 in Appendix 6.A.4. Most measures show that financial development was at a low level during the decades after the Second World War until the 1980s among the countries in our sample. Rajan and Zingales (2003) summarize the patterns by stating that "countries were more financially developed in 1913 than in 1980 and only recently have they surpassed their 1913 levels.". Kuvshinov and Zimmermann (2019), who document that stock market capitalization per GDP ratio was relatively stable from 1870 to the early 1980s and then tripled during the 1980s and 1990s, label the recent structural shift as the big bang.

The evolutions summarized above lay the groundwork for our empirical analysis on the role of credit constraint. We split our sample into three periods, and characterize 1900–1945 and 1985–2010 as periods of high financial development, and 1950–1980 as a period of low financial development. As high financial development corresponds to low credit constraint, and vice versa, we turn our focus to the theoretical predictions of Section 6.3. First, we expect that the downward sloping profile – familiar from Figure 6.3 with low credit constraint and Figure 6.6a – will be particularly distinguishable for 1900–1945 and 1985–2010. For 1950–1980, on the contrary, we expect not to find a down-ward sloping profile between the inequality-growth association and capital share.

Similarly to the full sample (Figure 6.6a) pooling data over periods 1900–1945 and 1985–2010 (Figures 6.7a and 6.7c) displays that the association between the top income shares and growth of per capita GDP is a decreasing function of capital share, α. However, when we set our focus on the period 1950-1980, the profile is flat and indicates that the relationship between the top income shares and growth is statistically insignificant for all values of α (Figure 6.7b). These findings correspond to the patterns described by Rajan and Zingales (2003), and, to our interpretation guided by our theoretical analysis, stem from loose credit

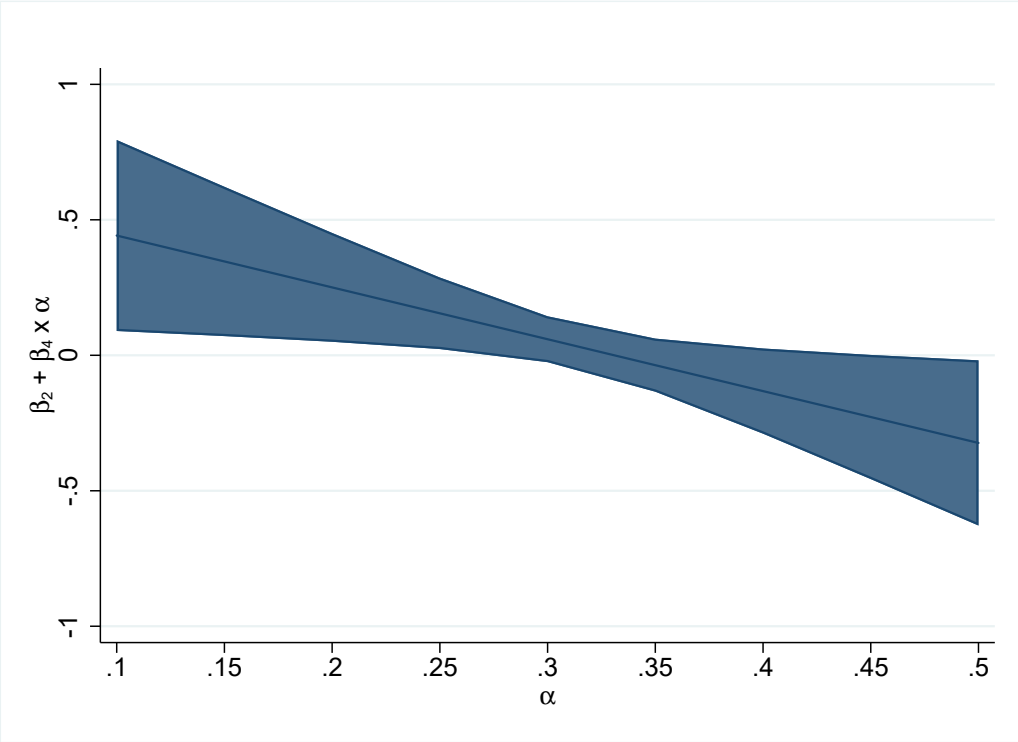


(a) 1900-1945, 67 observations



(b) 1950-1980, 88 observations

FIGURE 6.7 The association between growth of per capita GDP and top 1 % income share conditional on capital share (point estimate and 95 % confidence interval), β_2 and β_4 correspond to equation (6.14)



(c) 1985-2010, 75 observations

FIGURE 6.7 The association between growth of per capita GDP and top 1 % income share conditional on capital share (point estimate and 95 % confidence interval), β_2 and β_4 correspond to equation (6.14)

constraint during the first half of the twentieth century and between 1985 and 2010, whereas 1950-1980 was characterized by a more binding constraint.

Although Figures 6.7a and 6.7c look similar in terms of the down-ward sloping profile, there is a clear difference in the confidence intervals between the figures: the estimated association is much more precise in 1985-2010. This pattern may stem from improvements in the quality of data, or alternatively, it may represent the link between personal and functional income distributions becoming more similar across countries, and consequently, the relationship between our two distributional measures and growth can be estimated more precisely.

6.5 Conclusion

We have revealed that the division of income between capital and labor crucially affects the conclusions that we draw on how changes in income inequality are associated with subsequent growth of per capita GDP. We demonstrate this dependency both empirically and theoretically. Furthermore, we show how the interplay between the distribution of income – both personal and functional – and economic growth appears when we account for financial frictions.

Our empirical analysis relies on historical data on GDP, the capital share of

total national income and the top 1 % share of total national income. Constrained by data availability, we pool data from 13 developed countries, and following previous studies on the topic, we focus on five-year intervals. Using standard panel estimation techniques, we show that an increase in top 1 % income share is associated with higher subsequent growth of per capita GDP when capital share is low. Alternatively, under high capital share, the association between inequality and growth is negative. Our findings remained robust with respect to several tests: we included additional control variables, accounted for the level of income inequality, capital depreciation and different definitions of growth rates, excluded extreme observations, considered top 10 % and top 0.1 % shares in addition to the primarily used top 1 % and considered different panel estimation techniques.

To accompany our novel empirical finding, we make use of an established theoretical framework to demonstrate how personal and functional income distributions are connected with the accumulation of physical capital and economic growth. Both computational and capital market equilibrium analyses align with the empirical evidence, given that financial frictions are not excessive. The role of financial conditions arises from the data, too, as the inequality-growth relationship depends on the capital share during eras of high financial development, whereas this dependency is not present in the data under low financial development.

As our measure of income inequality focuses on the right tail of the income distribution, a complementary explanation for the observed empirical regularity may lie in the composition of income among the top earners. We have also entertained ideas regarding the accumulation of human capital, the potential role that new innovations play, and the labor supply decisions of households, to name some of the other potential channels. Investigating these possibilities calls for more nuanced data and different conceptual frameworks – both of which are beyond the scope of this study.

Our results should not be over-interpreted in terms of individual countries, forecasting or causality, and consequently, are not directly applicable for policy purposes. Instead, we stress the importance of our study in terms of incorporating functional income distribution into the extensive existing literature on the link between personal income distribution and overall economic activity.

6.A Appendix

6.A.1 Theoretical Equilibrium Outcomes

TABLE 6.2 Equilibrium outcomes with $\sigma = 0.29$, $\rho = 0$, and $A_1 = 0$.

y	k	c	i	n	r	w	s	α	$gini_{inc}$	$gini_w$
1.0317	1.3665	0.92092	0.1108	1	-0.0055069	0.92993	0.10739	0.1	0.15883	0.22978
1.1908	2.3948	0.99806	0.19279	1	0.018831	0.95417	0.16189	0.2	0.15883	0.24117
1.5524	4.332	1.2056	0.34682	1	0.027426	1.087	0.22341	0.3	0.15883	0.24483
2.3868	8.8016	1.6823	0.70452	1	0.028412	1.4326	0.29517	0.4	0.15883	0.28908
4.5504	20.7063	2.8927	1.6577	1	0.029799	2.2769	0.3643	0.5	0.15883	0.30774

TABLE 6.3 Equilibrium outcomes with $\sigma = 0.30$, $\rho = 0$, and $A_1 = 0$.

y	k	c	i	n	r	w	s	α	$gini_{inc}$	$gini_w$
1.0339	1.396	0.92091	0.11301	1	-0.0068116	0.93176	0.10931	0.1	0.16421	0.23077
1.1925	2.4117	0.99846	0.19406	1	0.01832	0.9554	0.16273	0.2	0.16421	0.24024
1.5518	4.3263	1.204	0.3478	1	0.027082	1.0885	0.22413	0.3	0.16421	0.25024
2.382	8.7572	1.682	0.70005	1	0.028885	1.4285	0.29389	0.4	0.16421	0.27514
4.5435	20.6432	2.8917	1.6518	1	0.030025	2.2722	0.36355	0.5	0.16421	0.31283

6.A.2 Country coverage and descriptive statistics

TABLE 6.4 Coverage of capital shares and top income shares in the original data (Bengtsson and Waldenström, 2018)

Country (ISO)	Capital share gross of capital depreciation	Capital share net of capital depreciation	Top 10 % income share	Top 1 % income share	Top 0.1 % income share
ARG	1913-2000	no data	no data	1932-1961 (3 NAs), 1970-1973, 1997-2004	1932-1961 (3 NAs), 1970-1973, 1997-2004
AUS	1911-2010	1911-2010	1941-2010	1921-2010	1921-2010
AUT	1924-1937, 1948-2010	1924-1937, 1948-2010	no data	no data	no data
BEL	1920-1939, 1960-2015	1920-1939, 1960-2015	no data	no data	no data
BRA	1920-2000		no data	no data	no data
CAN	1926-2011	1926-2011	1941-2010	1920-2010	1920-2010
DNK	1876-2015	1876-2015 (NAs for 1915-1920)	1903, 1908, 1915, 1917-1968, 1970-2010	1903, 1908, 1915, 1917-1968, 1970-2010 (1973 NA)	1903, 1908, 1915, 1917-1966, 1971-2010 (2 NAs)
FIN	1900-2015	1900-2015	1990-2009	1920-2009	no data
FRA	1900-2010	1900-2010	1900, 1910, 1915-2013	1900, 1910, 1915-2013	1900, 1910, 1915-2013

Table 6.4 continues

Country (ISO)	Capital share gross of capital depreciation	Capital share net of capital depreciation	Top 10 % income share	Top 1 % income share	Top 0.1 % income share
DEU	1891-1913, 1925-1938, 1950-2011	1891-1913, 1925-1938, 1950-2011	1891-1919, 1926, 1928, 1932, 1934, 1936, 1950, 1961, every third year for 1965-1998, 2001-2008	1891-1919, 1925-1938 (2 NAs), 1950, 1957, 1961, every third year for 1965-1998, 2001-2008	1891-1919, 1925-1938 (2 NAs), 1950, 1954, 1957, 1961, every third year for 1965-1998, 2001-2008
IRL	1938, 1944-2010	1938, 1944-2010	1938, 1943, 1975-2009	1938, 1943, 1975-2009	1922-1953, 1964-1990 (1974 NA)
JPN	1906-1940, 1953-2010	1906-1940, 1953-2010	1947-2010	1886-2010 (1946 NA)	1886-2010 (1946 NA)
NLD	1923-1938, 1949-2010	1923-1938, 1949-2010	1914-1939, 1941, 1946, 1950, 1952, 1953, 1957-1959, 1962, 1964, 1966, 1967, 1970, 1973, 1975, 1977, 1981, 1985, 1989-2012	1914-1939, 1941, 1946, 1950, 1952, 1953, 1957-1959, 1962, 1964, 1966, 1967, 1970, 1973, 1975, 1977, 1981, 1985, 1989-2012	1914-1939, 1941, 1946, 1950, 1952, 1953, 1957-1959, 1970, 1973, 1975, 1977, 1981, 1985, 1989-1999
NZL	1939-2010	1939-2010	1924-1930, 1933, 1934, 1936,1940, 1945-2010 (1961 NA)	1921-1930, 1933-1940, 1945-2010 (1961 NA)	1921-1930, 1933-1940, 1945-1989 (2 NAs)
NOR	1910-1939, 1946, 1949-2015	1910-1939, 1946, 1949-2015	1875, 1888, 1906, 1910, 1913, 1929 1948-2008 (1956 NA)	1875, 1888, 1892-1903, 1906, 1910, 1913, 1929 1938, 1948-2008 (1956 NA)	1875, 1895, 1896, 1898-1903, 1906, 1929 1938, 1948-2008 (1956 NA)

Table 6.4 continues

Country (ISO)	Capital share gross of capital depreciation	Capital share net of capital depreciation	Top 10 % income share	Top 1 % income share	Top 0.1 % income share
ESP	1900-2000	1900-2000	1981-2012	1981-2012	1954, 1955, 1957-1959, 1961, 1971, 1981-2012
SWE	1875-2015	1875-2015	1903, 1907, 1911, 1912, 1916, 1919, 1920, 1930, 1934, 1935, 1941, 1943-2012	1903, 1907, 1911, 1912, 1916, 1919, 1920, 1930, 1934, 1935, 1941, 1943-2012	1903, 1907, 1911, 1912, 1916, 1919, 1920, 1930, 1934, 1935, 1941, 1943-2012
GBR	1891-2011	1891-2011	1918, 1919, 1937, 1949, 1954, 1959, 1962-1979, 1981-2007, 2009	1918, 1919, 1937, 1949, 1951-1979 (1961 NA), 1981-2007, 2009	1913-1986 (2 NAs), 1993-2007, 2009
USA	1929-2010	1929-2010	1917-2012	1913-2012	1913-2012

Treatment of likely outliers. Setting the focus on the five-year non-overlapping windows reduces the impact of potential outliers in the time series for the top income shares and capital shares substantially. However, four suspicious cases – which all are treated by taking average of the previous and the next observation corresponding to the five-year windows – remain:

- Denmark 1915: all top income measures and both capital share measures
- Finland 1950: both capital share measures
- France 1945: both capital share measures
- Norway 2005: all top income measures and both capital share measures

The coverage of the estimation sample. The coverage (230 observations in total, 13 countries, 13-21 growth windows per country) is reported in Table 6.5.

TABLE 6.5 Estimation sample

For a given year t, the growth of per capita GDP is the annualized growth rate from t to $t+4$. The explanatory variables are averages over $t-5$ and $t-1$.

Year	AUS	CAN	DNK	FIN	FRA	DEU	JPN	NLD	NZL	NOR	SWE	GBR	USA
1900						✓							
1905					✓	✓							
1910			✓		✓	✓					✓		
1915			✓		✓	✓	✓			✓	✓		
1920			✓		✓	✓	✓			✓	✓		
1925			✓	✓	✓	✓	✓				✓	✓	
1930	✓		✓	✓	✓	✓	✓	✓					
1935	✓	✓	✓	✓	✓	✓	✓	✓		✓	✓		✓
1940	✓	✓	✓	✓	✓	✓	✓	✓			✓	✓	✓
1945	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓		✓
1950	✓	✓	✓	✓	✓		✓	✓	✓		✓		✓
1955	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
1960	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
1965	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
1970	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
1975	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
1980	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
1985	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
1990	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
1995	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
2000	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
2005	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
2010		✓	✓	✓	✓	✓		✓		✓	✓	✓	✓

TABLE 6.6 Descriptive statistics, five-year intervals

Variable	Mean	Std. dev.	Min	Max	Obs
Full sample, 1900–2010, see Table 6.5 in Appendix 6.A.2 for details					
Growth of per capita GDP	2.02 %	2.72 %	-18.93 %	12.81 %	230
Top 1 % income share	10.44 %	4.48 %	4.03 %	26.25 %	230
Capital share	26.10 %	6.70 %	11.91 %	44.25 %	230
1900–1945					
Growth of per capita GDP	1.62 %	4.43 %	-18.93 %	12.81 %	67
Top 1 % income share	15.75 %	3.63 %	7.42 %	26.25 %	67
Capital share	31.58 %	6.22 %	16.07 %	44.25 %	67
1950–1980					
Growth of per capita GDP	2.84 %	1.53 %	0.37 %	8.68 %	88
Top 1 % income share	8.61 %	1.95 %	5.13 %	14.13 %	88
Capital share	24.12 %	5.73 %	12.25 %	36.92 %	88
1985–2010					
Growth of per capita GDP	1.42 %	1.15 %	-0.95 %	4.50 %	75
Top 1 % income share	7.84 %	3.11 %	4.03 %	17.68 %	75
Capital share	23.52 %	5.21 %	11.91 %	33.51 %	75

Notes: The growth of per capita GDP correspond to annualized growth rate inside five-year windows while the top income share and capital share are averages over the five-year intervals preceding the growth windows and measure the share of total national income in percentages.

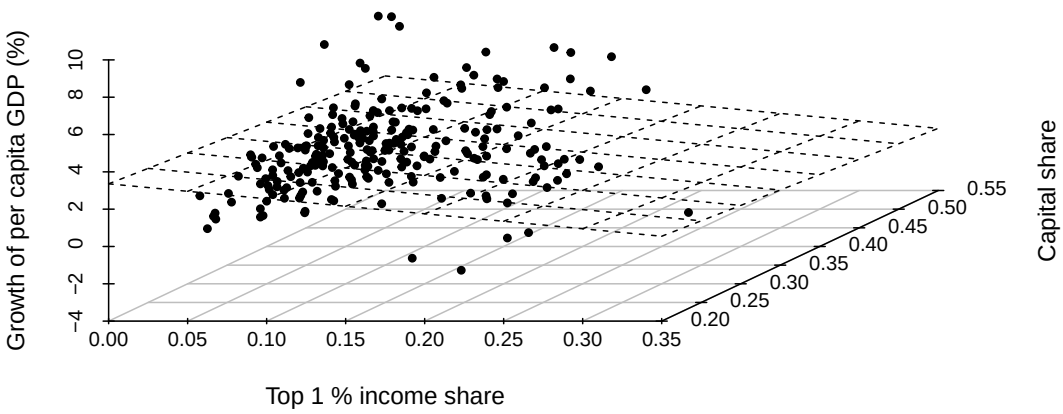


FIGURE 6.8 Pooled least squares regression plane: five-year non-overlapping windows, contemporaneous timing

6.A.3 Alternative empirical specifications

Potential dependency to the level of inequality rather than to capital share

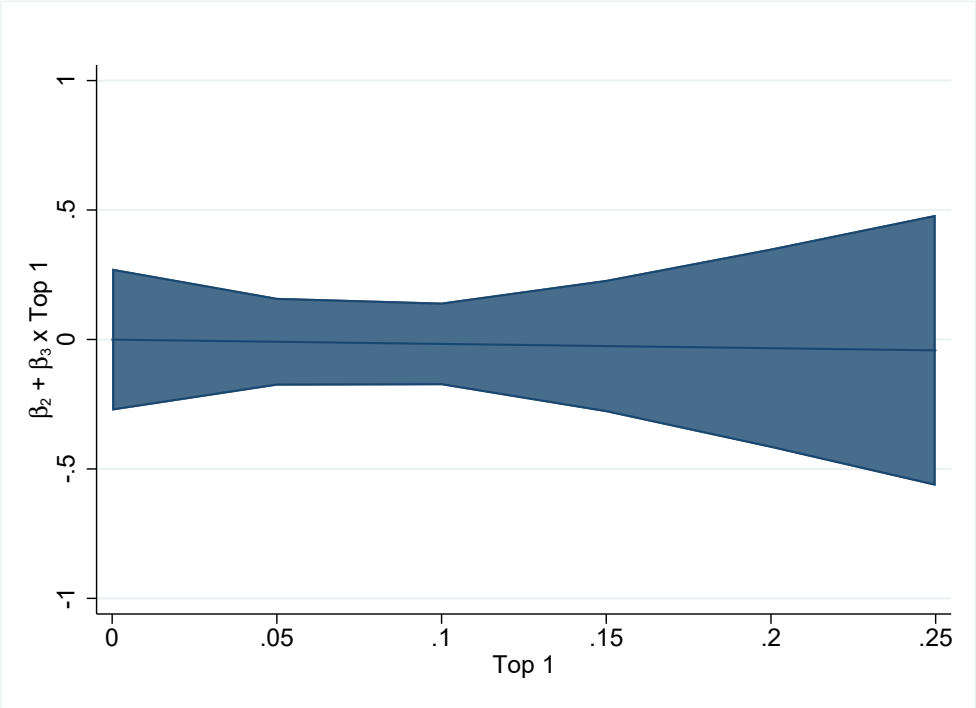
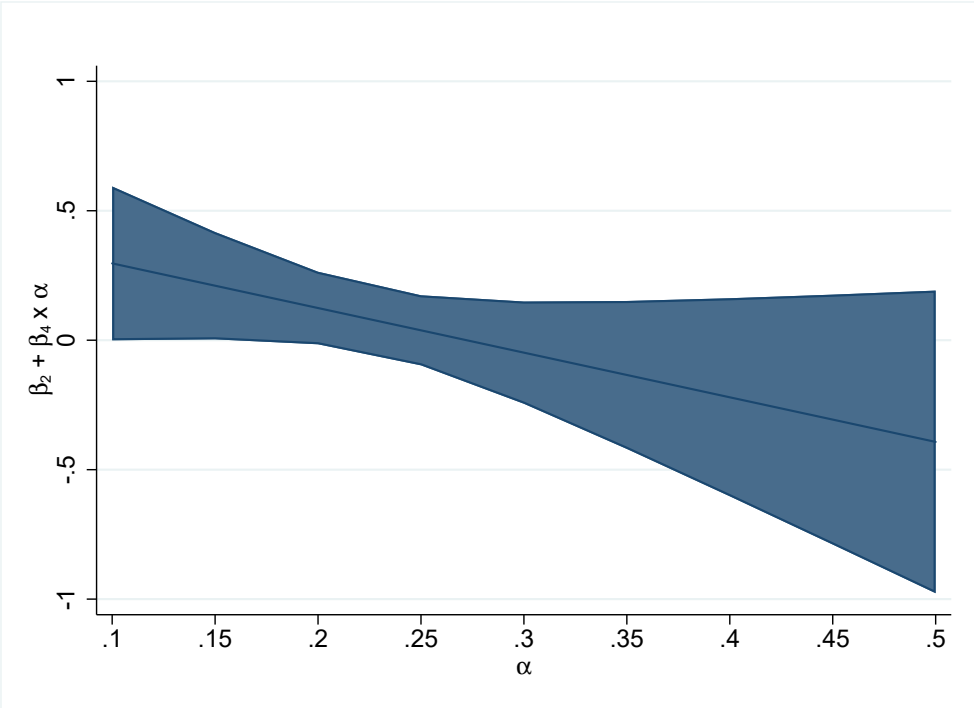
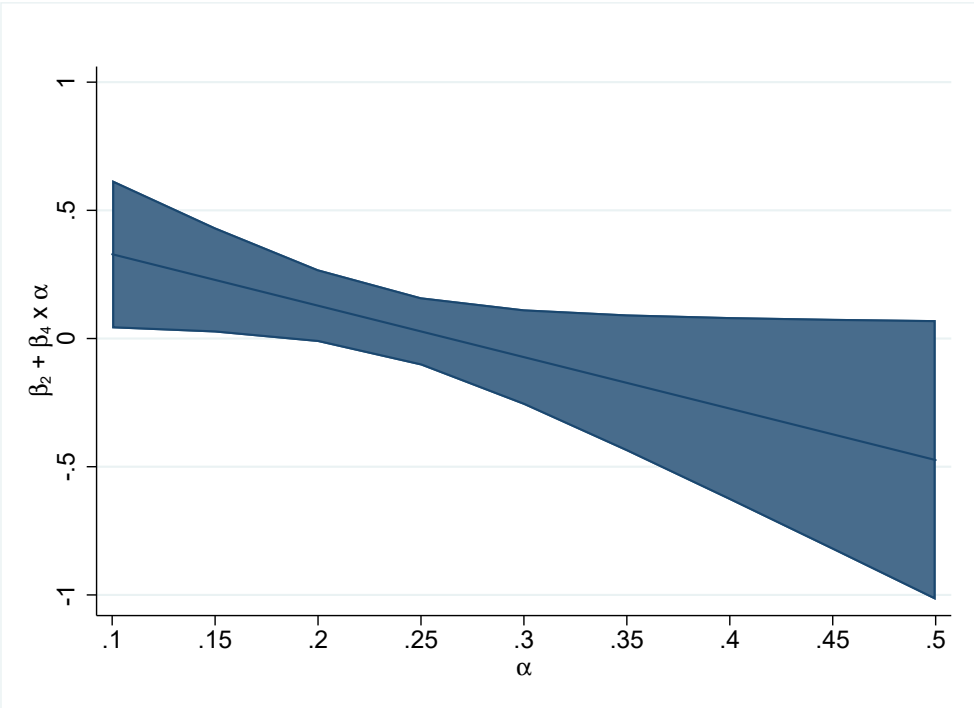


FIGURE 6.9 The association between growth of per capita GDP and top 1 % income share conditional on top1 % income share (point estimate and 95 % confidence interval), β_2 and β_3 correspond to equation (6.15)

The inclusion of additional variables as controls

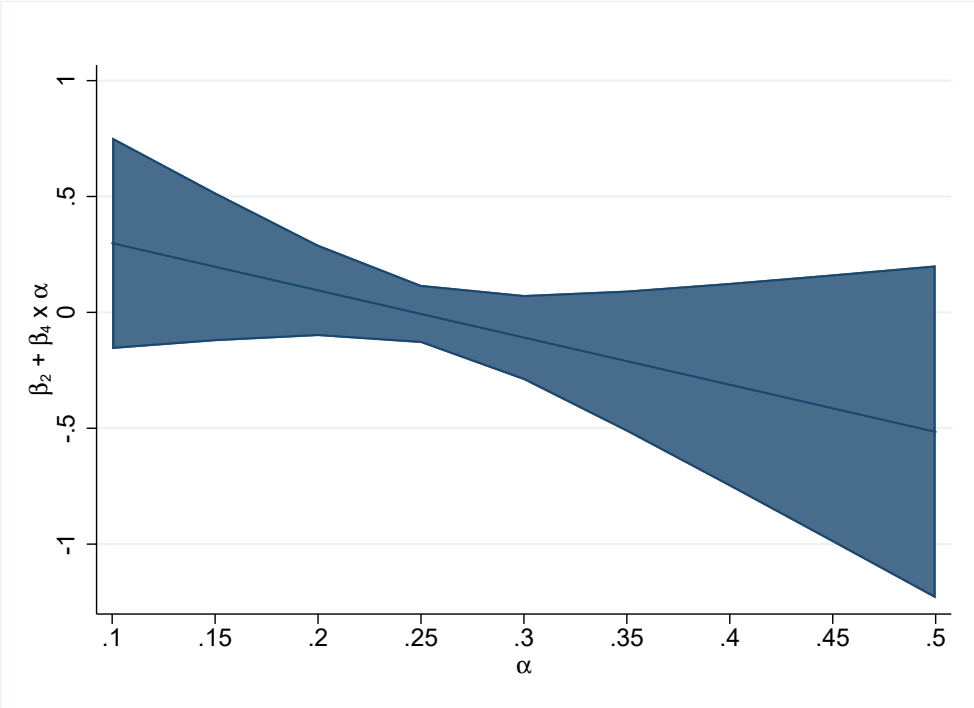


(a) Population growth and educational attainment as controls (230 obs)



(b) Population growth, educational attainment and investment per GDP as controls (212 obs)

FIGURE 6.10 The association between growth of per capita GDP and top 1 % income share conditional on capital share (point estimate and 95 % confidence interval)

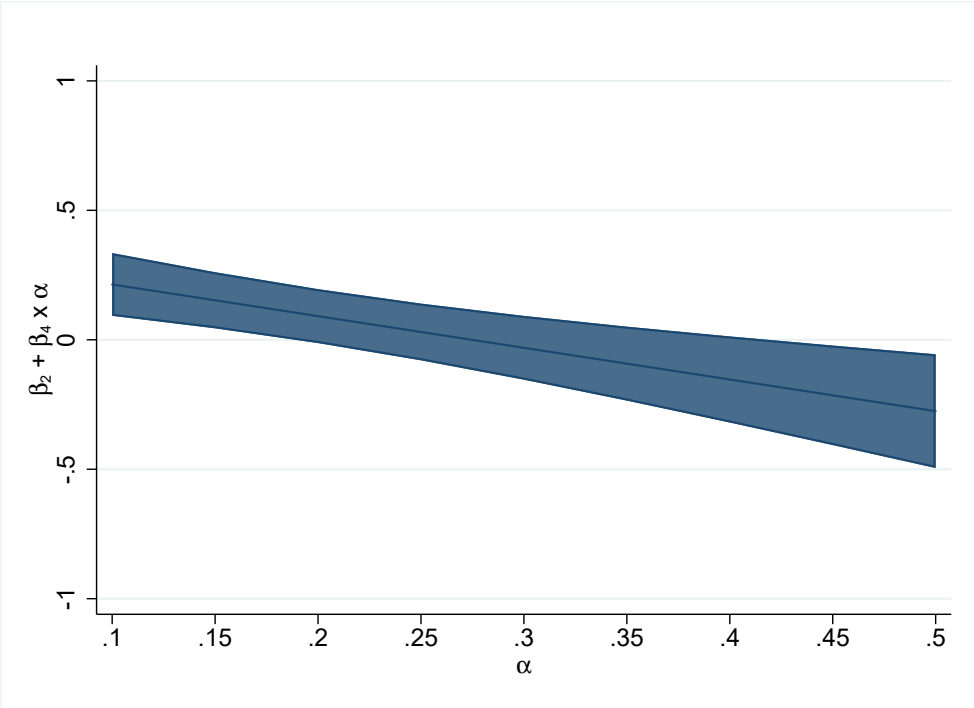


(c) Population growth, educational attainment, investment per GDP, public debt per GDP and the sum of exports and imports per GDP as controls (199 obs)

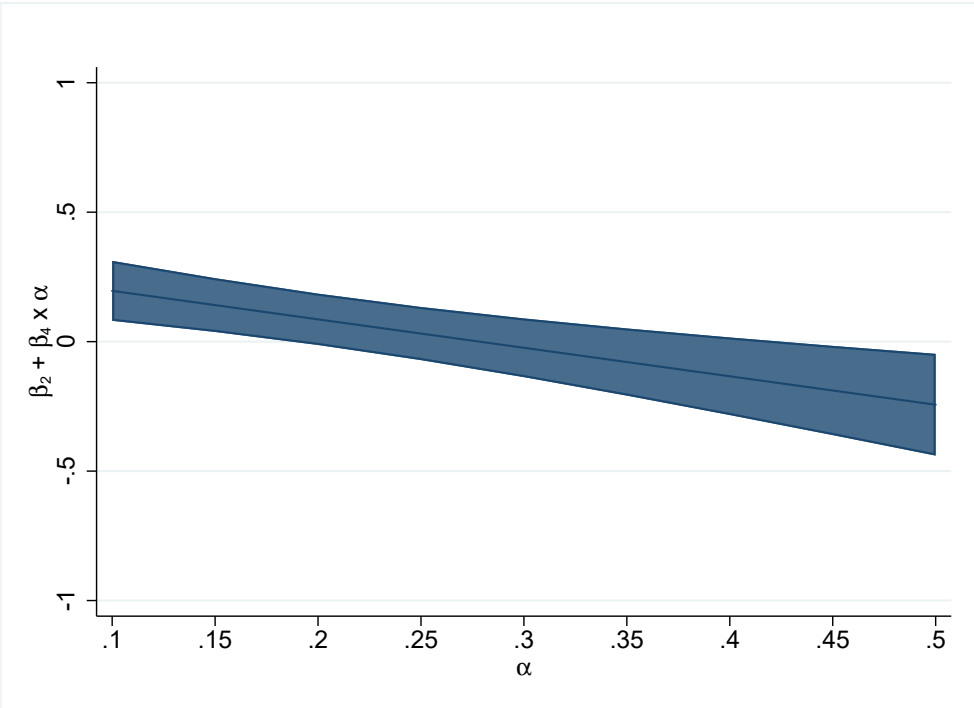
FIGURE 6.10 The association between growth of per capita GDP and top 1 % income share conditional on capital share (point estimate and 95 % confidence interval)

Notes: β_2 and β_4 correspond to equation (6.14) with the additional control variables listed in the captions.

Excluding the extreme growth rates of per capita GDP



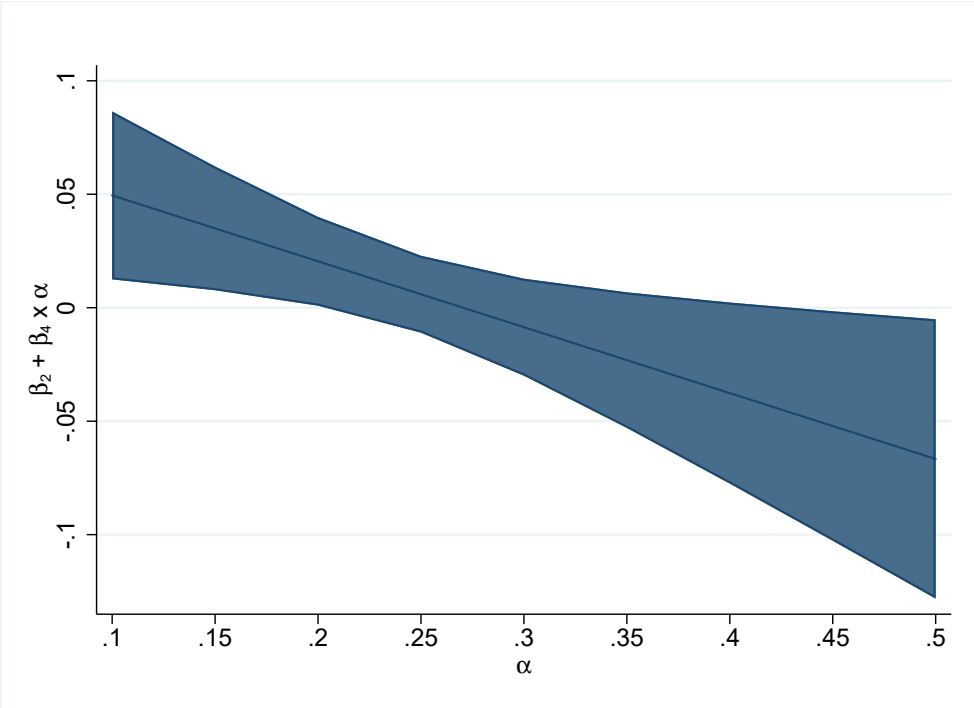
(a) Excluding the highest and lowest 5 % of the growth rates of per capita GDP



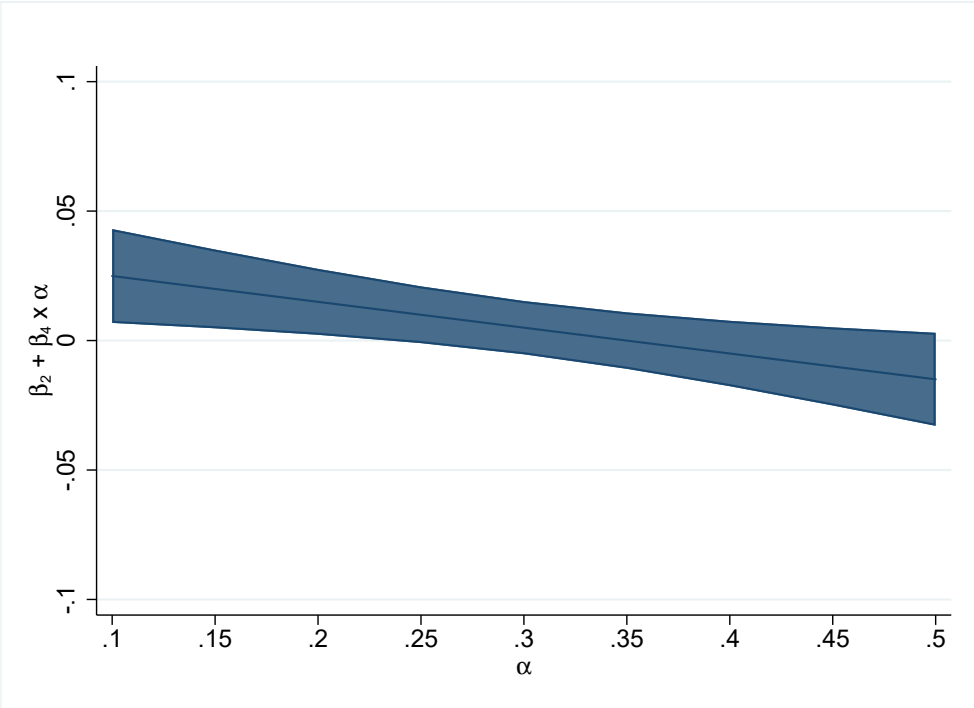
(b) Excluding the highest and lowest 10 % of the growth rates of per capita GDP

FIGURE 6.11 The association between growth of per capita GDP and top 1 % income share conditional on capital share and on top 1 % income share (point estimate and 95 % confidence interval), β_2 and β_4 correspond to equation (6.14) but lowest and highest growth rates of per capita GDP are excluded from the estimation sample

Top 10 % and top 0.1 %

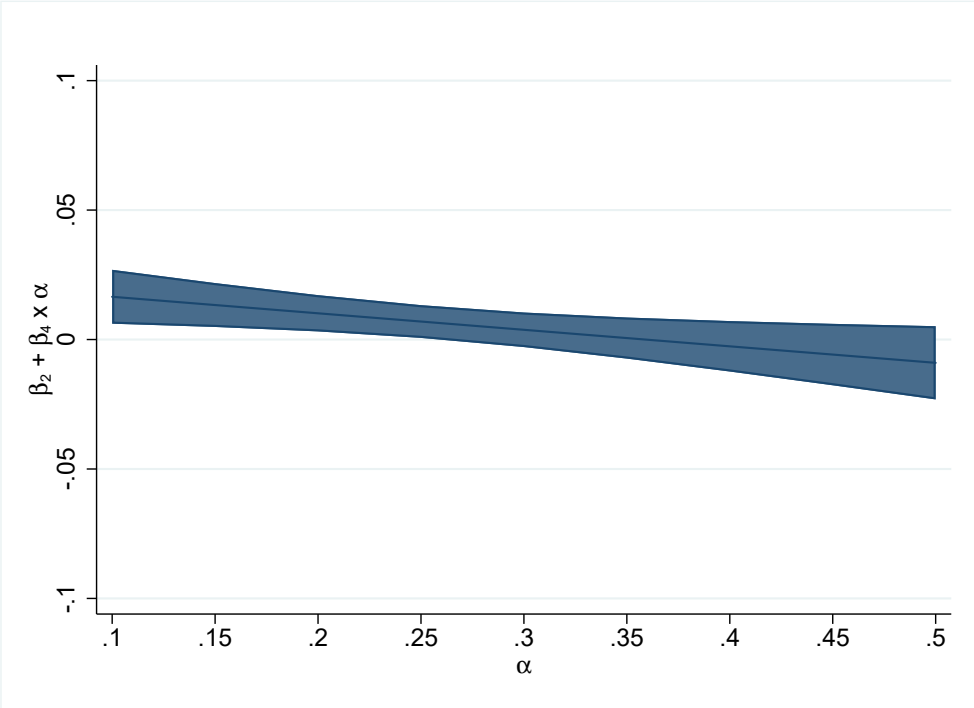


(a) Top 10 % share



(b) Top 1 % share

FIGURE 6.12 The association between growth of per capita GDP and different top income shares conditional on capital share (point estimate and 95 % confidence interval)

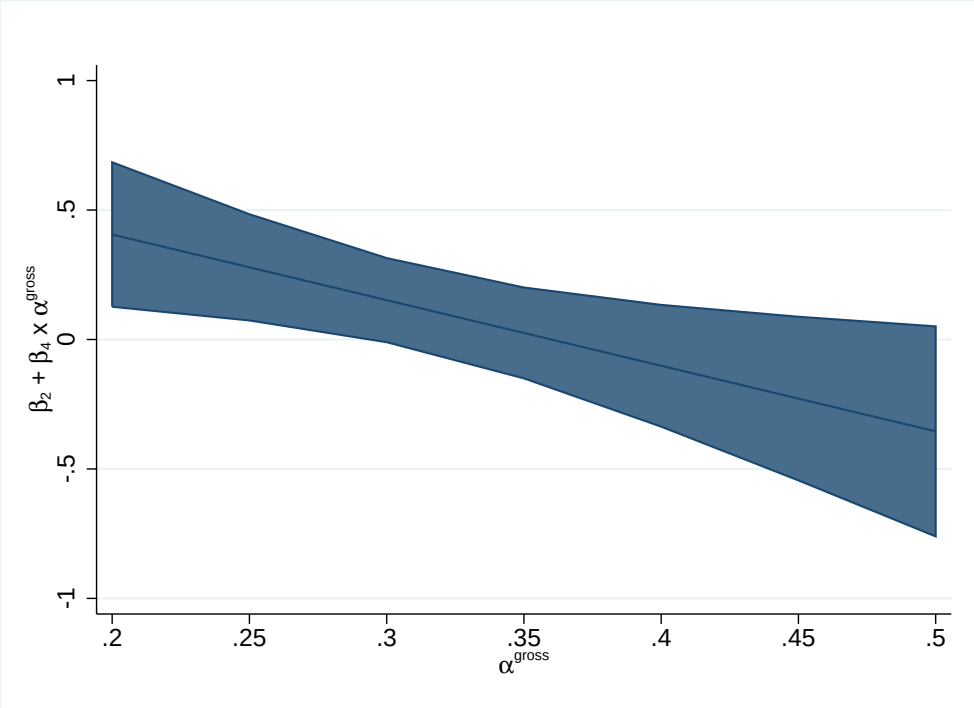


(c) Top 0.1 % share

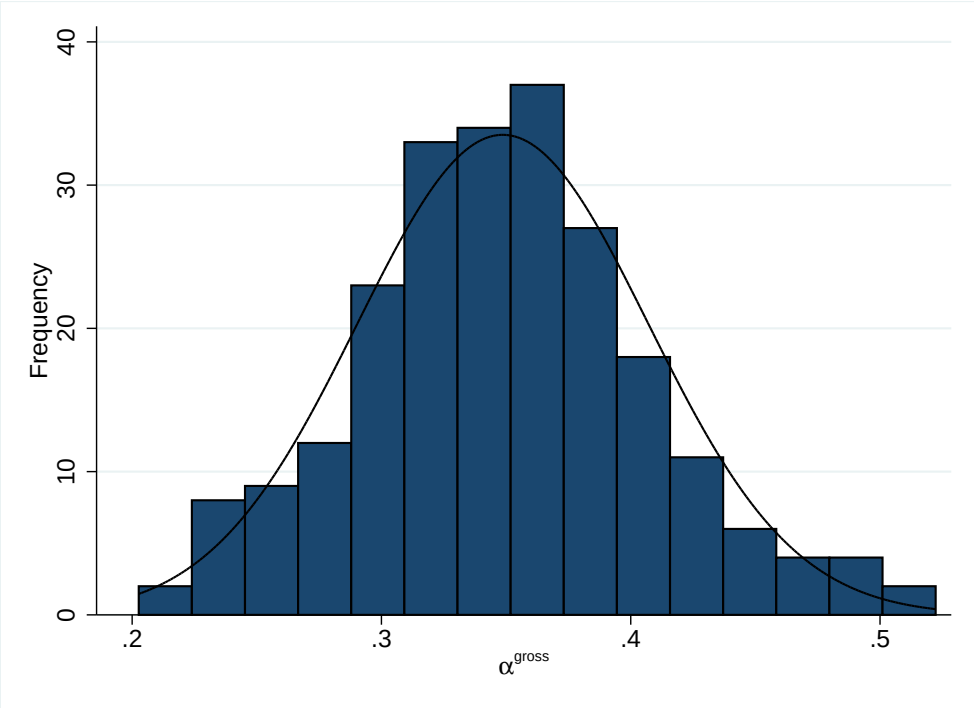
FIGURE 6.12 The association between growth of per capita GDP and different top income shares conditional on capital share (point estimate and 95 % confidence interval)

Notes: β_2 and β_4 correspond to equation (6.14) with top 1 % share in logs in Figure 6.12b, and to equation (6.14) with top 10 % and top 0.1 % share in logs in Figures 6.12a and 6.12c, respectively.

Capital shares gross of capital depreciation



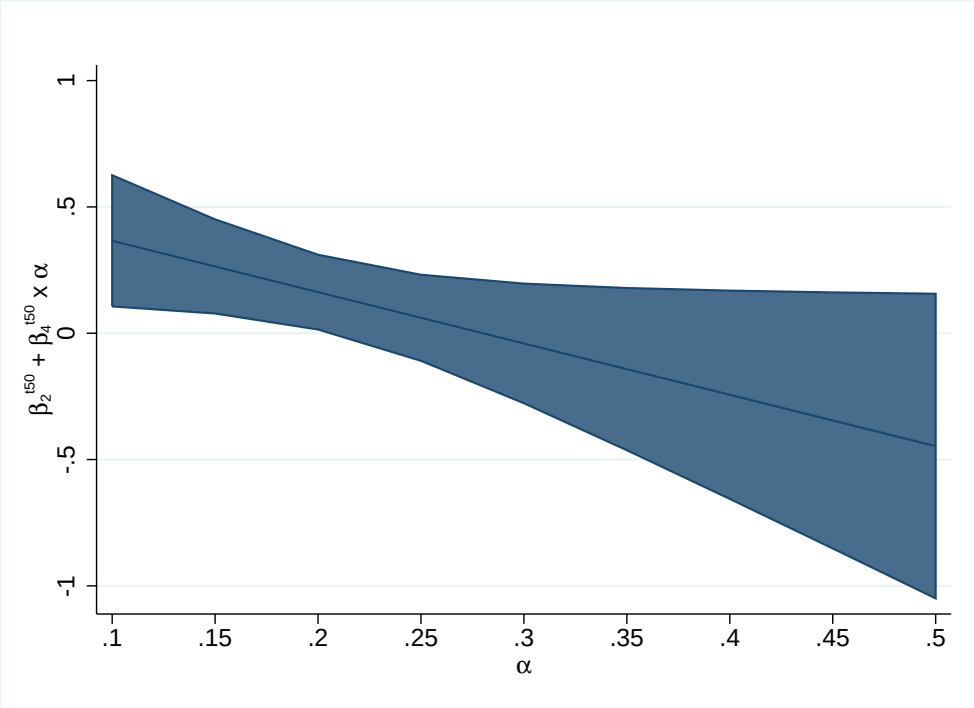
(a) Replication of Figure 6.6a with α gross of δ



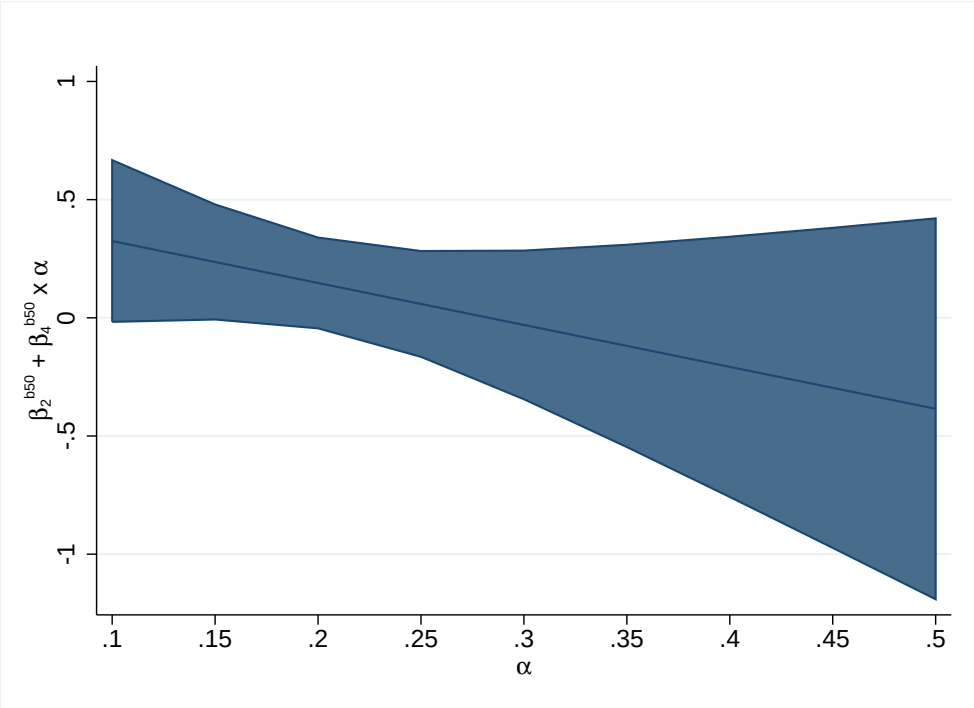
(b) Distribution of capital share gross of δ in the estimation sample

FIGURE 6.13 The association between growth of per capita GDP and top 1 % income share conditional on capital share (α) gross of capital depreciation (δ) (point estimate and 95 % confidence interval), β_2 and β_4 correspond to equation (6.14)

Addressing dependency to both the extent of inequality and capital share



(a) Top 1 % at the top half of the distribution



(b) Top 1 % at the bottom half of the distribution

FIGURE 6.14 The association between growth of per capita GDP and top 1 % income share conditional on capital share and on top 1 % income share (point estimate and 95 % confidence interval), β_2 and β_4 correspond to equation (6.16)

Average annual growth instead of annualized growth

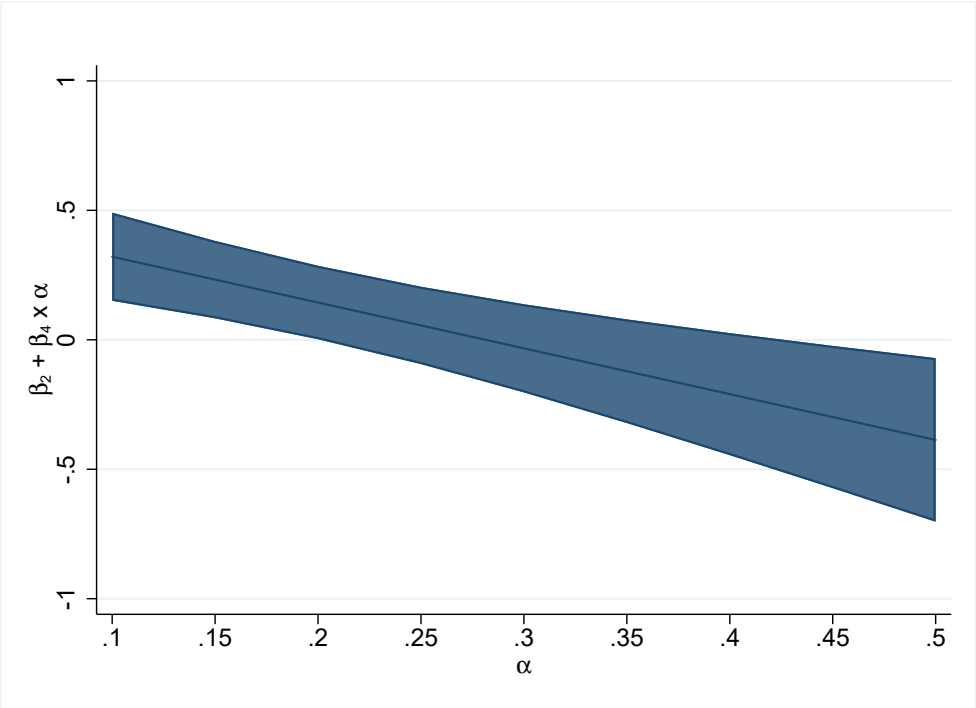
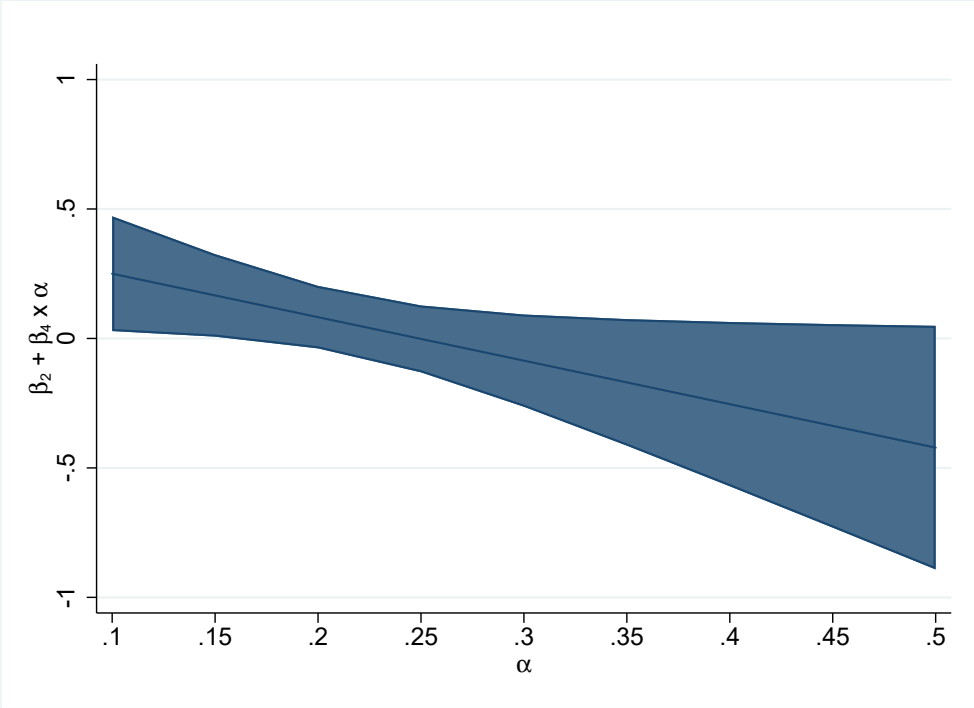
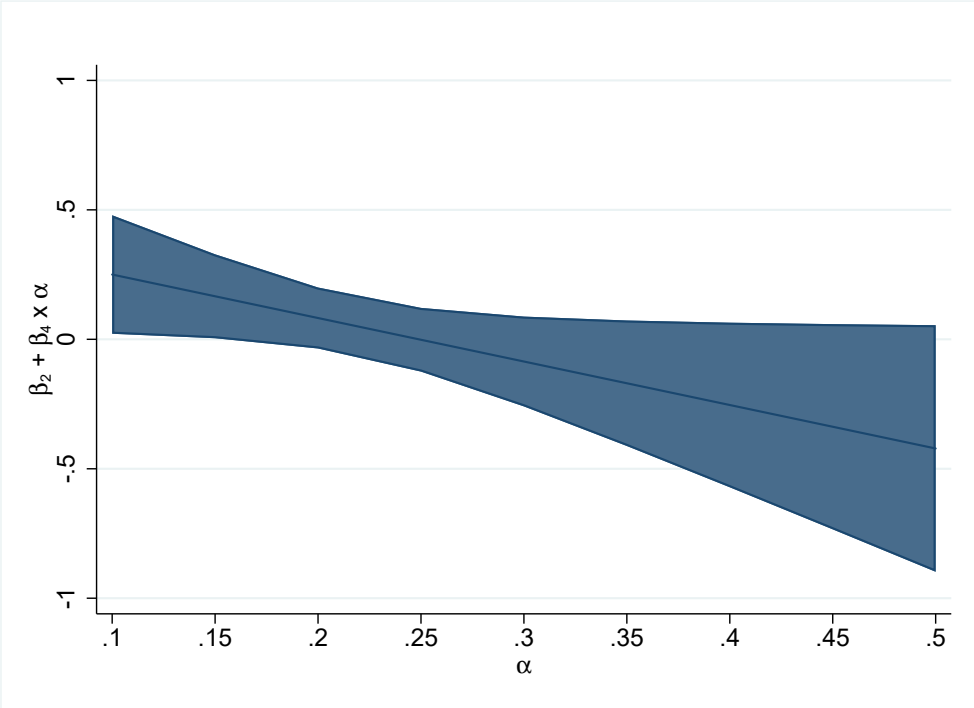


FIGURE 6.15 The association between growth of per capita GDP and top 1 % income share conditional on capital share (point estimate and 95 % confidence interval), average annual growth rates inside five-year windows

Different panel estimators



(a) Random effects



(b) Pooled OLS

FIGURE 6.16 The association between growth of per capita GDP and top 1 % income share conditional on capital share (point estimate and 95 % confidence interval), alternative panel estimators

6.A.4 Measures of financial development over long-run

TABLE 6.7 Data from Rajan and Zingales (2003)

No data for Finland and New Zealand. The original paper also includes Argentina, Austria, Belgium, Brazil, Chile, Cuba, Egypt, India, Italy, Russia, South Africa, Spain and Switzerland

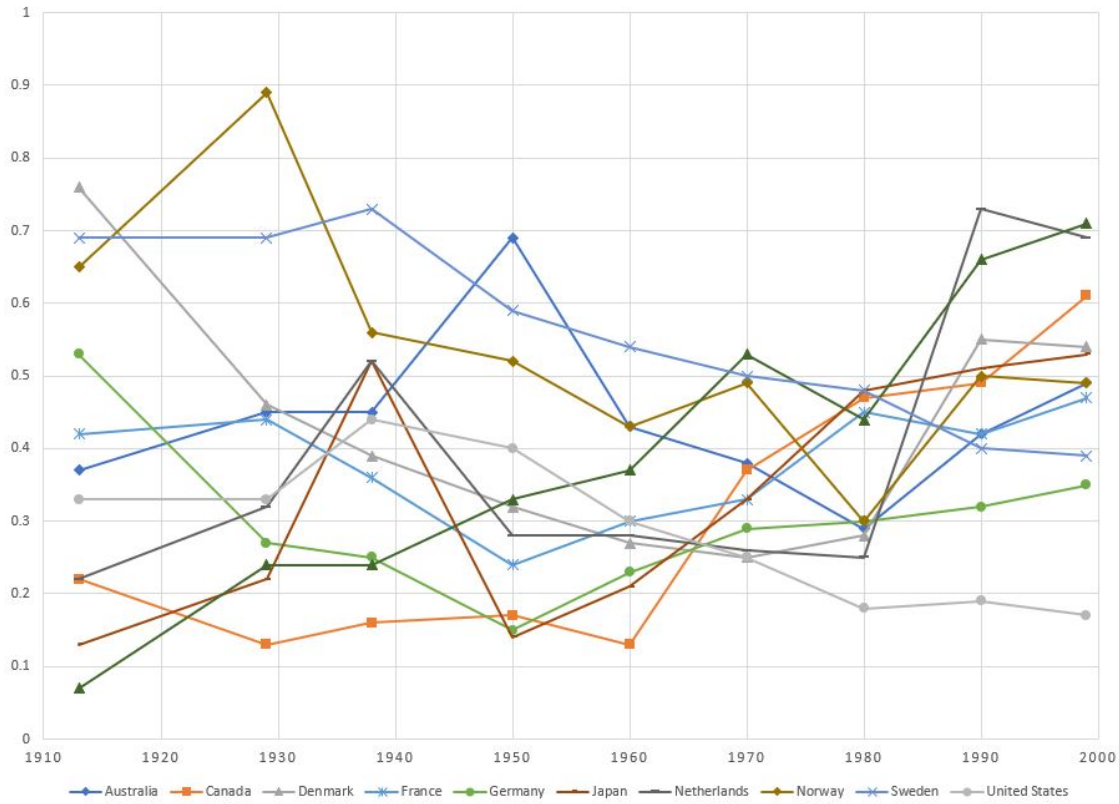
Panel A: Commercial and savings deposits to GDP									
Country	1913	1929	1938	1950	1960	1970	1980	1990	1999
Australia	0.37	0.45	0.45	0.69	0.43	0.38	0.29	0.42	0.49
Canada	0.22	0.13	0.16	0.17	0.13	0.37	0.47	0.49	0.61
Denmark	0.76	0.46	0.39	0.32	0.27	0.25	0.28	0.55	0.54
France	0.42	0.44	0.36	0.24	0.3	0.33	0.45	0.42	0.47
Germany	0.53	0.27	0.25	0.15	0.23	0.29	0.3	0.32	0.35
Japan	0.13	0.22	0.52	0.14	0.21	0.33	0.48	0.51	0.53
Netherlands	0.22	0.32	0.52	0.28	0.28	0.26	0.25	0.73	0.69
Norway	0.65	0.89	0.56	0.52	0.43	0.49	0.3	0.5	0.49
Sweden	0.69	0.69	0.73	0.59	0.54	0.5	0.48	0.4	0.39
UK	0.1	2.88	1.34	0.67	0.32	0.22	0.14	0.33	0.39
US	0.33	0.33	0.44	0.4	0.3	0.25	0.18	0.19	0.17
Panel B: Stock market capitalization (aggregate market value of equity of domestic companies) to GDP									
Country	1913	1929	1938	1950	1960	1970	1980	1990	1999
Australia	0.39	0.5	0.91	0.75	0.94	0.76	0.38	0.37	1.13
Canada	0.74		1	0.57	1.59	1.75	0.46	1.22	1.22
Denmark	0.36	0.17	0.25	0.1	0.14	0.17	0.09	0.67	0.67
France	0.78		0.19	0.08	0.28	0.16	0.09	0.24	1.17
Germany	0.44	0.35	0.18	0.15	0.35	0.16	0.09	0.2	0.67
Japan	0.49	1.2	1.81	0.05	0.36	0.23	0.33	1.64	0.95
Netherlands	0.56		0.74	0.25	0.67	0.42	0.19	0.5	2.03
Norway	0.16	0.22	0.18	0.21	0.26	0.23	0.54	0.23	0.7
Sweden	0.47	0.41	0.3	0.18	0.24	0.14	0.11	0.39	1.77
UK	1.09	1.38	1.14	0.77	1.06	1.63	0.38	0.81	2.25
US	0.39	0.75	0.56	0.33	0.61	0.66	0.46	0.54	1.52

Panel C: Amount of funds raised through public equity offerings (both initial public offerings and seasoned equity issues) by domestic companies divided by gross fixed capital formation

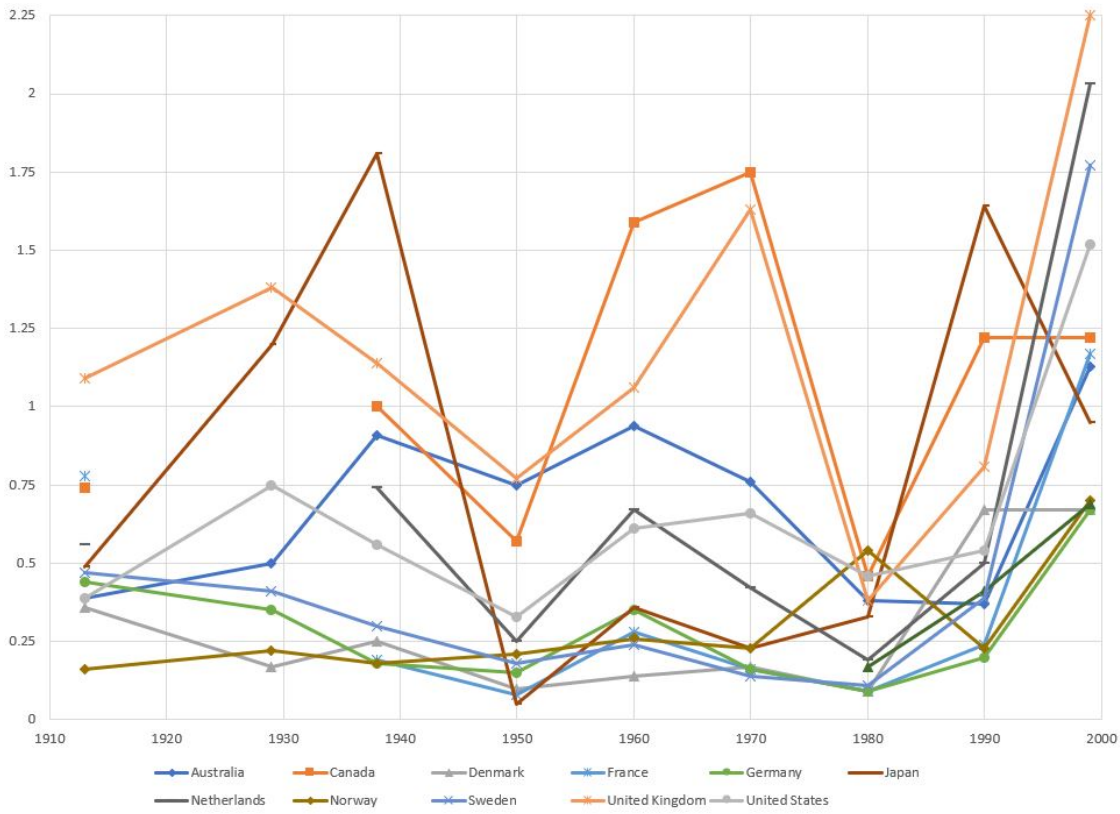
Country	1913	1929	1938	1950	1960	1970	1980	1990	1999
Australia		0.13		0.19	0.09	0.05	0.05	0.09	0.24
Canada			0.02	0.03	0.03	0.01	0.04	0.01	0.07
Denmark		0.03	0.01				0.01	0.08	0.09
France	0.14	0.26	0.03	0.02	0.04	0.04	0.06	0.02	0.09
Germany	0.07	0.17	0.06	0	0.04	0.02	0.01	0.04	0.06
Japan	0.08	0.13	0.75		0.15	0.03	0.01	0.02	0.08
Netherlands	0.38	0.61	0.45	0.02	0.02	0	0.01	0.1	0.67
Norway		0.05	0.01					0.04	0.06
Sweden	0.08	0.34	0.06	0.01	0.03	0	0	0.03	0.1
UK	0.14	0.35	0.09	0.08	0.09	0.01	0.04	0.06	0.09
US	0.04	0.38	0.01	0.04	0.02	0.07	0.04	0.04	0.12

Panel D: The number of domestic companies whose equity is publicly traded in a domestic stock exchange divided by the population in millions

Country	1913	1929	1938	1950	1960	1970	1980	1990	1999
Australia	61.74	76.92	84.88	122.05	93.72		68.53	63.89	64.91
Canada	14.65			66.61	62.43	55.2	50.52	42.99	130.13
Denmark	38.22	54.86	85.25	81.28	75.75	52.14	42.54	50.18	44.8
France	13.29		24.64	26.2	18.34	15.98	13.99	15.05	
Germany	27.96	19.73	10.91	13.22	11.33	9.07	7.46	6.53	12.74
Japan	7.53	16.65	19.48	9.15	8.35	15.19	14.8	16.76	20
Netherlands	65.87	95.48			21.42	15.95	15.12	17.39	15.14
Norway	33.51	41.5	45.98	37.98	37.1	37.9	44.53	44.8	49.62
Sweden	20.64	16.36	14.93	12.83	14.04	13.18	12.39	14.14	31.46
UK	47.06						47.22	29.63	31.11
US	4.75	9.72	9.16	8.94	9.33	11.48	23.11	26.41	28.88

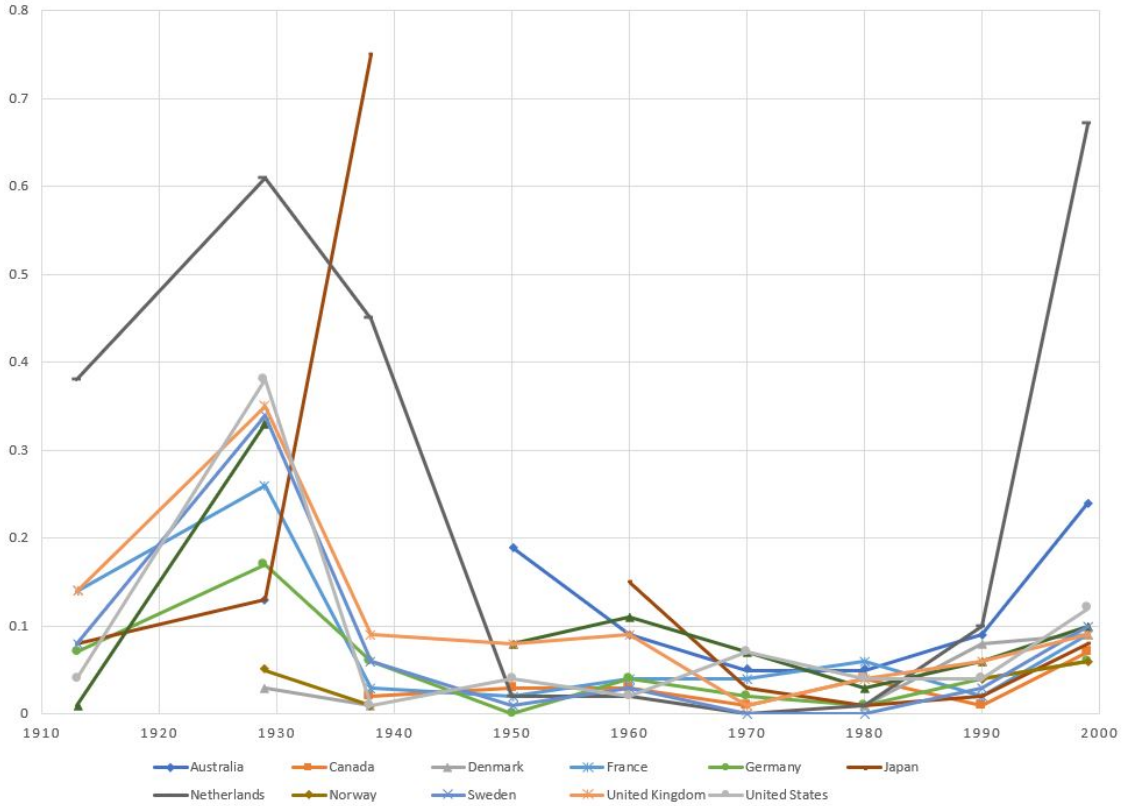


(a) Commercial and savings deposits to GDP

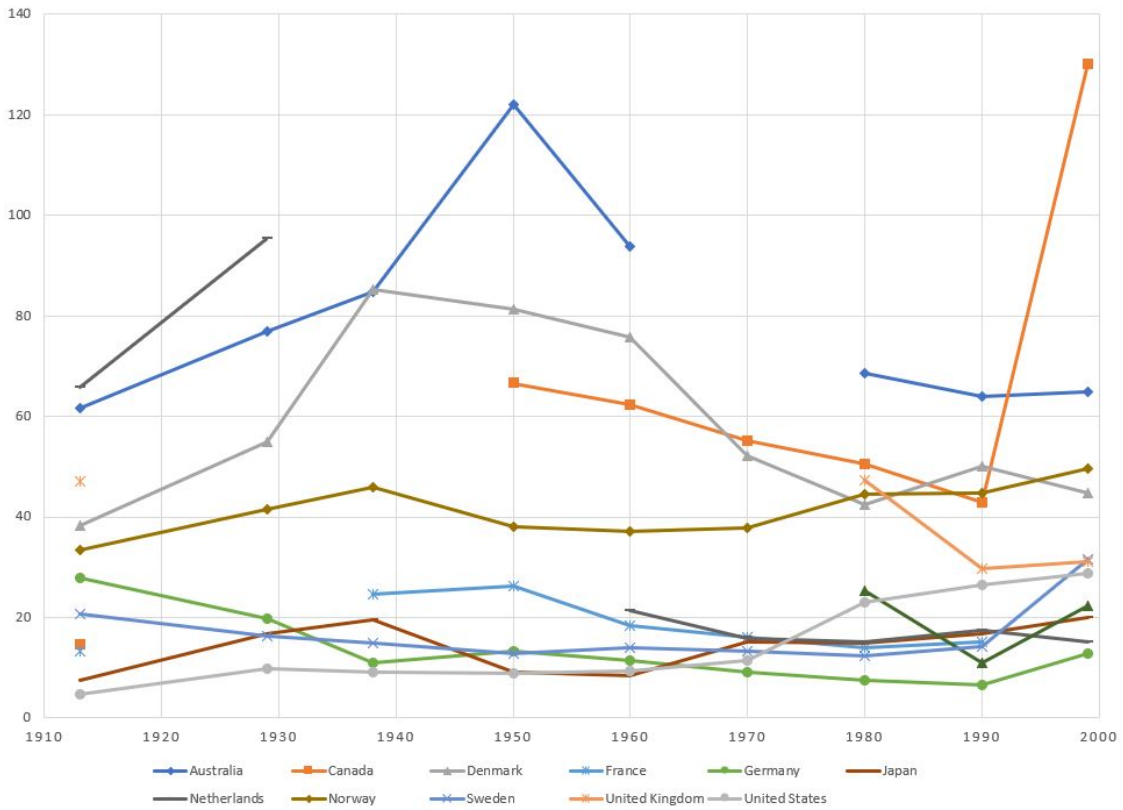


(b) Stock market capitalization (aggregate market value of equity of domestic companies) to GDP

FIGURE 6.17 Data from Rajan and Zingales (2003)



(c) Amount of funds raised through public equity offerings (both initial public offerings and seasoned equity issues) by domestic companies divided by gross fixed capital formation



(d) The number of domestic companies whose equity is publicly traded in a domestic stock exchange divided by the population in millions

FIGURE 6.17 Data from Rajan and Zingales (2003)

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YHTEENVETO (FINNISH SUMMARY)

Taloustieteellisiä tutkimuksia tuloerojen ja talouskasvun välisestä yhteydestä

Väitöskirjassa tarkastellaan, kuinka tuloerot ovat yhteydessä talouskasvuun. Väitöskirja koostuu johdantoluvusta ja viidestä tutkimuksesta. Johdantoluvussa esitellään teoreettinen viitekehys, käytettyjen kokonaistaloudellisten aineistojen ja tilastollisten menetelmien keskeiset piirteet, väitöskirjan tutkimuskysymykset sekä kootaan yhteen väitöskirjan tärkeimmät tulokset. Väitöskirjan neljä ensimmäistä tutkimusta ovat empiirisiä ja väittelijän yksin kirjoittamia, kun taas viides tutkimus sisältää sekä empiiristä että teoreettista tutkimusta ja on kirjoitettu yhdessä kolmen muun kirjoittajan kanssa.

Ensimmäinen tutkimus luo pohjan koko muulle väitöskirjalle havainnollistamalla, kuinka herkkiä tuloerojen ja talouskasvun välistä yhteyttä koskevat empiiriset tulokset ovat valinnoille, joita tutkija väistämättä kohtaa. Tutkimuksen tulokset osoittavat, että tuloerojen nousu näyttää olevan haitallista myöhemmälle talouskasvulle, jos maakohtaisia havaitsemattomia eroja ei oteta huomioon, kun taas näiden maakohtaisten erityispiirteiden huomioinen tuottaa sen johtopäätöksen, että tuloerojen ja talouskasvun välillä ei ole tilastollisesti merkitsevää yhteyttä. Laajalti käytetyn yleistetyn momenttimenetelmän edut suhteessa yksinkertaisempiin menetelmiin ovat epäselviä, mikä vahvistaa väitöskirjan lähtökohtaa siitä, että tuloeroja ja talouskasvua käsittelevät empiiriset tulokset tulee tulkita tilastollisina yhteyksinä eikä syy-seuraussuhteena. Sen sijaan johtopäätökset eivät keskeisesti riipu tuloeromittarin valinnasta tai tuloerojen tasosta.

Monet keskeiset tuloerojen ja talouskasvun välistä yhteyttä käsittelevät tutkimukset korostavat rahoitusolosuhteiden merkitystä. Väitöskirjan toinen tutkimus arvioi rahoitusinstituutioiden ja -markkinoiden kehittyneisyyden roolia tuloerojen ja talouskasvun välisen yhteyden kannalta. Tulokset osoittavat, että rahoitusmarkkinoiden ollessa riittävän kehittyneet tuloerojen kasvu on yhteydessä korkeampaan talouskasvuun matalan tulotason maissa. Vastaavaa riippuvuussuhdetta ei ole löydettävissä tarkasteltaessa rahoitusinstituutioita tai korkean tulotason maita. Tutkimuksen keskeinen löydös ei ole herkkä eri tuloeromittareiden tai tilastollisten menetelmien välillä.

Väitöskirjan kaksi ensimmäistä tutkimusta nojaavat kyselypohjaisiin aineistoihin, joissa tietoa yhdistellään useista maista. Näiden tutkimusten tilastolliset menetelmät eivät huomioi sitä mahdollisuutta, että talouskasvu saattaa reagoida eri tavalla nouseviin ja laskeviin tuloeroihin. Kolmas tutkimus sen sijaan keskittyy kuuteen yksittäiseen maahan, hyödyntää verorekisteripohjaisia pidemmän aikavälin kattavia aineistoja ja erittelee positiiviset ja negatiiviset muutokset tuloeroissa. Ranskassa ja Yhdysvalloissa laskevat tuloerot ovat olleet yhteydessä matalampaan myöhempään talouskasvuun, kun taas nousevien tuloerojen ja talouskasvun yhteys ei ole ollut tilastollisesti merkitsevä. Intiassa tilanne on ollut päinvastainen: nousevien tuloerojen ja talouskasvun välillä havaitaan positiivinen yhteys, ja laskevat tuloerot eivät näytä olleen yhteydessä muutoksiin

taloudellisessa toimeliaisuudessa. Australiassa, Kanadassa ja Japanissa tuloerojen ja talouskasvun välinen yhteys on ollut heikko.

Neljäs tutkimus esittelee historiallisen aineiston kansantalouden tulojen jakautumisesta työ- ja pääomatulojen kesken. Tutkimus osoittaa, että yhteinen yksittäinen havaitsematon tekijä selittää valtaosan maakohtaisten pääoman tulo-osuuksien vaihteluista. Tulos ei ole herkkä eri otosten tai eri tavoin huomioidun pääoman kulumisen huomioimisen välillä. Tämänkaltaista keskinäisriippuvuutta ei kyetä havaitsemaan aikasarjakuvioista tai maiden välisistä korrelaatiokertoimista. Löydetylle havaitsemattomalle tekijälle ei voida aukottomasti osoittaa taloudellista tulkintaa, mutta suurimmassa osassa maista kyseinen tekijä on vahvasti korreloitunut kansainvälisen kaupan määrän ja kokonaistuottavuuden kanssa.

Viides tutkimus osoittaa, että tuloerojen ja talouskasvun välinen yhteys riippuu siitä, kuinka kansantalouden tulot jakautuvat työ- ja pääomatulojen välillä. Suhteessa aiempaan tutkimuskirjallisuuteen päätulos on uusi. Sekä historialliseen aineistoon nojaava empiirinen tarkastelu että pääoman kertymisen merkitystä painottava teoreettinen analyysi havainnollistavat, että tuloerojen talouskasvun välinen yhteys on positiivinen pääoman tulo-osuuden ollessa matala, kun taas pääoman tulo-osuuden ollessa korkea yhteys on negatiivinen. Tulokset pätevät, kun rahoitukseen liittyvät kitkatekijät ovat riittävän matalat. Teoreettisesti keskeistä on kotitalouksien varautumissäästämisen ja kulutuksen tasoittamisen välinen yhteys, joka on riippuvainen siitä, kuinka tulot jakautuvat työ- ja pääomatulojen kesken.

Väitöskirja korostaa tuloerojen ja talouskasvun välisen yhteyden monimutkaisuutta. Tulokset osoittavat maakohtaisten erojen huomioimisen tärkeyden, rahoitusmarkkinoiden keskeisen roolin sekä sen, kuinka työ- ja pääomatulojen jakautumisen huomioiminen määrittää johtopäätöksiä. Aiheesta käytävän yhteiskunnallisen keskustelun kannalta on tärkeää huomioida kaksi seikkaa. Ensiksi, tuloerojen ja talouskasvun välistä syy-seuraussuhdetta – toisin sanoen tuloerojen vaikutusta talouskasvuun – on vaikeaa arvioida. Toiseksi, useissa maissa tapahtuvaa vaihtelua hyödyntävien tutkimusten tulosten tulkinta yksittäisen maan kannalta on hankalaa.