THREE ESSAYS ON INCOME INEQUALITY AND ECONOMIC GROWTH

by

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This dissertation is dedicated to

my wife Yao Wang and my daughter Mira J. Hou

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DISSERTATION

Presented to the Faculty of

The University of Texas at Dallas

in Partial Fulfillment

of the Requirements

for the Degree of

DOCTOR OF PHILOSOPHY IN

ECONOMICS

THE UNIVERSITY OF TEXAS AT DALLAS

August 2020

ACKNOWLEDGMENTS

I would like to express my heartfelt gratitude to my advisor, Dr. Donggyu Sul, for all his encouragement and guidance. His wonderful lectures arouse my strong interest in the study of Economics and he maintained an efficient communication with me to ensure that I can complete the dissertation smoothly. My thanks would also go to other supervisory committee members: Dr. Daniel Arce, Dr. Chi-Young Choi, Dr. Seth Giertz, and Dr. Dong Li for their invaluable guidance, support and helpful comments and suggestions throughout my PhD program. Finally, I am deeply indebted to my family and friends, who have supported me through these years. To all, thank you.

June 2020

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The University of Texas at Dallas, 2020

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The dissertation consists of three chapters on the relationship between income inequality and economic growth. The inequality-growth relationship has received much attention from both theoretical and empirical economists. However, their findings have largely been inconclusive. The first paper (Chapter 2) reviews the existing inequality-growth literature by considering bi-directional causality and nonlinearity issues. I first attempt to summarize channels and model specifications for both directions of effect. Reviewing the coefficients that measure the effect of inequality on growth, I show that estimates from cross sectional regressions are consistently negative, while estimates from panel regressions are inconclusive. The main issues in estimating this relationship raised in empirical studies are also discussed in this chapter. What are the relationship between inequality and growth? Is there any difference between the long-run and short-run? The second and third papers (Chapter 3 and Chapter 4) then capture the long-run and short-run relationship between inequality and growth respectively. The second paper uses newly proposed methods that test convergence to investigate the long-run relationship between income inequality and economic growth from a unique perspective. Both the relative convergence and weak-σ convergence approaches demonstrate a divergent result for inequality but a convergent result for income, which represents evidence that there is no long-run relationship between income inequality and economic growth. Common factor analysis is used to help interpret the long-run relationship between income inequality and

economic growth. Is there any short-run relationship? The conventional approach to panel regression struggles to capture the short-run dynamics of the relationship between inequality and economic growth. The third paper introduces a more general common factor framework by applying the Common Correlated Effects (CCE) estimator proposed by (Pesaran, 2006) and (Chudik and Pesaran, 2015) so that unobserved common factors with heterogeneous factor loadings can be accounted for. Using a panel VAR framework this paper finds that in the short-run no relationship between inequality and growth can be observed among advanced economies. While the results of this study differ from those of the existing panel analysis literature, they are consistent with the long-run relationship between inequality and growth discussed in the previous chapter. The change in income inequality is attributed to country specific policy rather than economic growth.

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CHAPTER 1

INTRODUCTION

A rich literature has attempted to estimate the relationship between income inequality and economic growth across countries, as well as within a country. Results have generally been plagued by disagreement regarding either sign or causality. This dissertation captures this inequality-growth relationship by summarizing the estimation issues of related studies, identifying the long-run relationship between income inequality and economic growth through convergence approaches, and addressing the short-run dynamics of inequality-growth relationship through panel regressions. This dissertation is therefore intended to establish a comprehensive understanding on the controversial relationship between income inequality and economic growth, and contribute to development economics.

Why are the findings from the previous studies regarding inequality-growth relationship so inconclusive? Chapter 2 summarizes the extensive literature by dividing them into two directions of causality. The channels of causality, specifications, estimation issues, and descriptive statistics of estimates in inequality-growth literature are considered. Specifically, the differences between long-run and short-run relationship are examined by investigating the estimation methods for cross sectional regressions and panel regressions. Authors of the relevant studies using cross sectional regressions argued that inequality reduces growth by using average growth rates over a relatively longer time horizon (typically 20-40 years). However, the cross sectional regression does not necessarily capture the long-run relationship as the negative estimate of inequality may come from two idiosyncratic terms in growth and inequality. The panel regressions targeting the short-run relationship are equally problematic since they are using either the initial value or the average value within some specific time intervals of inequality in the regression. The potential correlations between the trend in inequality and an idiosyncratic term of output will contaminate the estimation of short-run relationship. To tackle these issues, Chapter 2 then reviews empirical specifications and estimation issues, and provides descriptive statistics of 973 estimates from related papers. The results show that there are weak evidence of a negative relationship in cross sectional regressions while estimates from panel regressions cannot reach any consensus. This brings the following interesting questions: What is the long-run relationship between inequality and growth after eliminating estimation issues of cross sectional regressions? What is the short-run dynamics for inequality-growth relationship after eliminating estimation issues of panel regressions? Is there any difference between the short-run and long-run relationship? Chapter 3 and Chapter 4 attempt to answer these questions through different estimation methods.

Chapter 3 captures the long-run relationship between income inequality and economic growth through convergence approach. This paper differs substantially from the previous cross sectional regressions by focusing on two stochastic trend terms in income and inequality. The newly proposed convergence methods can then avoid the pitfalls of the augmented Solow regression and β convergence. It uses real GDP per capita from the Penn World Table (PWT) as a measure of income and the top income shares from the World Inequality Database (WID) as a measure of income inequality to investigate the convergence of those two variables. Common factor analysis is used to explain the relationship obtained from convergence results. The results show that there is not any common factor in inequality but income shares a single factor. Moreover, inequality is diverging while income is sub-club converging. Through the partial identification, no long-run relationship between inequality and growth can be obtained. However, is there any potential relationship between inequality and growth in the short-run? Chapter 4 provides this link in the short-run dynamics.

Chapter 4 directly addresses the short-run dynamics of inequality-growth relationship and tackles issues of panel regressions in the existing literature targeting the short-run relationship. This paper first points out the pitfalls of augmented Solow regressions in capturing the short-run dynamics of inequality-growth relationship and provides a New Keynesian framework to address this research question. In addition, it uses a panel VAR methodology which can consider both directions of causality. Moreover, the adoption of the Common Correlated Effects (henceforth CCE) approach allows me to account for unobserved common factors with heterogeneous factor loadings using similar data in the literature. The empirical results show a lack of correlation between inequality and growth which is consistent with the long-run identification of this relationship.

Chapter 5 finally concludes all the chapters and provides a summary of them. In general, the relationship between inequality and growth cannot be obtained, either in the long-run or the short-run. Income inequality in each country depends on country-specific policy, rather than economic growth. In the short-run a change in income inequality does not affect economic growth either.

CHAPTER 2

REVISITING THE INEQUALITY-GROWTH NEXUS: WHAT DO THE LITERATURE AND DATA SAY?

2.1 Introduction

There has been a heated debate regarding the inequality-growth relationship among both theoretical and empirical researchers, with the theoretical literature having the longer history of the two. The theoretical researchers have investigated several channels through which inequality may affect growth, and vice versa.

The empirical studies, on the other hand, have been restricted by data issues. Since the 1990s, empirical studies on the inequality-growth relationship have surged with the release of several new databases, such as the (Deininger and Squire, 1996) database (DS hereafter) and the Luxembourg Income Study Database (LIS hereafter). Even though the release of these new databases has not completely solved the availability and comparability issues of inequality data, they have provided substantial support for the empirical research into the inequality-growth relationship such that studies in this field over the past two decades have come to depend heavily on these databases. Additionally, Gini coefficients and income shares are two popular measures for income inequality. Nonetheless, the empirical literature has failed to reach any consensus on the inequality-growth relationship, suggesting that the selection of estimation approaches makes a big difference. We will therefore start with the transmission channels and then analyze the inconclusive relationship between inequality and growth and the corresponding econometric techniques.

Traditional survey studies of the inequality-growth relationship first discuss the transmission channels explored in the theoretical literature and then illustrate the corresponding findings of empirical studies (notably (Aghion et al., 1999), (Ehrhart, 2009), (Galbraith, 2009), (Voitchovsky, 2009), and (Neves and Silva, 2014)). Compared to the methodology of this traditional literature, meta-analysis is considered a superior alternative approach. It uses a quantitative approach to collect effects from many different papers focusing on the same research question. That said, meta-analysis has drawbacks of its own in studying the inequality-growth relationship as the data used in this literature is almost identical, biasing the results of meta-analysis. In this paper, we contribute to the inequality-growth literature by collecting estimation results and identifying pattern in a systematic way using percentile analysis to solve the meta-analysis issue and eliminate the subjectivity of traditional survey papers.

There are extensive empirical studies regarding the inequality-growth nexus (shown in Table 2.1). The majority of empirical studies focusing on the effects of inequality on growth (notably (Forbes, 2000)) regress the growth rate of per capita real GDP on lagged inequality measures. Others such as (Banerjee and Duflo, 2003) capture this relationship using a non-linear model specification by augmenting higher orders of inequality measures as independent variables. Studies using cross sectional data yield negative correlations between inequality and growth, while panel data specifications have not exhibited any single common result.

Previous literature considers income an important variable in exploring the determinants of inequality. Many studies use real GDP per capita, typically in logarithm format, in a linear specification when investigating the effect of other explanatory variables on inequality. On the other hand, the idea of a nonlinear relationship, originated by (Kuznets, 1955), attract more attention, but have produced mixed results.

To summarize, most of these studies only identify the determinants of either growth or inequality, but not both. Even though there are explorations of the inequality-growth relationship in both directions, identifying the direction of causality has still been difficult. Neither have previous studies reached an explicit agreement about model specification, i.e., whether model specification should be linear or not. The empirical literature thus fails to reach any consensus on the inequality-growth relationship, with most studies focusing on

Table 2.1. The number of papers in both directions and specifications

		Causality and specification			
		Direction1		Direction2	
Linear	Positive	[8][1]	(Forbes, 2000) (Li and Zou, 1998)	[8][5]	(Roine et al., 2009) (Bergh and Nilsson, 2010)
	Negative	[29][2]	(Deininger and Squire, 1998) (Herzer and Vollmer, 2012)	[8][6]	(Brueckner et al., 2015) (Bumann and Lensink, 2016)
	Mixed/Insig	[15][3]	(Barro, 2000) (Bjørnskov, 2008)	[17][7]	(Ghossoub and Reed, 2017) (Kraay, 2006)
Nonlinear	Quadratic	[3][4]	(Banerjee and Duflo, 2003) (Scholl and Klasen, 2016)	[22][8]	(Ahluwalia, 1976) (Barro, 2000)
	Cubic	[0]	N/A	[3][9]	(Lessmann and Seidel, 2017) (Park and Shin, 2017)
	Nonparametric	[0]	N/A	[1][10]	(Frazer, 2006)

-The number in the square bracket indicates the number of studies in corresponding categories.

-The representative papers are listed in the table. See Appendix for all papers included.

only one direction of causality and one specification. To fill this gap, our study summarizes empirical papers that explore both directions of causality in the inequality-growth relationship by reviewing empirical specifications, estimation issues, and descriptive statistics.

The remainder of this paper is organized as follows. Section 2.2 specifies the transmission channels and the theoretical justifications. Section 2.3 clarifies the empirical specifications. Section 2.4 analyzes estimation issues in the existing literature. The descriptive statistics of related coefficients are provided in section 2.5. Section 2.6 concludes this study and elaborates avenues for future research.

2.2 Transmission Channels

2.2.1 Growth Model

The general form of the aggregate production function in neoclassical growth theory can be written as: $Y = F(K, L, H, A)$, where Y represents the output, K and H measure the physical and human capital respectively, L denotes the labor, A is the technology, F is the production function. Assuming that the growth rate of population is constant, the basic Solow model then gives:

$$y(t) = A(t)f(k(t)) \tag{2.1}$$

and

$$\frac{\dot{k}(t)}{k(t)} = \frac{sf(k(t))}{k(t)} - (\delta + g + n) \tag{2.2}$$

where $y(t)$ stands for output per capita. $k(t)$ represents capital per capita while s is the saving rate, δ is depreciation and n is the population growth rate. Differentiating equation (2.1) with respect to time and dividing both sides by $y(t)$,

$$\frac{\dot{y}(t)}{y(t)} = g + \varepsilon_f(k(t))\frac{\dot{k}(t)}{k(t)} \tag{2.3}$$

where

$$\varepsilon_f(k(t)) \equiv \frac{f'(k(t))k(t)}{f(k(t))} \in (0,1) \tag{2.4}$$

is the elasticity of the $f(\cdot)$ function. For example, $\varepsilon_f = \alpha$ in a Cobb-Douglas production function. When ε_f is high, the model is close to an AK production function and convergence will be slow. The first-order Taylor expansion of equation (2.2) with respect to $lnk(t)$ around k^* is:

$$\begin{aligned}\frac{\dot{k}(t)}{k(t)} &\simeq (\frac{sf(k^*)}{k^*} - (\delta+g+n)) + (\frac{f'(k^*)k^*}{f(k^*)} - 1)s\frac{f(k^*)}{k^*}(lnk(t) - lnk^*) \\ &\simeq (\varepsilon_f(k^*) - 1)(\delta+g+n)(lnk(t) - lnk^*)\end{aligned} \tag{2.5}$$

because $\frac{sf(k^*)}{k^*} = \delta + g + n$ by the definition of steady-state value k^*. Substituting equation (2.5) into equation (2.3) yields:

$$\frac{\dot{y}(t)}{y(t)} \simeq \ g - \varepsilon_f(k^*)(1 - \varepsilon_f(k^*))(\delta+g+n)(lnk(t) - lnk^*) \tag{2.6}$$

The first-order Taylor expansions of $lny(t)$ with respect to $lnk(t)$ around lnk^* is:

$$lny(t) - lny^* \simeq \ \varepsilon_f(k^*)(lnk(t) - lnk^*) \tag{2.7}$$

From equation (2.6) and equation (2.7) we have:

$$\frac{\dot{y}(t)}{y(t)} \simeq \ g - (1 - \varepsilon_f(k^*))(\delta+g+n)(lny(t) - lny^*) \tag{2.8}$$

The sources of growth come from the rate of technological progress and convergence. Using discrete time approximations, (Barro and Sala-i Martin, 1992) write the transitional dynamics using a Cobb-Douglas production function:

$$lny_{it} = lny_{i0} \cdot e^{-\phi t} + lny^* \cdot (1 - e^{-\phi t}) = lny^* + (lny_{i0} - lny^*) \cdot e^{-\phi t} \tag{2.9}$$

where ϕ indicates the speed of adjustment to the steady state. Assuming that technological progress follows an exponential growth path: $A_{it} = A_{i0}e^{gt}$, the transitional dynamics under heterogeneous technology progress proposed by (Phillips and Sul, 2007a) become:

$$lny_{it} = lny^* + (lny_{i0} - lny^*) \cdot e^{-\phi t} + lnA_{i0} + g_{it}t \tag{2.10}$$

And the average growth rate of country i between time q and $t+q$ is:

$$\frac{lny_{it+q} - lny_{iq}}{t} = -b_{it}lny^* + b_{it}lny_{iq} - (\frac{1}{t} + b_{it})lnA_{iq} + \frac{1}{t}lnA_{it+q} \tag{2.11}$$

where

$$b_{it} = -(\frac{1 - e^{-\phi_{it}^{+}t}}{t}) < 0, \text{ with } \phi_{it}^{+} = \frac{\phi_{it+q}(t+q)}{t} - \frac{\phi_{iq}}{t} \tag{2.12}$$

The theoretical model can then be transformed into an empirical equation for cross-sectional and panel regression respectively. In the cross-sectional regression:

$$growth_{i,T,0} = \frac{lny_{iT} - lny_{i0}}{T-1} = \alpha_0 + b_1 lny_{i0} + X_{i0}'\delta + Z_i'\theta + u_i \tag{2.13}$$

where Z_i is used to proxy the variables from steady-state and X_{i0} comes from A_{i0}. X_{i0} are state variables which typically includes schooling, life expectancy etc. Z_i are control and environmental variables that will affect the steady state and, in turn, have an impact on per capita growth rate. Saving rate (as measured by the ratio of investment to real GDP), government consumption (as measured by the ratio of spending on defense and education to GDP), and growth rate of population represents the constituent parts of Z_i. These values are normally averages of data for a given time period.

On the other hand, the panel regression is:

$$growth_{i,t,t-k} = \frac{lny_{it} - lny_{it-k}}{k} = b_1 lny_{it-k} + X_{it-k}'\delta + X_{it}'\theta + \alpha_i + \eta_t + u_{it} \tag{2.14}$$

where X_{it-k} represents the proxy variables for A_{iq} whereas X_{it} measures A_{it+q}. The steady state variables are represented by the country fixed effects α_i.

(Galor and Zeira, 1993) propose an economic channel through which income distribution affects growth that justifies the inclusion of the inequality variable in the growth model. Later, (Galor and Zang, 1997) write per worker growth rate of income as:

$$growth_t = \frac{y_t - y_{t-1}}{y_{t-1}} = \frac{(1-\alpha)(1+\bar{r})}{n} - 1 + \frac{\bar{w}e}{y_{t-1}} + \frac{l_t^s}{y_{t-1}}[\bar{w}(\theta - 1)e - h(1+\bar{r})] \tag{2.15}$$

where l_t^s denotes the proportion of skilled workers in period t, i.e., $l_t^s = L_t^s/L_t$. l_t^s is determined in period $t-1$ by per-family income y_{t-1}, family size n, income distribution Q and required amount of human capital investment h:

$$l_t^s = l_t^s(y_{t-1}, n, Q, h) \tag{2.16}$$

where Q is the proxy of inequality. Because l_t^s is a function of predetermined variables, $growth_t$ can be expressed as:

$$growth_t = G(y_{t-1}, n, Q, e, h) \tag{2.17}$$

After taking the first-order approximation:

$$growth_t = G_n n + G_Q Q + G_y y_{t-1} + G_e e + G_h h + u_t \tag{2.18}$$

Another channel through which inequality could affect growth is politico-economic explanation. This reasoning captures the effect of fiscal policy on economic growth. Fiscal policy is affected by voter preferences regarding income distribution as each individual behaves like an economic agent when voting on tax rates (notably by (Alesina and Rodrik, 1994) and (Persson and Tabellini, 1994)). (Persson and Tabellini, 1994), for example, write the growth rate in politico-economic equilibrium as:

$$growth^* = G(w, r, \theta^*(w, r, e^m)) \tag{2.19}$$

where $\theta^*(\cdot)$ function can be derived from:

$$\underbrace{-\frac{D(r,\theta)e^m}{D(r,\theta) + r(1-\theta)}}_{\text{Marginal benefit of redistribution for median voter}} \quad + \quad \underbrace{\theta D_\theta(r,\theta)\frac{wr}{r + D(r,\theta)}}_{\text{Marginal cost of tax distortions}} = 0 \tag{2.20}$$

e is the endowment of corresponding skills and e^m determines the value of θ preferred by the median voter, which indicates the equilibrium policy, such that a change in the median voter would represent inequality. Additionally, w is the average skill level, r is the rate of return on assets, θ is the policy variable that measures redistribution, and $D(r, \theta_t) = d_t^i / c_{t-1}^i$ is the ratio of consumption in two periods (old and young). Therefore, a more unequal society will result in higher demand for redistribution financed by taxation, which would result in a lower rate of private investment and thus decreases future economic growth.

2.2.2 Inequality Model

Due to the lack of confirmed theory in the determination of inequality, different types of variables and regression equations are used in empirical studies, such as Q_{it}, lnQ_{it}, ΔQ_{it}, ΔlnQ_{it}, and various polynomial equations on the right hand side. To be specific, in previous studies that used linear specifications, income was used as a control for the effect of other explanatory variables for inequality, such as financial development, economic freedom, corruption, etc. A larger body of work, predicated on the Kuznets curve hypothesis, explores the nonlinearity of the inequality-growth relationship by augmenting the quadratic term of income as the explanatory variable. The Kuznets curve hypothesis suggests that inequality first rises in the process of economic development and then declines. More recent empirical studies provide evidence supporting the augmented Kuznets curve hypothesis proposed by (Conceicao and Galbraith, 2001). They show that in advanced economies, inequality increases again because of the monopolistic nature of the knowledge industry. In general, these studies use reduced-form regressions with different variables augmented.

Thus, the channels through which income affects inequality are demonstrated by augmenting explanatory variables on the right hand side of regression equations, such as human capital accumulation. However, the fact that there is no standard regression equation used to analyze the effect of income on inequality leads to mixed findings.

2.3 Empirical Specification

In this section, we provide the general form of the model specification for only one direction of causality, the effect of inequality on growth (henceforth referred to as direction 1), since there is no standard model specification for the effect of growth on inequality.

2.3.1 Cross-Sectional Regression in Direction 1

The general form of the cross-sectional regressions used is:

$$\frac{lny_{iT} - lny_{i0}}{T-1} = \alpha_0 + \beta_1 Q_{i0} + \beta_2 Q_i + \gamma y_{i0} + X'_{i0}\delta + Z'_i\theta + u_i \tag{2.21}$$

where Q_{i0} and Q_i measure inequality in terms of initial value and average value respectively. The average value, as stated by many authors, is an imperfect but established approach to dealing with the small sample data issue. y_{i0} is the initial per capita real GDP. X_{i0} denotes the initial value of our control variables $Z_i = (Z_{iT} - Z_{i0})/(T-1)$ denotes the average value of our control variables. The identifications after the corresponding restrictions are imposed are as follows:

$$\begin{cases} \frac{lny_{iT}-lny_{i0}}{T-1} = \alpha_0 + \beta_1 Q_{i0} + \gamma y_{i0} + X'_{i0}\delta + Z'_i\theta + u_i, \text{ for } \beta_2 = 0 \\ \frac{lny_{iT}-lny_{i0}}{T-1} = \alpha_0 + \beta_1 Q_{i0} + \gamma y_{i0} + X'_{i0}\delta + u_i, \text{ for } \theta = 0 \\ \frac{lny_{iT}-lny_{i0}}{T-1} = \alpha_0 + \beta_1 Q_{i0} + \gamma y_{i0} + Z'_i\theta + u_i, \text{ for } \delta = 0 \\ \frac{lny_{iT}-lny_{i0}}{T-1} = \alpha_0 + \beta_2 Q_i + \gamma y_{i0} + X'_{i0}\delta + Z'_i\theta + u_i, \text{ for } \beta_1 = 0 \\ \frac{lny_{iT}-lny_{i0}}{T-1} = \alpha_0 + \beta_2 Q_i + \gamma y_{i0} + X'_{i0}\delta + u_i, \text{ for } \theta = 0 \\ \frac{lny_{iT}-lny_{i0}}{T-1} = \alpha_0 + \beta_2 Q_i + \gamma y_{i0} + +Z'_i\theta + u_i, \text{ for } \delta = 0 \end{cases} \tag{2.22}$$

Papers that define inequality as the initial value: (Alesina and Rodrik, 1994), (Persson and Tabellini, 1994), (Birdsall et al., 1995), (Clarke, 1995), (Perotti, 1996), (Birdsall and Londoño, 1997), (Galor and Zang, 1997), (Deininger and Squire, 1998), (Li and Zou, 1998), (Tanninen, 1999), (Forbes, 2000), (Sylwester, 2000), (Castelló and Doménech, 2002), (Keefer and Knack, 2002), (Bleaney and Nishiyama, 2004), (Odedokun and Round, 2004), (Knowles, 2005), (Sarkar, 2007), (Woo, 2011), (Castells-Quintana and Royuela, 2017)

Papers that define inequality as the average value: (Deininger and Squire, 1998), (Davis and Hopkins, 2011)

Papers that use both X_{i0} and Z_i as the control variables: (Birdsall et al., 1995), (Clarke, 1995), (Birdsall and Londoño, 1997), (Galor and Zang, 1997), (Tanninen, 1999), (Sylwester, 2000), (Castelló and Doménech, 2002), (Bleaney and Nishiyama, 2004), (Odedokun and Round, 2004), (Davis and Hopkins, 2011), (Woo, 2011)

Papers that use X_{i0} as the only control variables: (Alesina and Rodrik, 1994), (Persson and Tabellini, 1994), (Perotti, 1996), (Li and Zou, 1998), (Forbes, 2000), (Sylwester, 2000), (Keefer and Knack, 2002), (Knowles, 2005), (Woo, 2011), (Castells-Quintana and Royuela, 2017)

Papers that use Z_i as the only control variables: (Deininger and Squire, 1998), (Sarkar, 2007)

2.3.2 Panel Regression in Direction 1

The general form of the panel regressions used is:

$$\begin{aligned}\frac{lny_{it} - lny_{it-k}}{k} =& \beta_1 Q_{it-k} + \beta_2 Q_{it-k-1} + \beta_3 Q_{it} + \gamma_1 lny_{it-k} + \gamma_2 lny_{it-k-1} \\ &+ X'_{it-k}\delta_1 + X'_{it-k-1}\delta_2 + X'_{it}\delta_3 + \alpha_i + \eta_t + u_{it}\end{aligned} \tag{2.23}$$

where Q_{it-k}, Q_{it-k-1}, and Q_{it} are the measures of inequality for country i at the beginning of the period, the year immediately preceding each period, and the current period respectively. lny_{it-k} and lny_{it} are the logarithm of per capita GDP at the beginning of the period and current period. k defines the period interval (normally 5 or 10 years). X_{it-k}, X_{it-k-1}, and X_{it} denote the vector of control variables in the corresponding period of inequality variables. α_i is the country fixed effect while η_t is the time effect. The error term is demonstrated by u_{it}. Specifically, the identifications after corresponding restrictions are imposed are as follows:

$$\begin{cases} \frac{lny_{it}-lny_{it-k}}{k} = \beta_1 Q_{it-k} + \gamma_1 lny_{it-k} + X'_{it-k}\delta_1 + \alpha_i + \eta_t + u_{it}, \text{for } \beta_2, \beta_3, \gamma_2, \delta_2, \delta_3 = 0 \\ \frac{lny_{it}-lny_{it-k}}{k} = \beta_2 Q_{it-k-1} + \gamma_2 lny_{it-k-1} + X'_{it-k-1}\delta_2 + \alpha_i + \eta_t + u_{it}, \text{for } \beta_1, \beta_3, \gamma_1, \delta_1, \delta_3 = 0 \\ \frac{lny_{it}-lny_{it-k}}{k} = \beta_3 Q_{it} + \gamma_1 lny_{it-k} + X'_{it}\delta_3 + \alpha_i + \eta_t + u_{it}, \text{for } \beta_1, \beta_2, \gamma_2, \delta_1, \delta_2 = 0 \\ \frac{lny_{it}-lny_{it-k}}{k} = \beta_1 Q_{it-k} + X'_{it-k}\delta_1 + \alpha_i + \eta_t + u_{it}, \text{for } \beta_2, \beta_3, \gamma_1, \gamma_2, \delta_2, \delta_3 = 0 \end{cases} \tag{2.24}$$

The choice of k: As k increases, the estimated coefficients become smaller. (More mathematical evidence can be found in the Appendix.)

With y_{it-k} and without y_{it-k}: Suppose $y_{it} = \rho y_{it-k} + e_{it}$ where ρ is the AR(1) coefficient of y_{it}, subtracting y_{it-k} from both sides yields: $y_{it} - y_{it-k} = (\rho - 1)y_{it-k} + e_{it}$. Therefore, if $\rho \neq 1$, the y_{it-k} term needs to be included on the RHS of the estimation equation.

There are four types of inequality variables: the lagged value Q_{it-k}, the current value Q_{it}, the average during the lagged period $Q_{it-k} = (\sum_{s=t-2k}^{t-k} Q_{is})/k$, and the average during the current period under concern $Q_{it} = (\sum_{s=t-k}^{t} Q_{is})/k$. The initial levels of inequality within each period Q_{it-k} are more commonly used to handle the potential endogeneity problem. For example, if growth is measured from 1965 to 1970, it would be regressed on inequality in 1965. Although the endogeneity problem cannot be fully eliminated, employing the stock inequality measure at the beginning of the period rather than a contemporaneous value or a flow value throughout the period may substantially reduce the impact of potential endogeneity issues (notably (Forbes, 2000)). Moreover, the initial level can also allow for a slow acting impact ((Gründler and Scheuermeyer, 2018)). Averages could also be utilized as an alternative to current or lagged inequality, as inequality data is not always available on an annual basis. Using the previous example, if the inequality variable in 1965 is not available, either the data closest to 1965 or the average within that period will be used as alternatives.

Papers that define inequality as a one-period lagged value: (Persson and Tabellini, 1994), (Li and Zou, 1998), (Barro, 2000), (Deininger and Olinto, 2000), (Forbes, 2000), (Banerjee and Duflo, 2003), (De La Croix and Doepke, 2003), (Galbraith and Kum, 2003), (Iradian, 2005), (Voitchovsky, 2005), (Barro, 2008), (Bjørnskov, 2008), (Castelló-Climent, 2010a), (Castelló-Climent, 2010b), (Chambers and Krause, 2010), (Andrews et al., 2011), (Davis and Hopkins, 2011), (Malinen, 2013), (Halter et al., 2014), (Ostry et al., 2014), (Thewissen, 2014), (Bagchi and Svejnar, 2015), (Naguib, 2015), (Lee and Son, 2016), (Scholl and Klasen, 2016), (Caraballo et al., 2017), (Gründler and Scheuermeyer, 2018)

Papers that define inequality as the contemporaneous or latest available value: (Galbraith and Kum, 2003), (Lundberg and Squire, 2003), (Bengoa and Sanchez-Robles*, 2005), (Gründler and Scheuermeyer, 2018)

Papers that exclude lny_{it-k} term: (Khalifa et al., 2010)

Papers that use other estimation equations: (Abida and Sghaier, 2012), (Herzer and Vollmer, 2012), (Malinen, 2012), (Muinelo-Gallo and Roca-Sagalés, 2013)

Papers that estimate the general form by POLS/2SLS/3SLS: (Persson and Tabellini, 1994), (Barro, 2000), (Voitchovsky, 2005), (Barro, 2008), (Chambers and Krause, 2010), (Andrews et al., 2011), (Malinen, 2013), (Scholl and Klasen, 2016)

Papers that estimate the general form by FE: (Li and Zou, 1998), (Deininger and Olinto, 2000), (Forbes, 2000), (Banerjee and Duflo, 2003), (Galbraith and Kum, 2003), (Iradian, 2005), (Voitchovsky, 2005), (Bjørnskov, 2008), (Castelló-Climent, 2010b), (Chambers and Krause, 2010), (Andrews et al., 2011), (Davis and Hopkins, 2011), (Thewissen, 2014), (Bagchi and Svejnar, 2015), (Naguib, 2015), (Scholl and Klasen, 2016)

Papers that estimate the general form by RE: (Li and Zou, 1998), (Forbes, 2000), (Banerjee and Duflo, 2003), (Bjørnskov, 2008), (Castelló-Climent, 2010b), (Andrews et al., 2011), (Davis and Hopkins, 2011), (Bagchi and Svejnar, 2015), (Naguib, 2015)

Papers that estimate the general form by GMM: (Deininger and Olinto, 2000), (Forbes, 2000), (Banerjee and Duflo, 2003), (De La Croix and Doepke, 2003), (Voitchovsky, 2005), (Castelló-Climent, 2010a), (Castelló-Climent, 2010b), (Malinen, 2013), (Halter et al., 2014), (Ostry et al., 2014), (Naguib, 2015), (Lee and Son, 2016), (Scholl and Klasen, 2016), (Caraballo et al., 2017), (Gründler and Scheuermeyer, 2018)

2.4 Estimation Issue

2.4.1 Estimation Issue in Cross-Sectional Regression

The most commonly used cross-sectional technique in the 1990s suffers from the following issues. The first has to do with the cross-sectional inequality-growth literature's use of time averaged growth and initial inequality. This approach is used to eliminate business cycle effects. However, it is criticized in the literature because of omitted variable bias. It is a source of sensitivity that makes the negative effect of inequality on growth ambiguous. For example, this negative effect disappears when regional dummies, fertility or other explanatory variables are included, or when there are controls for the DCs/LDCs and democratic/non democratic categories. Moreover, even though the DS dataset improves the quality of Gini coefficients substantially, there are still measurement error issues for inequality variables. Normally inequality data comes from household surveys from each country. There is, however, huge heterogeneity in the collection and reporting of inequality data across countries. This heterogeneity could pose serious problems for estimation in studies of cross-country income inequality. More mathematical evidence of omitted variable bias and measurement error can be found in the Appendix.

2.4.2 Estimation Issue in Panel Regression

The panel technique has long been regarded as the best alternative to overcome the problems of the cross-sectional technique, as it can solve the time-invariant omitted variable issue and address the question of how changes in inequality are associated with changes in growth.

Nonetheless, this approach is not without issues of its own. First and most importantly, income trends across time for every country, whilst Gini coefficients only trend across time for some countries. Empirical studies of both directions thus suffer from non-stationarity issues that bring into question the validity of their findings. Second, the time-variant omitted variable bias still affects the regression resul ts. Third, due to the availability of inequality data a 5-year or 10-year period panel is typically employed in panel regressions modeling economic growth. This method, however, does not completely avoid the missing value problem and significantly shrinks time span T. Using the 5-year panel as an example, the size of T is typically 5 or 6, which is too small. After taking one lagged period, which is common in the literature, there are indeed fewer observations for each country. Using the average or the nearest available observations results in more inaccurate estimates.

Specifically, the commonly used fixed effect model that uses a lagged dependent term as one of the explanatory variables will bias the coefficient ((Nickell, 1981)). Regardless of the correlation between $lny_{i,t-k}$ and u_{it}, the coefficients in a dynamic panel model become inconsistent because T is not large enough. GMM thus needs to be adopted when there is a lagged dependent term on the RHS. After taking first difference to alter the estimation into GMM, however, the authors (1) lose one additional observation when T is originally short, (2) has issues typical of first difference GMM such as weak instruments, and (3) drives the level case into a first difference case which wipes out the long-run relationship. Furthermore, the general form of panel regression consists of a common time effect that imposes a homogeneous assumption. However, η_t is supposed to be heterogeneous with the form $\lambda_i \eta_t$ and so the factor augmented regression needs to be considered. [1]

While previous literature suggests various channels through which inequality could potentially impact on growth, this relationship remains ambiguous. It is necessary to interpret

[1] See Appendix A for more details of estimation issues.

these simple empirical results more carefully, regardless of whether the coefficients are positive or negative. The issues or concerns listed above, in turn, underline the necessity of thoughtful data selection and identification strategy.

2.5 Descriptive Statistics

In this section, only the inequality coefficients from direction 1 are presented as these are the only comparable variables. Since we are focusing on the estimated coefficients of inequality in growth regression, articles that did not provide any such estimates, such as theoretical articles and case studies, are the first to be excluded. Furthermore, in order to make the coefficients more comparable, we drop the "outliers" which are not included in the estimation methods listed above. Our target variable is the coefficient associated with inequality, β, in our general form. Applying all these criteria, we are left with 973 coefficients from 51 papers.

We then attempt to explain the heterogeneity of the inequality coefficients using descriptive statistics. The characteristics reflected in cross sectional regressions are: the estimation techniques, the definition of inequality, the data sources, the data quality, the choice of countries, the inequality variables, and the control variables. In panel regressions, the interval k is considered an additional characteristic.

2.5.1 Coefficients in Full Sample

Among those 973 coefficients, 322 are collected from cross sectional regressions and 651 are collected from panel regressions. The descriptive statistics for the full sample are illustrated in Table 2.2 and Table 2.3 for cross sectional and panel regressions respectively. All the cross sectional estimates yield a negative coefficients in 80 percentile except the estimates in different choices of countries. More importantly, the estimates with WLS, non-Gini inequality, non-DS databases, and whole country samples reveal a 95 percentile negative effect. Additionally, among regressions where the control variables only cover either initial variables or the average variables, the coefficients become negative in 95 percentile. Because cross sectional estimation is capturing long-run impacts, as established in the literature, it shows consistently that initial inequality is detrimental to long-run growth.

The results of panel estimations, however, are not as consistent as the results of cross sectional estimations. Two notable results are fixed effects estimates, of which the 10 percentile coefficient is positive, and panel cointegration estimates, of which the 90 percentile coefficient is negative. This implies that in the short run when using fixed effects estimation, an increase in a country's level of inequality will correlate with economic growth within that country, regardless of inequality variables, data sources, data quality, choice of countries, or interval k. The panel cointegration estimation accounts for the negative results in the case of interval $k = 1$ because $k = 1$ was used in almost all the panel cointegration regressions.

2.5.2 Coefficients in Selected Sample

To avoid giving any papers disproportionate weight in our results we restricted ourselves to collecting 5 estimates or less from each study. The estimates selected will be either those for main regressions or those preferred by the original authors. We will also use the average and median estimates later as a robustness check. The number of coefficients is thus reduced to 190 in the selected sample, among which 69 are cross sectional estimates and 121 are panel estimates. In general, the descriptive statistics for the selected sample remain similar to those for the full sample. One significant difference is that relatively more estimates are negative in the selected sample than in the full sample cross sectional regressions (Table 2.4 and Table 2.5).

2.5.3 Coefficients in GMM

GMM is one of the most common methods used to test the inequality-growth relationship. Models using it comprise the largest proportion of all estimation techniques. Therefore, it is essential to analyze the coefficients from GMM regressions. Table 2.6 and Table 2.7 highlight the descriptive statistics for GMM regressions. We obtain a negative coefficient in 80 percentile for less developed countries and a positive coefficient in 20 percentile for $k \geq 10$ in the full sample. Furthermore, the coefficients from non-Gini inequality are negative in 80 percentile and the coefficients from $k \geq 10$ are positive in 20 percentile. Nonetheless, all of these results suffer from a lack of observations.

2.6 Conclusion

Most of the studies in this rich literature tend to explore the inequality-growth relationship by identifying the determinants of either growth or inequality, but not both. Even though other studies have explored both directions of causality in the inequality-growth relationship, identifying the direction of causality is still difficult. This paper summarizes the inequality-growth literature for both directions of causality in terms of channels of causality, specifications, estimation issues, and descriptive statistics of coefficients. For empirical studies focusing on direction 1, the standard augmented Solow regression leads to an early consensus on the negative impact of inequality on growth in cross-sectional regressions, while panel specifications do not exhibit any consensus. As for determinants of inequality, the majority of studies verify the Kuznets Curve hypothesis using reduced form regressions, among which different orders of nonlinearity are utilized. Empirical results are sensitive to model specifications.

From the descriptive statistics for inequality coefficients, the existing cross-sectional regressions used to analyze the effect of inequality on growth normally estimate a negative coefficient regardless of data source, measure of inequality, data quality, or choice of controls, suggesting that countries with a more polarized income distribution tend to grow slower. However, estimations from panel regressions remain inconclusive. Within panel regressions, fixed effect estimations are more likely to yield positive coefficients of inequality, while panel cointegration estimations are more likely to yield a negative inequality-growth relationship. Similar results can be obtained when a selected coefficient sample is used. Due to the potential estimation issues of these commonly used methods, empirical findings are mixed.

Table 2.2. Cross sectional regression in full sample

		Statistics											
		Mean	se	Median	Max	Min	5%	10%	20%	80%	90%	95%	obs
All	All	-0.068	0.011	-0.045	0.098	-2.508	-0.162	-0.112	-0.077	-0.016	-0.001	0.022	322
Method	OLS	-0.071	0.012	-0.047	0.098	-2.508	-0.163	-0.113	-0.079	-0.017	-0.002	0.023	278
Method	WLS	-0.060	0.012	-0.047	-0.016	-0.274	-0.097	-0.078	-0.073	-0.031	-0.024	-0.022	20
Method	2SLS	-0.040	0.010	-0.028	0.002	-0.171	-0.155	-0.119	-0.061	-0.001	0.000	0.002	24
Q definition	Gini	-0.064	0.015	-0.039	0.061	-2.508	-0.137	-0.089	-0.070	-0.015	0.007	0.025	195
Q definition	NonGini	-0.075	0.015	-0.050	0.098	-1.780	-0.195	-0.144	-0.092	-0.020	-0.006	-0.002	127
Data source	DS	-0.042	0.004	-0.037	0.098	-0.283	-0.151	-0.110	-0.072	-0.005	0.022	0.034	157
Data source	NonDS	-0.093	0.020	-0.050	0.008	-2.508	-0.197	-0.113	-0.080	-0.027	-0.012	-0.003	165
Data quality	High	-0.070	0.016	-0.039	0.098	-2.508	-0.162	-0.114	-0.073	-0.014	0.000	0.033	183
Data quality	Low	-0.066	0.013	-0.049	0.025	-1.780	-0.155	-0.108	-0.078	-0.022	-0.002	0.015	139
Countries	Whole	-0.075	0.012	-0.048	0.025	-2.508	-0.153	-0.107	-0.077	-0.021	-0.010	-0.002	272
Countries	DCs	-0.003	0.018	0.017	0.050	-0.243	-0.092	-0.027	-0.021	0.038	0.042	0.046	15
Countries	LDCs	-0.043	0.014	-0.028	0.098	-0.283	-0.199	-0.158	-0.085	0.024	0.035	0.051	35
Q variable	Initial	-0.055	0.006	-0.044	0.098	-1.780	-0.152	-0.104	-0.073	-0.016	-0.002	0.023	308
Q variable	Average	-0.367	0.187	-0.066	0.008	-2.508	-1.585	-1.002	-0.472	-0.031	-0.008	0.003	14
Controls	X+Z	-0.072	0.016	-0.044	0.098	-2.508	-0.173	-0.125	-0.077	-0.008	0.016	0.033	178
Controls	X	-0.073	0.016	-0.052	0.002	-1.780	-0.155	-0.115	-0.082	-0.022	-0.014	-0.003	115
Controls	Z	-0.026	0.003	-0.022	0.025	-0.055	-0.052	-0.048	-0.043	-0.015	-0.011	-0.006	29

Table 2.3. Panel regression in full sample

		Statistics											
		Mean	se	Median	Max	Min	5%	10%	20%	80%	90%	95%	obs
All	All	0.029	0.010	0.003	2.850	-1.200	-0.305	-0.144	-0.052	0.099	0.168	0.415	651
Method	LS	-0.066	0.017	-0.036	0.156	-0.497	-0.369	-0.265	-0.119	0.045	0.057	0.065	65
Method	FE	0.128	0.015	0.082	1.225	-0.105	-0.005	0.002	0.022	0.163	0.249	0.498	150
Method	RE	0.030	0.020	0.033	0.349	-0.399	-0.140	-0.093	-0.030	0.104	0.136	0.286	48
Method	GMM	0.009	0.017	-0.004	2.850	-1.200	-0.326	-0.182	-0.052	0.039	0.129	0.452	349
Method	Co-int	-0.108	0.018	-0.110	0.101	-0.456	-0.265	-0.234	-0.165	-0.013	-0.010	0.015	34
Q definition	Gini	0.039	0.016	0.012	2.850	-1.200	-0.346	-0.231	-0.095	0.119	0.286	0.571	413
Q definition	NonGini	0.010	0.006	0.001	0.530	-0.440	-0.088	-0.055	-0.031	0.051	0.111	0.164	238
Data source	DS	0.093	0.015	0.038	1.498	-0.440	-0.091	-0.036	-0.011	0.154	0.293	0.560	235
Data source	NonDS	-0.007	0.014	-0.005	2.850	-1.200	-0.322	-0.218	-0.095	0.062	0.112	0.248	416
Data quality	High	0.037	0.012	0.002	2.850	-1.200	-0.312	-0.133	-0.047	0.108	0.183	0.452	535
Data quality	Low	-0.007	0.014	0.011	0.700	-0.344	-0.293	-0.192	-0.078	0.052	0.075	0.124	116
Countries	Whole	0.024	0.015	0.004	2.850	-1.080	-0.322	-0.206	-0.069	0.108	0.166	0.397	354
Countries	DCs	0.063	0.015	0.012	1.540	-0.456	-0.106	-0.043	-0.022	0.088	0.174	0.395	237
Countries	LDCs	-0.079	0.037	-0.032	0.610	-1.200	-0.663	-0.382	-0.142	0.000	0.107	0.422	60
Interval k	k1	-0.096	0.023	-0.107	0.244	-0.497	-0.433	-0.242	-0.165	-0.008	0.064	0.097	44
Interval k	k3-7	0.036	0.011	0.005	2.850	-1.200	-0.292	-0.106	-0.033	0.105	0.170	0.419	562
Interval k	k10-20	0.065	0.054	-0.003	1.498	-0.440	-0.357	-0.161	-0.062	0.058	0.233	0.902	45
Q variable	Initial	0.033	0.011	0.003	2.850	-1.200	-0.298	-0.131	-0.048	0.102	0.170	0.422	627
Q variable	Current	-0.085	0.026	-0.048	0.066	-0.316	-0.306	-0.300	-0.196	0.038	0.043	0.054	24

Table 2.4. Cross sectional regression in selected sample

		Statistics											
		Mean	se	Median	Max	Min	5%	10%	20%	80%	90%	95%	obs
All	All	-0.049	0.005	-0.047	0.050	-0.187	-0.131	-0.092	-0.079	-0.018	-0.004	0.000	69
Method	OLS	-0.046	0.005	-0.045	0.050	-0.187	-0.112	-0.088	-0.078	-0.017	-0.002	0.001	60
Method	WLS+2SLS	-0.070	0.017	-0.059	-0.005	-0.171	-0.155	-0.138	-0.095	-0.042	-0.031	-0.018	9
Q definition	Gini	-0.053	0.006	-0.050	0.050	-0.187	-0.135	-0.093	-0.078	-0.022	-0.013	-0.004	55
Q definition	NonGini	-0.033	0.010	-0.023	0.001	-0.111	-0.093	-0.083	-0.061	-0.002	-0.001	-0.001	14
Data source	DS	-0.053	0.007	-0.050	0.050	-0.187	-0.134	-0.093	-0.076	-0.024	-0.018	-0.002	38
Data source	NonDS	-0.044	0.008	-0.033	0.008	-0.171	-0.120	-0.083	-0.078	-0.005	-0.002	0.000	31
Data quality	High	-0.045	0.007	-0.039	0.050	-0.187	-0.128	-0.091	-0.073	-0.018	-0.009	0.007	43
Data quality	Low	-0.056	0.008	-0.050	0.001	-0.171	-0.125	-0.097	-0.080	-0.031	-0.002	-0.001	26
Countries	Whole	-0.051	0.005	-0.047	0.008	-0.187	-0.129	-0.092	-0.078	-0.019	-0.005	-0.002	61
Countries	DCs	0.015	0.035	0.015	0.050	-0.020	-0.017	-0.013	-0.006	0.036	0.043	0.047	2
Countries	LDCs	-0.051	0.026	-0.057	0.046	-0.143	-0.127	-0.111	-0.079	-0.017	0.015	0.030	6
Q variable	Initial	-0.050	0.005	-0.048	0.050	-0.187	-0.132	-0.093	-0.079	-0.018	-0.004	-0.001	64
Q variable	Average	-0.037	0.013	-0.039	0.008	-0.074	-0.068	-0.063	-0.052	-0.025	-0.008	0.000	5
Controls	X+Z	-0.052	0.009	-0.047	0.050	-0.187	-0.153	-0.121	-0.076	-0.019	-0.001	0.021	34
Controls	X	-0.052	0.006	-0.050	0.001	-0.129	-0.103	-0.089	-0.081	-0.024	-0.010	-0.003	29
Controls	Z	-0.018	0.006	-0.015	-0.004	-0.047	-0.040	-0.034	-0.020	-0.009	-0.006	-0.005	6

Table 2.5. Panel regression in selected sample

		Statistics											
		Mean	se	Median	Max	Min	5%	10%	20%	80%	90%	95%	obs
All	All	0.045	0.024	0.010	0.933	-1.020	-0.241	-0.103	-0.044	0.107	0.297	0.565	121
Method	LS	-0.037	0.028	-0.033	0.066	-0.488	-0.159	-0.075	-0.058	0.047	0.055	0.059	19
Method	FE	0.146	0.043	0.054	0.933	-0.040	-0.022	0.003	0.014	0.183	0.360	0.741	31
Method	RE	0.053	0.026	0.060	0.284	-0.154	-0.074	-0.029	-0.003	0.106	0.123	0.184	14
Method	GMM	-0.034	0.045	-0.010	0.778	-1.020	-0.406	-0.303	-0.104	0.051	0.220	0.501	45
Method	Co-int	-0.031	0.008	-0.022	-0.009	-0.068	-0.066	-0.065	-0.053	-0.013	-0.012	-0.010	8
Q definition	Gini	0.058	0.030	0.017	0.933	-1.020	-0.345	-0.131	-0.037	0.130	0.385	0.737	97
Q definition	NonGini	-0.005	0.010	-0.008	0.112	-0.086	-0.060	-0.057	-0.049	0.035	0.058	0.089	24
Data source	DS	0.156	0.036	0.051	0.933	-0.154	-0.038	-0.032	-0.010	0.297	0.649	0.791	56
Data source	NonDS	-0.050	0.028	-0.013	0.560	-1.020	-0.406	-0.241	-0.087	0.050	0.102	0.150	65
Data quality	High	0.057	0.033	0.003	0.933	-1.020	-0.317	-0.112	-0.055	0.126	0.385	0.743	87
Data quality	Low	0.015	0.024	0.011	0.560	-0.344	-0.151	-0.055	-0.033	0.048	0.096	0.195	34
Countries	Whole	0.001	0.027	-0.005	0.747	-1.020	-0.344	-0.109	-0.061	0.064	0.159	0.301	80
Countries	DCs	0.192	0.055	0.057	0.933	-0.241	-0.042	-0.013	0.006	0.423	0.778	0.847	31
Countries	LDCs	-0.057	0.054	-0.032	0.160	-0.488	-0.324	-0.159	-0.069	0.006	0.079	0.120	10
Interval k	k1	-0.072	0.044	-0.030	0.066	-0.488	-0.305	-0.122	-0.068	-0.013	-0.009	0.028	11
Interval k	k3-7	0.046	0.028	0.015	0.862	-1.020	-0.277	-0.105	-0.041	0.110	0.298	0.562	94
Interval k	k10-20	0.123	0.075	-0.005	0.933	-0.061	-0.057	-0.048	-0.037	0.107	0.531	0.817	16
Q variable	Initial	0.048	0.026	0.010	0.933	-1.020	-0.287	-0.105	-0.050	0.108	0.298	0.641	112
Q variable	Current	0.011	0.011	0.011	0.056	-0.044	-0.034	-0.023	-0.014	0.041	0.046	0.051	9

Table 2.6. GMM estimators in full sample

			Statistics											
			Mean	se	Median	Max	Min	5%	10%	20%	80%	90%	95%	obs
All	All	All	-0.003	0.008	-0.014	2.850	-2.508	-0.242	-0.131	-0.068	0.056	0.128	0.246	973
CS	All	All	-0.068	0.011	-0.045	0.098	-2.508	-0.162	-0.112	-0.077	-0.016	-0.001	0.022	322
Panel	All	All	0.029	0.010	0.003	2.850	-1.200	-0.305	-0.144	-0.052	0.099	0.168	0.415	651
Panel	LS	All	-0.066	0.017	-0.036	0.156	-0.497	-0.369	-0.265	-0.119	0.045	0.057	0.065	65
Panel	FE	All	0.128	0.015	0.082	1.225	-0.105	-0.005	0.002	0.022	0.163	0.249	0.498	150
Panel	RE	All	0.030	0.020	0.033	0.349	-0.399	-0.140	-0.093	-0.030	0.104	0.136	0.286	48
Panel	Coin	All	-0.108	0.018	-0.110	0.101	-0.456	-0.265	-0.234	-0.165	-0.013	-0.010	0.015	34
Panel	GMM	All	0.009	0.017	-0.004	2.850	-1.200	-0.326	-0.182	-0.052	0.039	0.129	0.452	349
Panel	GMM	Gini	0.016	0.030	-0.008	2.850	-1.200	-0.438	-0.315	-0.142	0.074	0.388	0.754	193
Panel	GMM	NonGini	0.001	0.005	-0.003	0.222	-0.335	-0.058	-0.037	-0.027	0.021	0.039	0.113	156
Panel	GMM	DS	0.043	0.019	0.000	1.498	-0.114	-0.061	-0.036	-0.020	0.052	0.109	0.252	99
Panel	GMM	NonDS	-0.004	0.022	-0.009	2.850	-1.200	-0.398	-0.294	-0.096	0.037	0.141	0.528	250
Panel	GMM	High	0.013	0.019	-0.004	2.850	-1.200	-0.342	-0.143	-0.041	0.031	0.129	0.446	292
Panel	GMM	Low	-0.010	0.026	-0.004	0.700	-0.344	-0.309	-0.267	-0.134	0.064	0.131	0.304	57
Panel	GMM	Whole	0.002	0.026	-0.005	2.850	-1.080	-0.364	-0.297	-0.109	0.047	0.233	0.539	187
Panel	GMM	DCs	0.047	0.020	0.002	1.540	-0.335	-0.053	-0.037	-0.025	0.046	0.106	0.229	133
Panel	GMM	LDCs	-0.123	0.057	-0.016	0.170	-1.200	-0.768	-0.672	-0.054	-0.001	0.003	0.100	29
Panel	GMM	k5	0.003	0.016	-0.004	2.850	-1.200	-0.328	-0.186	-0.055	0.038	0.121	0.389	344
Panel	GMM	k10	0.465	0.298	0.060	1.498	-0.030	-0.020	-0.010	0.010	0.922	1.210	1.354	5
Panel	GMM	t-k	0.016	0.017	-0.003	2.850	-1.200	-0.332	-0.141	-0.039	0.041	0.135	0.484	333
Panel	GMM	t	-0.133	0.033	-0.131	0.066	-0.316	-0.309	-0.305	-0.293	0.006	0.038	0.047	16

Table 2.7. GMM estimators in selected sample

			Statistics											
			Mean	se	Median	Max	Min	5%	10%	20%	80%	90%	95%	obs
All	All	All	0.011	0.016	-0.019	0.933	-1.020	-0.163	-0.095	-0.063	0.054	0.133	0.395	190
CS	All	All	-0.049	0.005	-0.047	0.050	-0.187	-0.131	-0.092	-0.079	-0.018	-0.004	0.000	69
Panel	All	All	0.045	0.024	0.010	0.933	-1.020	-0.241	-0.103	-0.044	0.107	0.297	0.565	121
Panel	LS	All	-0.037	0.028	-0.033	0.066	-0.488	-0.159	-0.075	-0.058	0.047	0.055	0.059	19
Panel	FE	All	0.146	0.043	0.054	0.933	-0.040	-0.022	0.003	0.014	0.183	0.360	0.741	31
Panel	RE	All	0.053	0.026	0.060	0.284	-0.154	-0.074	-0.029	-0.003	0.106	0.123	0.184	14
Panel	Coin	All	-0.031	0.008	-0.022	-0.009	-0.068	-0.066	-0.065	-0.053	-0.013	-0.012	-0.010	8
Panel	GMM	All	-0.034	0.045	-0.010	0.778	-1.020	-0.406	-0.303	-0.104	0.051	0.220	0.501	45
Panel	GMM	Gini	-0.038	0.060	-0.010	0.778	-1.020	-0.620	-0.348	-0.183	0.116	0.265	0.560	34
Panel	GMM	NonGini	-0.024	0.010	-0.011	0.033	-0.086	-0.072	-0.057	-0.050	-0.003	0.009	0.021	11
Panel	GMM	DS	0.092	0.058	0.001	0.778	-0.030	-0.028	-0.025	-0.011	0.060	0.345	0.615	16
Panel	GMM	NonDS	-0.104	0.059	-0.050	0.560	-1.020	-0.762	-0.364	-0.241	0.039	0.180	0.264	29
Panel	GMM	High	-0.062	0.062	-0.010	0.778	-1.020	-0.734	-0.357	-0.113	0.023	0.144	0.428	30
Panel	GMM	Low	0.020	0.053	-0.010	0.560	-0.344	-0.272	-0.186	-0.047	0.080	0.220	0.350	15
Panel	GMM	Whole	-0.088	0.048	-0.023	0.560	-1.020	-0.591	-0.348	-0.113	0.020	0.056	0.169	35
Panel	GMM	DCs	0.179	0.120	0.057	0.778	-0.241	-0.170	-0.100	-0.027	0.443	0.625	0.702	8
Panel	GMM	LDCs	0.056	0.104	0.056	0.160	-0.048	-0.038	-0.027	-0.006	0.118	0.139	0.150	2
Panel	GMM	k5	-0.058	0.045	-0.011	0.560	-1.020	-0.420	-0.344	-0.106	0.033	0.160	0.267	41
Panel	GMM	k10	0.207	0.191	0.040	0.778	-0.030	-0.023	-0.015	0.000	0.347	0.563	0.670	4
Panel	GMM	t-k	-0.035	0.046	-0.011	0.778	-1.020	-0.410	-0.313	-0.104	0.053	0.230	0.516	44
Panel	GMM	t	0.006	N/A	0.006	0.006	0.006	0.006	0.006	0.006	0.006	0.006	0.006	1

CHAPTER 3

THE LONG-RUN RELATIONSHIP BETWEEN INEQUALITY AND GROWTH: A CONVERGENCE APPROACH

3.1 Introduction

The inequality-growth relationship has been paid considerable attention since the beginning of the last century. Using the United States as an example, the level of income inequality there suffered a sharp decrease during the Great Depression and World War II. It later bottomed out in the 1970s and has been mounting since the 1980s. Figure 3.1 shows the distribution of income in the United States (both the top 10% and top 1%) from 1913 to 2014 (Data source: World Inequality Database). It seems that there is a close relationship between income inequality and economic growth as income inequality changes with economic growth. In practice, however, the intensive debate regarding the inequality-growth relationship is not conclusive, especially as both income inequality and the results of country-level analysis vary dramatically across countries.

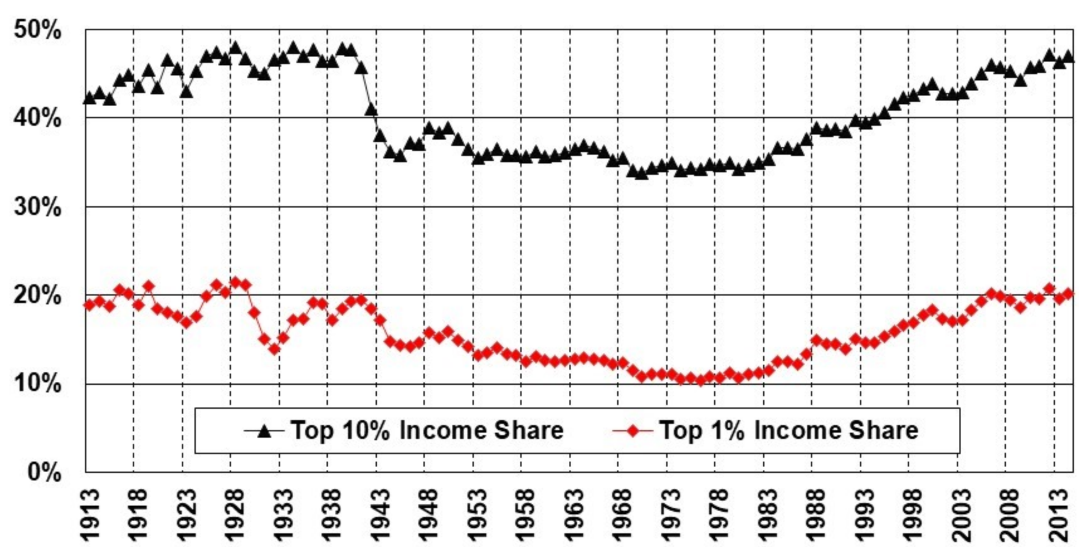


Figure 3.1. Share of total income in United States, 1913-2014

The puzzling relationship between inequality and growth plagues policy makers around the world. When income within a population is distributed unevenly, income inequality occurs. Are the rich getting richer and the poor getting poorer? Income inequality appears because only a group of people are rich. It seems that economic growth results in income inequality. However, this relationship implies that governments committed to reducing inequality would mitigate economic growth in order to mitigate income inequality, which obviously does not happen. On the other hand, if economic growth helps to mitigate income inequality, then why hasn't the world witnessed diminishing inequality in fast growing economies, such as those of China and India? The relationship between income inequality and economic growth is thus much more complicated than it would at first appear. This is reflected in the fact that researchers are far from reaching a consensus on this question. Hence, understanding the causality of that relationship is important.

The literature on the inequality-growth relationship that uses country-level analysis is, in general, large and still growing. Early studies using cross-sectional regressions documented the negative impact of inequality on growth through the standard augmented Solow regression ((Alesina and Rodrik, 1994), (Birdsall et al., 1995), (Clarke, 1995), (Galor and Zang, 1997), and (Perotti, 1996) etc.). This model offers an attractive framework for dealing with the issues that researchers are trying to overcome in studies of economic growth. Researchers claim that cross-country regression captures the long-run relationship by using average growth rate in T years (typically 20-40 years). However, two idiosyncratic terms of growth and inequality may produce a negative coefficient of inequality. In addition, the practice of averaging across a longer time horizon does not necessarily capture the long-run relationship and depends largely on the specific time horizon being used.

Starting with (Forbes, 2000), a large number of studies began using panel data models with fixed effects to examine the effect of inequality on economic growth across countries ((Andrews et al., 2011), (Bjørnskov, 2008), (Castelló-Climent, 2010b), (Chambers and

Krause, 2010), (Galbraith and Kum, 2003), and (Voitchovsky, 2005) etc.). While the results of this literature were conflicting, most researchers found a positive relationship. The authors of this work argue that these results represent the short to medium run relationship between inequality and growth, as their analyses generally used shorter time horizons (for example 5 years in (Forbes, 2000)). However, because their analyses regressed growth rate within a specific time horizon on a measure of inequality, they were not able to truly capture short run relationship due to potential correlations between the growth rate of inequality and the idiosyncratic term of output. Ultimately, establishing the short run relationship requires the first difference of inequality, which this strand of the literature lacks. Furthermore, the use of a 5-year interval as the demarcation point between short and long run is arbitrary, reflecting more a lack of data as the interval method is only used when insufficient inequality data is available. The exact demarcation point between the short-run and long-run thus becomes more irrelevant the more inequality data is available.

Additionally, other country-level analyses using sub-sample regressions indicate a statistically insignificant linear relationship ((Barro, 2000)), while analyses that augment the quadratic term of inequality as the additional regressor indicate a non-linear relationship ((Banerjee and Duflo, 2003)). Their studies also suffer from the issues of panel data analysis used in (Forbes, 2000) and other related papers.

One of the most popular questions in recent decades has been why some countries are more developed than others and whether less-developed countries can catch up with advanced economies. Testing economic convergence attracts broad attention in studies of economic growth. The most commonly used method to test convergence is β convergence, as proposed by (Barro and Sala-i Martin, 1992). They test the relationship between growth rate and initial value. Specifically, if the coefficient of initial output β is significantly negative then convergence will happen. Such empirical evidence would support the Solow model, which predicts that initially poor countries grow faster than initially rich countries and that poor countries can eventually catch up to rich countries. The problem with this approach lay in the inconsistent estimation of the coefficient β from ordinary least squares, as there is a possibility of estimating a negative coefficient when there is divergence.

Given the pitfalls in the literature, this paper makes the effort to identify the long-run relationship between income inequality and economic growth through a convergence approach that uses real GDP per capita from the Penn World Table (PWT) as a measure of income and that uses the portion of total income held by those with incomes in the 90th percentile of income earners (henceforth "Top Income Share" from the World Inequality Database (WID) as a measure of income inequality. Moreover, we identify the stochastic processes of income and inequality through common factor analysis, which is used to explain the relationship obtained from convergence results. Various real GDP per capita measures from the Penn World Table (PWT) are also introduced as a robustness check.

From the comprehensive dataset for both inequality measures and income measures, common factor analysis illustrates that there is a single factor with income but no factors with inequality. In addition, we conclude that income is sub-club converging but that inequality is diverging. Overall, no long-run relationship between growth and inequality can be obtained based on the convergence results. This is a partial identification of the inequality-growth relationship.

This paper largely builds on three strands of existing literature. The first strand is comprised of papers that attempt to capture the long-run relationship between inequality and growth using a cross-country framework and that averages economic growth over a given set of decades. Our convergence method substantially solves the issues of cross-sectional regression using averages of economic growth to address the long-run relationship between inequality and growth.

The second strand of literature forms the foundation for this paper's theoretical and empirical analysis. This is the widely used β convergence literature that discusses the speed at which less developed countries catch up to rich countries. The relative convergence and weak-σ convergence methods allow us to deal with the issues of β convergence and hence to investigate the inequality-growth relationship.

Papers on common factor analysis comprise the third relevant strand of literature, and are drawn on to interpret the long-run relationship between inequality and growth. Specifically, estimating the number of common factors in income and inequality helps us to better understand the structure and results from convergence analysis.

Compared to the previous literature, this paper, to our knowledge, is the first to identify the long-run relationship between income inequality and economic growth using a convergence perspective rather than a causality method. Also, we establish stochastic processes of income and inequality to elaborate on the convergence results and on the long-run relationship between income inequality and economic growth. Additionally, through relative convergence and weak-σ convergence methods, this paper re-estimates the convergence of income such that the pitfalls of β convergence are resolved.

The remainder of this paper is organized as follows. Section 3.2 provides a brief review of relevant literature. Section 3.3 describes the methodology, especially the comparison of relative convergence and weak-σ convergence with β convergence. Section 3.4 presents the data and sources, while empirical results and robustness checks are provided in Section 3.5. Finally, Section 3.6 draws the main conclusions.

3.2 Related Literature

3.2.1 The Relationship between Income Inequality and Economic Growth

Studies on the relationship between income inequality and economic growth vary in many aspects, including in their methodologies, data sources, measures of income inequality, etc. Understanding the relevant causality is crucial to capturing this relationship. A fundamental argument proposed by (Kuznets, 1955) describes a complex relationship between income inequality and economic growth. The trade-off between income inequality and economic growth has since been widely established by both theoretical and empirical analysis. Yet, evidence on the inequality-growth relationship has been mixed in magnitude, sign, or even causal direction.

One of the most popular arguments is that income inequality is negatively related to economic growth. Through an equilibrium model of open economies, (Galor and Zeira, 1993) investigate how the aggravation of inequality induces credit constraints in imperfect capital markets that leads to a fall in investments in human capital. They also examine how income and wealth distributions are related to economic growth and further explore the negative relationship between income inequality and economic growth. Inequality may also reduce growth by increasing the fertility rate among the poor ((De La Croix and Doepke, 2003)). politico-economic is another way explaining the negative relationship between inequality and growth. It stresses how fiscal policy, such as a redistributive tax, can be a vector through which inequality reduces growth. Fiscal policy is affected by voter preferences as income distribution worsens and individuals vote on tax rates as self-interest economic agents. (notably by (Alesina and Rodrik, 1994) and (Persson and Tabellini, 1994)). The standard Solow regression empirically provides supporting evidence of the negative effect inequality has on growth.

(Galor and Tsiddon, 1997), on the other hand, explores a theoretical positive relationship between inequality and growth in terms of a local home environment externality and a global technological externality that determine a country's human capital. Polarization and inequality in the early stages of development become necessary ingredients for poor countries to catch up to rich countries in the future. The panel regressions with fixed effects used in later studies empirically demonstrates the possibly positive effect of inequality on growth using averages across a shorter time horizon.

Both positive and negative impacts have been found in previous studies, and even an inverted-U curve relationship. For example, (Castelló-Climent, 2010a) focuses on the effects of both income and human capital inequality on economic growth while controlling for the income level of countries all over the world. Specifically, they find a negative effect of income and human capital inequality on economic growth globally as well as among low and middle-income economies, but a positive effect when the sample is concentrated on higher-income countries. (Banerjee and Duflo, 2003) capture the inequality-growth relationship using a nonlinear model specification that yields an inverted U-shaped relationship between economic growth and changes in inequality.

3.2.2 The Convergence of Income and Inequality

As one of the most popular methods exploring economic growth, the convergence question, explained as whether the economy of different countries will converge or diverge over time, has also been an important topic of economists over recent decades. The neoclassical growth model (i.e., (Solow, 1956)) indicates that there are diminishing returns to capital and labor, which will result in the convergence of the countries' economy. According to this theory, poorer countries are away from the point of diminishing returns while richer countries are more likely to suffer from diminishing returns to a larger extent. Hence, poorer countries tend to catch up to richer countries when they start to industrialize.

Whether convergence could happen and when it would happen? There are several approaches in the existing studies addressing the convergence of income across countries. A negative coefficient of initial income in the growth equation would indicate a β convergence wherein initially poor countries grow faster than initially rich countries and poor countries can eventually catch up to rich countries. Convergence in income inequality was first identified by (Benabou, 1996). He argued that convergence could happen anywhere in the distribution of income, not just at the mean. With convergence, income inequality will thus decrease in countries with higher initial inequality level and will increase in countries with lower initial inequality level.

3.2.3 Summary of Previous Literature and Methodology

The existing literature, however, is far from conclusive regarding the relationship between income inequality and economic growth, the approach to testing that relationship, and even the causality of between them. Broadly speaking, there are several shortcomings of the previous literature. First, there is no consensus on the relationship between income inequality and economic growth. Second, while the convergence approach has been employed to study income or inequality separately, few studies have used convergence approaches to capture the relationship between them. Third, cross-sectional regressions cannot capture the long-run relationship and the most commonly used β convergence method struggles to explain the convergence of both income and inequality.

Therefore, the aim of our study is to explore the long-run relationship between income inequality and economic growth through a new convergence perspective. To capture this long-run relationship, common factor analysis is introduced to help interpret convergence results.

3.3 Methodology of Convergence

3.3.1 Pitfalls of β Convergence

The most commonly used method to test convergence is β convergence, as proposed by (Barro and Sala-i Martin, 1992), which examines the relationship between growth rate and initial income.

$$\frac{y_{iT} - y_{i0}}{T} = \alpha + \beta y_{i0} + \mathbf{z_i}^{'}\gamma + u_i \tag{3.1}$$

where y_{iT} denotes the income of country i at year T and y_{i0} is the initial income. If the estimated coefficient of initial income, β, is significantly negative, convergence will happen, empirical evidence that would represent supporting evidence of the Solow growth model, i.e., initially poor countries grow faster than initially rich countries and poor countries can catch up rich countries eventually.

However the issues of beta convergence are also obvious. Consider the following example explained by (Sul, 2019) where the true data generating process is:

$$y_{it} = b_i t + e_{it}, \;\; e_{it} = \rho e_{it-1} + v_{it} \tag{3.2}$$

where y_{it} is equal to the interaction of growth rate b_i and time trend t plus an error term. $b_i \sim iid\mathcal{N}(o, \sigma_b^2)$ and $v_{it} \sim iid\mathcal{N}(o, 1)$. e_{it} follows an AR(1) process. The relationship between initial value and growth rate is positive because:

$$\mathbb{E}\frac{1}{n}\sum_{i=1}^{n}(b_i + e_{i1})b_i = \sigma_b^2 \tag{3.3}$$

According to the condition of β convergence, income is diverging across countries as the positive relationship between initial y_{i1} and growth rate b_i indicate that initially rich countries grow faster than poor ones.

Nonetheless, convergence can still hold because ρ is less than 1 and wrong initial subgrouping leads to statistical illusion of β convergence. Therefore, in general, β convergence is just a necessary condition but not a sufficient condition for convergence.

Clearly, these pitfalls indicate that inference based on β convergence may create misleading results, hence, incorrectly estimating the inequality-growth relationship. To enable our partial identification of the relationship between inequality and growth, new convergence methods will be used and introduced in the following sections.

3.3.2 Relative Convergence

(Phillips and Sul, 2007b) offered a new convergence test of relative convergence that adopted a cross sectional average to express the relative value. Suppose that $y_{it} = b_{it}\theta_t$. Relative convergence then requires that in the long run, the limit of y_{it} over y_{jt} goes to one for any i not equal to j. Specifically:

$$\lim_{t \to \infty} \frac{y_{it}}{y_{jt}} = 1, for\ i \neq j. \tag{3.4}$$

where y_{it} is either the income or inequality in country i at year t. To eliminate the effect of θ_t, cross sectional average of y_{it} is applied as θ_t does not vary with the cross section. According to this, the function h_{it} is defined as:

$$h_{it} = \frac{y_{it}}{\frac{1}{n}\sum_{i=1}^{n} y_{it}} = \frac{b_{it}}{\frac{1}{n}\sum_{i=1}^{n} b_{it}} \tag{3.5}$$

where h_{it} is measured by a ratio of y_{it} to its cross sectional average. Even though transformation of $\frac{y_{it}}{y_{jt}}$ can also remove the θ_t term, (Phillips and Sul, 2007b) explained that y_{jt} fluctuates more than the cross sectional average of y_{it} so that the cross sectional average works better than a specific y_{jt}. The cross sectional mean of h_{it} is 1 and H_t is thus the variance of h_{it}, which converges to zero.

$$H_t = \frac{1}{n}\sum_{i=1}^{n} (h_{it} - 1)^2 \tag{3.6}$$

Then we use the following log t regression to express the convergence.

$$log(\frac{H_1}{H_t}) - 2logL(t) = \alpha + \beta logt + u_t \tag{3.7}$$

If t_b is greater than 1.65, the null hypothesis of convergence cannot be rejected.

The relative convergence method has a strong restriction that $y_{it} \geq 0$ needs to be satisfied for all i and t. If there is negative value of y_{it}, the variance of h_{it} will be affected as well as the testing result. Weak-σ convergence can be an appropriate alternative given the issues with relative convergence.

3.3.3 Weak-σ Convergence

Another method for testing convergence is weak-σ convergence (Kong et al., 2019). Weak-σ convergence happens when the cross sectional dispersion declines over time, i.e., the covariance of cross sectional variance of y_{it} and t becomes less than or equal to zero.

$$Cov(K_t, t) \leq 0 \tag{3.8}$$

where K_t is the cross sectional variance of y_{it}. The weak-σ convergence method then regresses the cross sectional variance on time t, as shown in the following equation.

$$\begin{aligned} K^y_{nt} =& a + \phi t + u_t \\ where\ K^y_{nt} =& \frac{1}{n}\sum_{i=1}^{n}(y_{it} - \frac{1}{n}\sum_{i=1}^{n} y_{it})^2 \end{aligned} \tag{3.9}$$

Specifically, if t_ϕ is less than negative 1.65, then it is weakly σ converging since as t increases, the cross sectional variance of y_{it} decreases. This is “weakly” σ convergent because the cross sectional variance of y_{it} converges to zero only when the long-run average does not vary across the cross section i, i.e., $a_i = a$ for all i.

3.3.4 Comparison of Relative Convergence and Weak-σ Convergence

Depending on the structure of common factors, i.e., whether common factors contain distinct or weak trend components, weak-σ convergence and relative convergence have their own disadvantages. Specifically, relative convergence does not hold when common factors have weak trend components while weak-σ convergence becomes more restrictive when there are distinct trend components in common factors. Hence, we can combine the use of these two methods to test the convergence of inequality and income and solve the potential issues of β convergence.

3.4 Data

The main data used in this paper comes from two major sources. The main components are: Real GDP per capita from 1970-2014 as taken from the Penn World Table (PWT) and Top Income Share from 1980-2012 as taken from the World Inequality Database (WID). Here, we focus on providing an introduction of these two relevant components.

Specifically, income across countries is mainly measured by Real GDP per capita from the Penn World Table (PWT) which covers 156 countries and regions in the world. Income inequality is captured by Top Income Share from the World Inequality Database (WID), which contains 25 countries and regions. In the remaining part of this section, we will describe details of the data used in the main identification as well as in the sensitivity test.

3.4.1 Income Data

The aggregated income data is measured by real GDP per capita. One of the most commonly used databases for real GDP per capita is the Penn World Table (PWT). This source provides detailed data on real GDP at the country-level in which most of the countries all over the world are included. According to distinctive concentration, the types of real GDP are divided into 5 categories: $RGDP^{NA}$, $RGDP^{e}$, $RGDP^{o}$, $CGDP^{e}$, and $CGDP^{o}$. (Feenstra et al., 2015) provide a comprehensive introduction and specifies the suitable circumstances in which each of these measures of Real GDP should be used. As mentioned by the authors, the C-prefix real GDP measures are suitable for comparing real GDP levels across countries in each year while the R-prefix real GDP measures are suitable for comparing real GDP levels across countries and across years. Furthermore, $RGDP^{NA}$, which is the closest variable to the earlier versions of real GDP data in the PWT, is the best-suited among them if the object is to compare the growth performance of economies. Hence, data on income in this paper primarily focuses on $RGDP^{NA}$, as this data suits our goal of evaluating country

Table 3.1. Convergence tests of income and inequality

Income Level	**Countries**	β	t_β	**Convergence**
Relative Convergence	156	-0.543	-26.294	No
Weak-σ Convergence	156	0.006	3.007	No
Income Inequality	**Countries**	β	t_β	**Convergence**
Relative Convergence	25	-0.996	-10.370	No
Weak-σ Convergence	25	0.001	10.030	No

growth performance. The other measures of real GDP per capita are also applied to test the sensitivity of our results.

3.4.2 Inequality Data

The convergence test and common factor analysis require the T dimension to be fairly large. Fortunately, we were able to gather annual Top Income Share data with few missing values. Measuring country-level income inequality in consecutive years is difficult since doing so depends on household survey or administrative records that not always available, especially in less developed countries. The main inequality data obtained from the World Inequality Database (WID) contains different percentiles of income shares at the country-level with few missing values. Top Income Share is one of the most popular measures for income inequality, as it demonstrates the share of total income earned by those with incomes in the 90th percentile of incomes in their nation. Taking Top Income Share as the example, if this index is high it shows that people with high incomes have a larger share of total income, which represents inequality. While multiple percentage indices, such as proportion of total income earned by those with incomes among the top 1% of all incomes, are also included in the database, the Top Income Share has the best coverage not only in terms of the number

Table 3.2. Clustering clubs of income

Club	b	t_b
Club 1 [80]	0.237***	5.950
Club 2 [44]	0.115***	2.110
Club 3 [11]	0.200	1.612
Club 4 [9]	-0.016	-0.257
Club 5 [12]	-0.441	-1.330

of countries the available data encompasses but also in terms of time horizon. This is why it is used as our main inequality measure. We first drop the countries with continuous years of missing data and then use linear prediction based on Gini Index data from the World Income Inequality Database or from the World Development Indicator (WDI) to fill in the gaps. We thus have country-level income inequality data for 26 countries and regions. After dropping the Russian Federation due to a lack of corresponding real GDP data in the Penn World Table (PWT) for the 1980s we ended up with annual income inequality data for a total of 25 countries and regions.

3.5 Empirical Results

In this section, we first consider whether income and inequality across countries are converging over time. The econometric analysis of the convergence test for income and inequality follows the steps entailed by the methods outlined in Section 3.3. Using common factor analysis, we report and interpret the partial identification of the long-run relationship between inequality and growth.

3.5.1 Convergence

In the first part of this section, the estimation results of relative convergence and weak-σ convergence are exhibited. The convergence results for both income and inequality are demonstrated in Table 3.1. Both the relative convergence and weak-σ convergence tests present divergence in income and inequality, indicating that countries are moving apart in terms of both income and inequality.

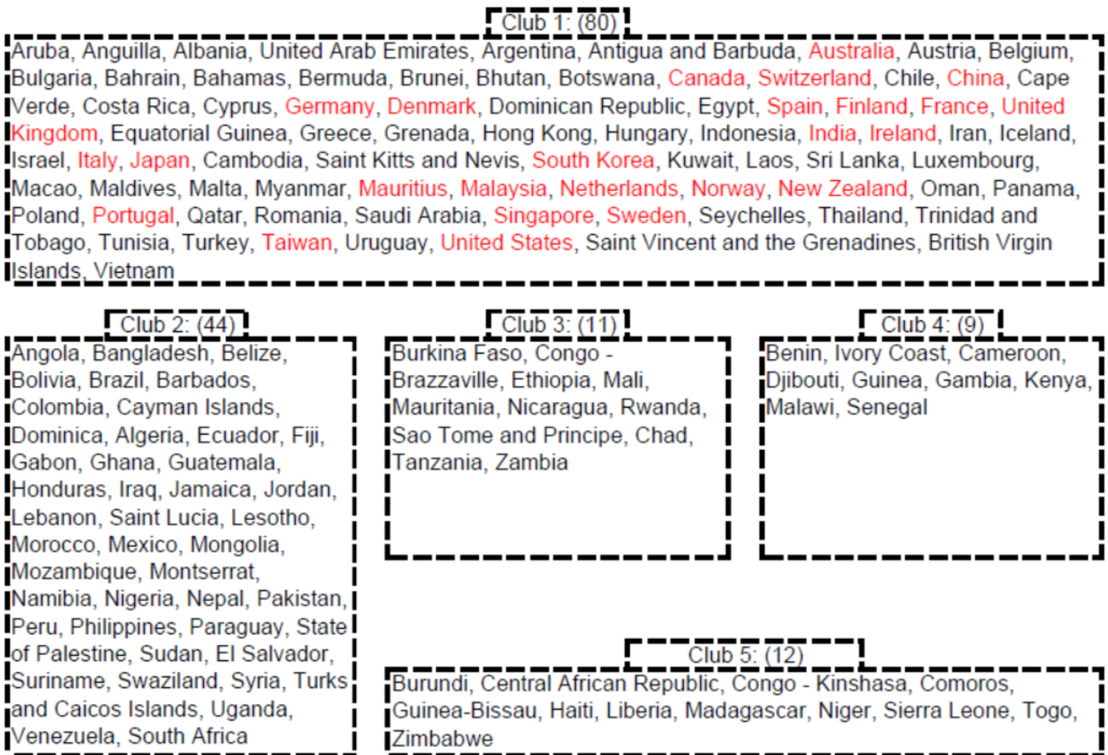


Figure 3.2. Income clustering clubs

The 156 countries and regions of the sample do not exhibit catch-up effects when analyzed as a whole. Are there any clustering clubs for income? Based on (Phillips and Sul, 2007b), we further test for sub-club convergence using the clustering method. Table 3.2 shows the results of sub-convergent clubs from clustering procedures for 156 countries and regions over the period from 1970-2014. The clustering method classifies the income data into five sub-convergent clubs. The first convergence club consists of a large group of 80 countries and

Table 3.3. Weak σ-convergence in clustering clubs with income

Club	ϕ	t_{ϕ}	**Convergence**
Club 1 [80]	-0.022***	-37.95	Yes
Club 2 [44]	-0.007***	-4.087	Yes
Club 3 [11]	-0.008***	-17.45	Yes
Club 4 [9]	-0.005***	-5.788	Yes
Club 5 [12]	0.001	0.315	No

regions. Intuitively, relatively poor countries are catching up to the rich ones within each club.

The countries and regions in different clubs are arranged according to each of the five sub-convergent clubs. All countries and regions in the inequality dataset (marked in red) are included in club 1. This club verifies the fact that the incomes of the countries and regions in it are converging over time.

Table 3.4. Convergence tests of income and inequality for same countries

Income Level	**Countries**	β	t_{β}	**Convergence**
Relative Convergence	25	0.371	11.681	Yes
Weak σ Convergence	25	-0.014	-63.231	Yes
Income Inequality	**Countries**	β	t_{β}	**Convergence**
Relative Convergence	25	-0.996	-10.370	No
Weak σ Convergence	25	0.001	10.030	No

Table 3.5. Number of common factors in income

Samples	Δy_{it}	$\Delta y_{it} - \frac{1}{n}\sum \Delta y_{it}$	**Countries**
Whole	1	1	156
Rolling	1	1	156
Recursive	1	1	156
Samples	Δy_{it}	$\Delta y_{it} - \frac{1}{n}\sum \Delta y_{it}$	**Countries**
Club 1	1	1	80
Rolling	1	1	80
Recursive	1	1	80

Table 3.3 demonstrates the weak-σ convergence results in those five clubs. The income is convergent in clubs 1, 2, 3, and 4 while club 5 fluctuates. It also supports the results from the relative convergence test and shows the robustness of our convergence analysis.

The convergence results for those same 25 countries and regions only are extracted and shown in Table 3.4. Both the relative convergence and weak-σ convergence tests show divergence in income inequality but convergence in income for the same countries and regions. The convergence results are robust because both methods illustrate the same results.

After obtaining the convergence results, how to identify the long-run relationship based on those convergence results above? For our sample inequality is divergent but income among the same countries is convergent, hence the divergence of inequality cannot therefore be explained by the convergence of income. Intuitively, in the long-run, there's no relationship between income and inequality. However, this is only a partial identification of the long-run relationship between inequality and income as our findings do not substantively evidence the other direction from inequality to income. The next step is to interpret the partial

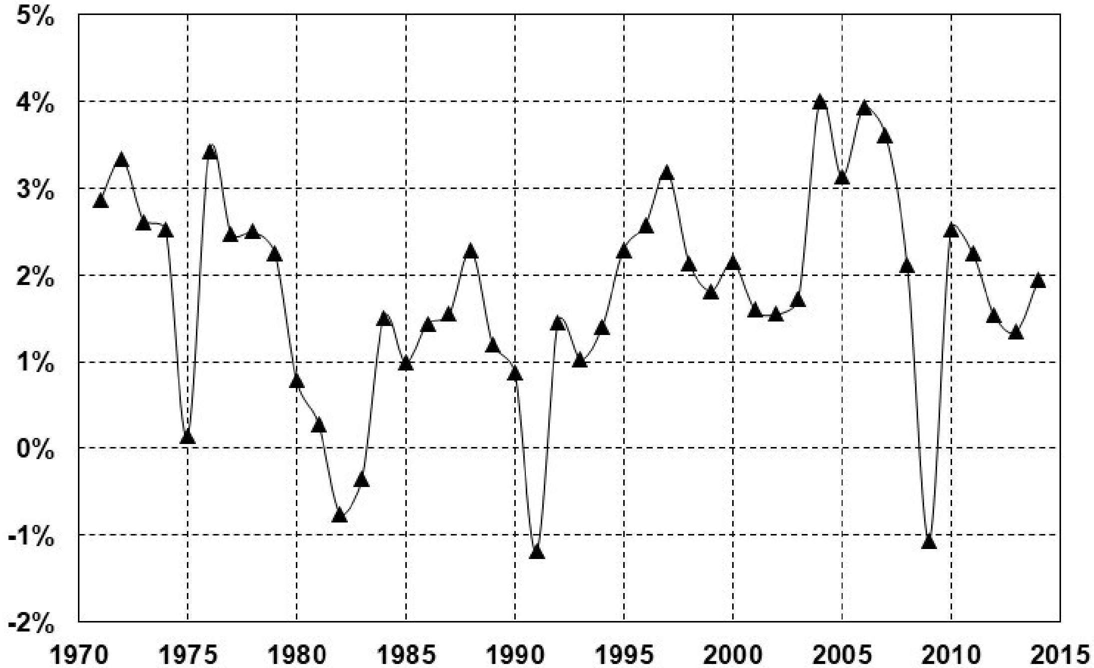


Figure 3.3. The average growth rate of income (difference of log GDP)

identification of the relationship between income and inequality. Common factor analysis is thus introduced in the following section.

3.5.2 Common Factor Analysis

To estimate the number of common factors, (Bai and Ng, 2002) proposed the following $IC2$ criterion.

$$\begin{aligned} IC_2(k) &= lnV(k, \hat{F}^k) + k(\frac{n+T}{nT})lnC_{nT} \\ V(k, \hat{F}) &= \frac{1}{nT}\sum_{i=1}^{n}\sum_{t=1}^{T}(\tilde{y}_{it} - \hat{\lambda}_i^{k'}\hat{F}_t^k)^2 \end{aligned} \tag{3.10}$$

where V is the overall variance of idiosyncratic terms. $\hat{\lambda}_i^{k'}$ and $\hat{F}_t^k$ are the estimates of the factor loadings and common factors up to k. The second term in this equation is the penalty function which is an increasing function of k. The optimal factor number can be obtained by minimizing the $IC2$ function above. Rolling and Recursive samples will also be used to check the number of common factors.

Table 3.5 shows the estimation of factors numbers in income. A single factor has been obtained for income. Testing the homogeneity of the factor loading is equally important as it shows whether countries react similarly to the common factor. (Parker and Sul, 2016) applied a cross sectional mean to test the homogeneity of factor loading. Specifically, after subtracting the cross sectional mean, if the number of common factors becomes zero then we can conclude a homogeneous factor loading. In this table we still get a single factor. However, it does not necessarily represent heterogeneous factor loadings across countries since y_{it} shows clear evidence of serial dependence, as shown in Figure 3.3.

After accounting for the serial dependence in the first difference of real GDP per capita (in logarithm), Table 3.6 tells us the reason why there is still one factor under the homogeneous factor loading conditions. The first difference of the logarithm of real GDP per capita Δy_{it} is persistent and it leads to one factor result, as indicated in Table 3.5. This implies that even if the true factor loading is homogeneous, we could still possibly get one factor after eliminating the cross sectional mean because the Δy_{it} is not $I(0)$. This requires us to take the second difference to reduce the degree of serial dependence. The new results are shown in Table 3.6.

After taking the second difference of y_{it}, the number of common factors becomes 0 when applying (Parker and Sul, 2016) methodology. This indeed captures the result of homogeneous factor loading. For inequality, however, the number of common factors is always zero regardless of the difference level. It is explained by the pure idiosyncratic term in inequality.

3.5.3 Interpretation of the Long-run Relationship

After getting the number of common factors and the factor loadings, how can we make the connection between this result and the explanation of that long-run relationship? As for

Table 3.6. Number of common factors in income and inequality

Samples	$\Delta^2 y_{it}$	$\Delta^2 y_{it} - \frac{1}{n}\sum \Delta^2 y_{it}$	**Countries**
Whole	1	0	156
Rolling	1	0	156
Recursive	1	0	156
Samples	$\Delta^2 y_{it}$	$\Delta^2 y_{it} - \frac{1}{n}\sum \Delta^2 y_{it}$	**Countries**
Club 1	1	0	80
Rolling	1	0	80
Recursive	1	0	80
Samples	$\Delta^2 x_{it}$	$\Delta^2 x_{it} - \frac{1}{n}\sum \Delta^2 x_{it}$	**Countries**
Whole	0	0	25
Rolling	0	0	25
Recursive	0	0	25

income, suppose the true data generating process is:

$$y_{it} = \alpha_i + \beta_i \theta_t + \lambda_i F_t + y_{it}^o \tag{3.11}$$

where $\theta_t = O_p(t)$, $F_t = O_p(t^{1/2})$. The cross sectional correlation is 0.367 which is relatively high. In addition, income is sub-club convergent and has only a single common factor. After taking the first difference, we have the following function:

$$\Delta y_{it} = \beta_i + \lambda \Delta F_t + \Delta y_{it}^o \tag{3.12}$$

Δy_{it} can be explained by way of a single factor. The factor loading is homogeneous across countries, i.e., $\lambda_i = \lambda$ for all i. The technology spillovers among countries are a good example. Consequently, in the long-run the income could converge within the group. The relative convergence test shows $\lim_{t\to\infty} \frac{y_{it}}{y_{jt}} = 1$ within a club.

$$\lim_{t\to\infty} \frac{y_{it}}{y_{jt}} = \begin{cases} \frac{\beta_i}{\beta_j} + O_p(t^{-1/2}), \textit{divergent across clubs.} \\ 1 + O_p(t^{-1/2}),\ \textit{convergent within a club.} \end{cases} \tag{3.13}$$

For inequality, similarly, suppose the DGP is:

$$x_{it} = a_i + \gamma_i \eta_t + \delta_i G_t + x_{it}^o \tag{3.14}$$

where $\eta_t = O_p(t), G_t = O_p(t^{1/2})$. Different from income, it is divergent and has no common factor (The cross sectional correlation is 0.157 which is relatively low). Hence inequality contains a pure idiosyncratic term. After taking the first difference, we have:

$$\Delta x_{it} = \gamma_i + \delta_i \Delta G_t + \Delta x_{it}^o = \gamma_i + \Delta x_{it}^o \tag{3.15}$$

The relative convergence test implies that $\lim_{t\to\infty} \frac{x_{it}}{x_{jt}} = \frac{\gamma_i}{\gamma_j}$ due to inequality divergence across countries.

In summary, based on the common factor analysis we find evidence for the convergence results and then according to the convergence test, we can draw the conclusion that because divergence of inequality cannot be explained by the convergence of income, partially there's no relationship between inequality and growth in the long-run.

3.5.4 Sensitivity Test

Finally, we provide some sensitivity tests using different measurements for income and inequality. In general, our empirical results are robust when using income share earned by the top 1% of income earners and different real GDP per capita measures. The 25 countries and regions in our sample are in sub-convergent clubs for every measure of GDP.

Table 3.7. Convergence tests of income ($RGDP^E$ and $RGDP^O$) and inequality (1%)

Income ($RGDP^E$)	**Countries**	β	t_β	**Convergence**
Relative Convergence	156	-0.661	-19.068	No
Weak σ Convergence	156	0.013	6.228	No
Income ($RGDP^O$)	**Countries**	β	t_β	**Convergence**
Relative Convergence	156	-0.417	-4.247	No
Weak σ Convergence	156	0.002	0.745	No
Inequality (1%)	**Countries**	β	t_β	**Convergence**
Relative Convergence	25	-0.576	-11.902	No
Weak σ Convergence	25	0.001	1.840	No

3.6 Conclusion

In this paper, we provide new depth to convergence testing of real GDP per capita, as well as of inequality, in order to partially identify the long-run relationship between income inequality and economic growth. Applying common factor analysis enables us to better interpret our partial identification of inequality-growth relationship. With the framework of convergence and common factor analysis, our identification of the long-run relationship is expected to avoid the issues of cross-sectional regression across countries, as well as the commonly used β convergence approach.

From common factor analysis, correlation of inequality is low and no common factor is found. Economically, inequality is unique to each country and consists only of pure idiosyncratic terms. Every country has its own characteristics such that only pure idiosyncratic terms show up in inequality data. On the other hand, the correlation of income among countries is high and one factor has been found. Factor loading is homogeneous across countries. Technology is one potential common factor that affects the development of countries all over the world. It is therefore hard to establish a long-run connection between inequality and growth.

From convergence analysis, income is divergent but has sub-convergent clubs. Among the same countries, income is convergent but inequality is divergent. For the relationship between inequality and growth, the divergence in inequality cannot be explained by the convergence in income. Partially, there's no long-run relationship between growth and inequality. The change of income inequality is attributed to country specific policy rather than economic growth.

This study contributes a partial identification of the long-run inequality-growth relationship using convergence testing. One particular avenue for future research lies in the reconciling of an identification of the impact of inequality on income with the findings of this study in order to get a general picture of the inequality-growth relationship in the long-run. Another issue to be dealt with is to test the sensitivity of our results using more inequality data. It might be difficult given the data characteristics of inequality.

CHAPTER 4

THE SHORT-RUN DYNAMICS OF INEQUALITY-GROWTH RELATIONSHIP: EVIDENCE FROM PANEL REGRESSIONS

4.1 Introduction

In recent years large parts of the world have been plagued by the aggravation of income inequality and its potential effects on economic growth. Policymakers and economists have been exploring whether sustainable growth could reduce income inequality. The inequality-growth relationship both across countries and within specific countries represents one of the key topics in this existing literature. While some previous studies have contributed to the literature on the long-run inequality-growth relationship by providing cross-sectional regressions of average economic growth on initial inequality over longer time horizons (e.g., (Alesina and Rodrik, 1994), (Deininger and Squire, 1998), (Persson and Tabellini, 1994)), other more recent studies have relied on country-level panel regressions that have used shorter time horizons to capture the short- or medium-run relationship between income inequality and economic growth (e.g., 5-year panel in (Andrews et al., 2011), (Forbes, 2000), (Halter et al., 2014), 10-year panel in (Barro, 2000)).

Even though there has been a surge of studies regarding the effect of income inequality on economic growth, the empirical findings from these papers are inconclusive. More specifically, authors of the early relevant work using cross sectional regressions argued that inequality reduces growth by citing average growth rates over T years (typically 20-40 years). However, this does not necessarily capture the long-run relationship as there are two idiosyncratic terms in growth and inequality that may produce a negative coefficient of inequality. Later work utilized panel regressions, usually using 5-year averages. This later body of work found that inequality might actually promote growth. However, this approach fails to capture the short-run relationship as there are potential correlations between the trend in inequality and an idiosyncratic term of output.

Combined with the results discussed in Chapter 2, this begs an interesting question: Is there any difference between the short-run and long-run relationship? (Forbes, 2000) asserted that her approach concentrates on the medium or short-run relationship between inequality and growth where previous cross sectional regressions focused on the long-run. Her positive result does not contradict the negative relationship that had been previously established in the literature, but even so the existing literature is still flawed on a number of grounds. First, regarding model specification, is there any reason to use the level data of the inequality variable when testing for the short-run relationship? If both the $I(0)$ variable, growth, and the $I(1)$ variable, inequality, are included in the regression equation along with trend in inequality, then the short-run relationship cannot be captured.

Second, for the time span, is there any reason why 5-year is the appropriate interval used to capture the short- or medium-run changes to the inequality-growth relationship? Even though different time horizons are used in the literature, there is no consensus defining the short-, medium-, or long-run. The 5-year average most commonly used in short-run analyses is arbitrary and is principally used due to a lack of data availability. For example, while a 6-year average does not necessarily yield similar results to those of a 5-year average, these differences cannot be attributed to capture of the long term relationship instead of the short-run relationship as a 6-year average is not substantively different from a 5-year average. Even if different estimation results have been found using time intervals of various size, the only conclusion that can be inferred from such evidence is that the relationship is positive (negative) when using the t-year average and becomes negative (positive) when using a t+1-year average. It cannot be concluded in such a case that the difference between them captures any differences between the long-run and short-run relationship. In general, the conventional averaging procedure does not work well in capturing the short-run relationship between inequality and growth ((Wan et al., 2006)).

Third, country-level economic growth does not depend only on country-specific characteristics, but rather on other factors held in common by the countries included in the sample.

However, the commonly used year fixed effects in the regression does not address cross sectional dependence across countries and can hence bias the estimates of the inequality-growth relationship.

This paper directly addresses these questions and tackles these challenges in the existing literature. First, this paper distinguishes between the long-run and short-run relationship between inequality and growth. By focusing on the dynamic short-run relationship, this work is closely related to studies investigating the effect of inequality on growth that use country-level panel data. However, this paper provides a New Keynesian framework while also pointing out the pitfalls of panel regressions that aim to capture short-run dynamics. Second, a panel VAR methodology is used to explore both directions of causality. Third, the adoption of the Common Correlated Effects (henceforth CCE) approach allows me to account for unobserved common factors with heterogeneous factor loadings using similar data in the literature.

The lack of available inequality data is an important factor in cross country inequality studies, as country-level inequality data are relatively limited and not available for every year. Hence, existing studies suffer from the data availability issues of inequality data. This paper uses a new dataset measuring inequality with data from The Standardized World Income Inequality Database (SWIID). This is the inequality data used in this paper to analyze the short-run relationship between income inequality and economic growth. This dataset's advantage is that it has the broadest possible sample of countries and years, thereby allowing me to capture the short-run dynamics of the inequality-growth relationship. Applying a flexible missing data algorithm, The Standardized World Income Inequality Database ((Solt, 2016)) provides consistent Gini Coefficients of net and market incomes for a large number of countries and years. Compared to other databases, such as the World Income Inequality Database (WIID) and Luxembourg Income Study (LIS), SWIID enables analysis of inequality studies across countries by optimizing the number of countries and years covered.

Meanwhile, it keeps the income inequality data comparable. Through these improvements, measurement error can be reduced and many panel estimation techniques can be used to examine the short-run relationship, such as first-difference transformation.

The results suggest that, in the short-run, a change in income inequality is not associated with economic growth and economic growth does not affect income inequality. This result is robust to a number of variations in the variable measures, to alternative samples, and to different lag order selections.

The remainder of this paper is organized as follows. Section 4.2 provides a brief review of related Literature. Section 4.3 describes the empirical model and estimation technique. Section 4.4 presents the empirical results and robustness checks. Finally, Section 4.5 draws the main conclusions.

4.2 Literature Review

4.2.1 The Channels

There are several channels through which inequality could affect growth. The theoretical framework of the inequality-growth relationship predicts a negative effect of inequality on growth in several mechanisms. (Galor and Zeira, 1993) analyze the effect of income distribution on growth under an imperfect capital market. They demonstrate that the distribution of wealth significantly affects the aggregate economic activity in both the short-run and long-run since higher inequality represents more credit constraints. With capital market imperfections, a more unequal distribution of wealth restricts the degree of specialization and lowers wages and productivity ((Fishman and Simhon, 2002)). Different from this economic channel, another channel through which inequality can possibly affect growth is politico-economic in nature. This channel captures the effect of fiscal policy on economic growth. Fiscal policy is affected by voter preferences regarding income distribution as each individual behaves like an economic agent when voting on tax rates (notably by (Alesina and Rodrik, 1994) and (Persson and Tabellini, 1994)) . An increase in inequality is associated with tax redistribution, which reduces investment incentives and hence deters growth. Moreover, inequality, as argued by (De La Croix and Doepke, 2003), could be negatively related to growth because of the rise of fertility rates and falls in human capital investment, especially among the poor.

Theories suggesting that inequality may promote growth also focus on economic and political factors. Temporarily high inequality is necessary for human capital accumulation given local home environment externalities and global technological externalities, which enhances future growth in some less developed countries ((Galor and Tsiddon, 1997)). Additionally, increased inequality could be helpful for economic growth in so much as it bolsters middle class support for public education ((Saint-Paul and Verdier, 1993)). Similarly, (Li and Zou, 1998) demonstrate that a more equal income distribution can lead to lower economic growth since the income taxation rate in such societies is generally higher.

The theoretical framework of the channels through which inequality affects growth is mixed. Research on both the economic channel and the politico-economic channel have yielded both positive and negative effects of inequality on growth, which promotes discussion in this complicated topic.

4.2.2 Empirical Evidence of Inequality-Growth Nexus

The empirical evidence on the inequality-growth relationship is also inconclusive. Early studies regarding the inequality-growth nexus attempted to find the long-run relationship using a cross-sectional regression method. Generally a negative relationship between inequality and growth is found when using an augmented Solow regression (notably (Alesina and Rodrik, 1994), (Birdsall et al., 1995), (Clarke, 1995), (Galor and Zang, 1997), (Perotti, 1996), and (Persson and Tabellini, 1994) etc.). Researchers argue that the augmented Solow regression captures the long-run relationship as it derives average growth rate from a longer time horizon, typically 20-40 years. However, the effect estimated using this approach may actually be based more on two idiosyncratic terms of growth and inequality, which implies that the estimate does not necessarily reflect the long-run relationship. In addition, the empirical results are highly sensitive to the specific time horizon being used.

Starting with (Forbes, 2000), a large number of studies began using panel data models with fixed effects to examine the short-run effect of inequality on growth (such as (Andrews et al., 2011), (Bjørnskov, 2008), (Castelló-Climent, 2010b), (Chambers and Krause, 2010), (Galbraith and Kum, 2003), and (Voitchovsky, 2005) etc.). While the results of this literature were conflicting, most researchers found a positive relationship, as opposed to the negative relationship found in work using cross-sectional regressions. Unlike the cross-sectional studies, the literature on panel analysis was primarily focused on regressions using intervals of a specific time horizon, such as 5-year intervals in (Forbes, 2000). As mentioned in the Introduction Section t-year intervals do not inherently represent the short-run, and are used principally due to data availability issues. Furthermore, panel analysis was not able to truly capture the short run relationship due to potential correlations between the growth rate of inequality and the idiosyncratic term of output. Thus, if anything, we may also expect cross-sectional dependence across countries, a possibility which was not addressed in the existing literature.

Therefore, the empirical studies on the inequality-growth relationship provide evidence which is just as mixed as the evidence from theoretical studies. Compared to previous studies, this paper avoids the estimation issues and revisits the short-run relationship between inequality and growth using panel data across countries.

4.3 Empirical Model and Estimation Technique

In this section, the details of model specification are provided. This study estimates the short-run dynamic of the inequality-growth relationship using a VAR approach with Common Correlated Effects which is different from the most commonly used empirical method.

4.3.1 Specification

To investigate endogenous interactions between income inequality and economic growth, a large annual dataset encompassing 20 advanced economies over a period from 1970–2017 is subjected to a panel VAR approach. The panel VAR approach can address the endogeneity issue since it allows for endogenous interactions among all the variables in the system. To be specific, the panel VAR approach in this study considers the fact that while economic growth might have an impact on income inequality, economic conditions might also itself be influenced by income inequality. This sample was chosen for several reasons. First, income inequality data reveal that higher frequency macroeconomic data are not suitable for this study since annual inequality data with continuity are already the best fit across countries. Second, the data on the 20 advanced economies provides better coverage with which to construct all variables selected for this study, especially for the income inequality data which typically suffers from availability issues due to a lack of relevant data from developing countries. Third, income inequality data on the 20 advanced economies suffer fewer problems of comparability compared to the data on developing countries. Fourth, the developed country sample is suitable for studying open economies.

What are the endogenous variables included in the model to address the short-run dynamics? The augmented Solow model is one of the most popular methods used by macroeconomists to study the inequality-growth relationship. Correspondingly, this study's model includes investment, education, and other growth variables. However, these are variables that affect the long-run, steady-state level. Assume a Solow growth model with homogeneous but exogenous technology across all countries. Further assume constant population growth rate and discount rate. The general form of the aggregate production function in neoclassical growth theory can be written as: $Y = F(K, L, H, A)$, where Y represents the output, K and H measure the physical and human capital respectively, L denotes the labor, A is the state of technology, F is the production function. Growth here stems from convergence and the rate of technological progress. The transitional path can be derived from a log-linearized approximation of the Solow model, which is similar to those estimated by (Barro, 1991). Using discrete time approximations, (Barro and Sala-i Martin, 1992) write the transitional dynamics using a Cobb-Douglas production function:

$$lny_{it} = lny_{i0} \cdot e^{-\phi t} + lny^* \cdot (1 - e^{-\phi t}) = lny^* + (lny_{i0} - lny^*) \cdot e^{-\phi t} \tag{4.1}$$

where ϕ indicates the speed of adjustment to the steady state. Assuming that technological progress follows an exponential growth path ($A_{it} = A_{i0}e^{gt}$), then the transitional dynamics under heterogeneous technology progress proposed by (Phillips and Sul, 2007a) become:

$$lny_{it} = lny^* + (lny_{i0} - lny^*) \cdot e^{-\phi t} + lnA_{i0} + g_{it}t \tag{4.2}$$

And the average growth rate of country i between time q and $t + q$ is:

$$\frac{lny_{it+q} - lny_{iq}}{t} = -b_{it}lny^* + b_{it}lny_{iq} - (\frac{1}{t} + b_{it})lnA_{iq} + \frac{1}{t}lnA_{it+q} \tag{4.3}$$

where

$$b_{it} = -(\frac{1 - e^{-\phi_{it}^{+}t}}{t}) < 0, \text{ with } \phi_{it}^{+} = \frac{\phi_{it+q}(t+q)}{t} - \frac{\phi_{iq}}{t} \tag{4.4}$$

The theoretical model can then be transformed into the empirical equations for cross-sectional and panel regressions respectively. For the cross-sectional regression:

$$growth_{i,T,0} = \frac{lny_{iT} - lny_{i0}}{T-1} = \alpha_0 + b_1 lny_{i0} + X_{i0}'\delta + Z_i'\theta + u_i \tag{4.5}$$

where Z_i is used to proxy the variables from steady-state and X_{i0} comes from A_{i0}. X_{i0} are state variables which typically include schooling, life expectancy, etc. Z_i are control and environmental variables that will affect the steady state and then have an impact on per capita growth rate. Savings rate (as measured by the ratio of investment to real GDP), government consumption (as measured by the spending on defense and education to GDP), and growth rate of population are the component parts of Z_i. They are normally the average values within a related period. On the other hand, the panel regression is:

$$growth_{i,t,t-k} = \frac{lny_{it} - lny_{it-k}}{k} = b_1 lny_{it-k} + X'_{it-k}\delta + X'_{it}\theta + \alpha_i + \eta_t + u_{it} \tag{4.6}$$

where X_{it-k} indicates the proxy variables for A_{iq} and X_{it} measures A_{it+q}. The steady-state variables are demonstrated by the country fixed effects α_i. The addition of inequality variables in the augmented Solow regression thus allows it to capture long-run rather than short-run dynamics.

In contrast, this paper focuses instead on how the economy works in the short-run, specifically the short-run dynamics of the inequality-growth relationship. A New Keynesian framework of the form widely used in the literature is presented.

$$x_t = \delta x_{t-1} + (1-\delta)\mathbb{E}_t x_{t+1} + \phi[i_t - \mathbb{E}_t(\pi_{t+1} - \bar{\pi}) - \bar{r}] + g_t \tag{4.7}$$

$$\pi_t - \bar{\pi} = \theta(\pi_{t-1} - \bar{\pi}) + (1-\theta)\beta\mathbb{E}_t(\pi_{t+1} - \bar{\pi}) + \lambda x_t + u_t \tag{4.8}$$

where x_t is the output gap, π_t the inflation, and i_t the nominal interest rate. These are the three key variables in the system. Additionally, $\bar{\pi}$ and $\bar{r}$ are the inflation target and natural rate of interest, both of which are steady state values. The inclusion of the lagged terms captures variable persistence that would be unexplained in the model without them (i.e., (Dennis and Ravenna, 2008) and (Galı and Gertler, 1999)). g_t and u_t are demand shock and supply shock respectively. Both g_t and u_t evolve according to an AR(1) process, i.e.,

$g_t = \rho_g g_{t-1} + \varepsilon_t^g$ and $u_t = \rho_u u_{t-1} + \varepsilon_t^u$, with $\varepsilon_t^g \sim i.i.d.(0, \sigma_g^2)$ and $\varepsilon_t^u \sim i.i.d.(0, \sigma_u^2)$. For the model parameters, $0 < \delta < 1$, $0 < \theta < 1$, $0 < \beta < 1$, $\phi < 0$, and $\lambda > 0$.

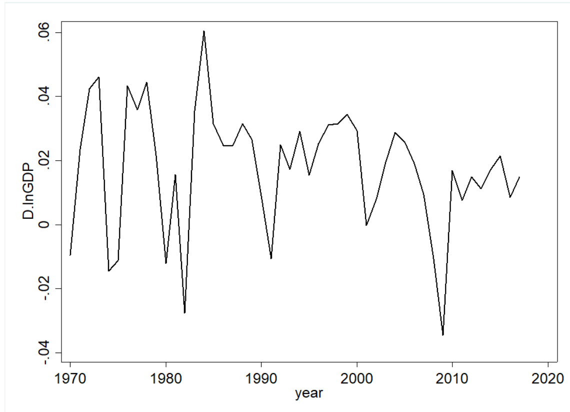
Therefore, to capture the short-run dynamics of the economy, this study's model includes real output, interest rate, and inflation as its main macroeconomic variables. A change in interest rate will affect production via its effect on investment. Also, a change in output is associated with a change in interest rate through the money market. Inflation is another key macroeconomic variable that affects output through wages, at least in the short-run.

Given that exchange rates are an important variable to account for when analyzing open economies, and given the openness of the economies in the data, exchange rates are thus incorporated in the model in addition to the main macroeconomic variables. Exchange rates must be analyzed since they affect exports and money demand, and hence the macroeconomic system writ large.

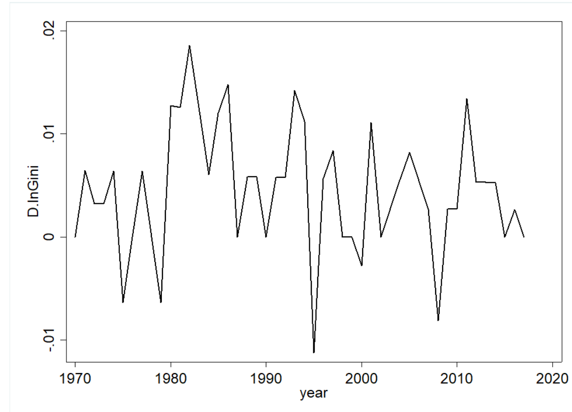
In summary, the set of macroeconomic variables in this study's model specification includes growth of real GDP per capita, inflation, interest rate, and exchange rate ((Georgiadis, 2015) etc.). As the data used in this paper contains a relatively short sample period, only a small number of variables are considered. This can also avoid the issue of the degrees of freedom in each country-specific VAR model.

4.3.2 Overview of the Data

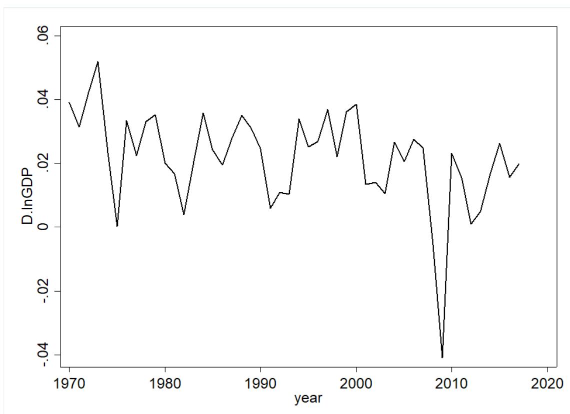
The dataset consists of annual data on GDP per capita, inequality measures, and other key macroeconomic variables for 20 advanced economies from 1970 to 2017. Data on GDP are collected from the Penn World Table ((Feenstra et al., 2015)). Data on income inequality comes from The Standardized World Income Inequality Database (SWIID, (Solt, 2016)). Figure 4.1 shows the growth of real GDP per capita and the Gini coefficient for the US only, as well as the country-averages of 20 advanced economies from this sample. It is noteworthy in Figure 4.1(a) that the volatility of per capita GDP growth after 1990 declines except for



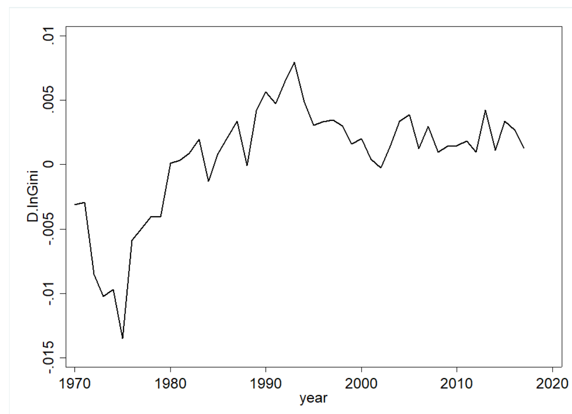
(a) US real GDP per capita growth



(b) US Gini coefficient growth



(c) Average real GDP per capita growth



(d) Average Gini coefficient growth

Figure 4.1. Growth of real GDP per capita and Gini coefficient: 1970-2017

the years around the 2008 recession. However, the impact of the 2008 recession seems to be larger among developed countries, judging from Figure 4.1(c). Income inequality, indicated by Figure 4.1(d), rises substantially after the 1980's in developed countries while the income inequality in the US is more volatile (Figure 4.1(b)).

Other endogenous variables include inflation, interest and exchange rates. Inflation data are collected from the World Development Indicator (WDI) of the World Bank. Data on exchange rates are downloaded from the Bank for International Settlements (BIS). Interest rate data are mainly from the International Financial Statistics (IFS) of the International

Monetary Fund (IMF) while a few countries are supplemented by interest rates from OECD Statistics.

Nonstationarity issues, which are very common in macroeconomic data, may result in spurious regressions. To address this, unit root tests are conducted before moving on to the empirical analysis. Several procedures are commonly used to test the unit root in time series data as well as in panel data. Table 4.1 shows the results of the unit root tests for both the US time series and for the panel series that encompasses data for 20 countries. For the US time series, both ADF ((Dickey and Fuller, 1979)) and PP ((Phillips and Perron, 1988)) tests are presented. For the panel unit root tests, a Breitung test ((Breitung and Das, 2005)) and an ADF ((Maddala and Wu, 1999), (Choi, 2001)) test are displayed. The Breitung test, as stated by the author, is substantially more powerful than other panel unit root tests for modest sized data sets such as N=20 and T=30, which is suitable for this study. As Breitung assumes that all panels have a common autoregressive parameter, i.e., $\rho_i = \rho$ for all i, this paper conducts another test with a heterogeneous autoregressive parameters assumption, the ADF test. Similar results can be obtained from other unit root test procedures.

The Augmented Dickey-Fuller and Phillips-Perron tests have the same null hypothesis: that the time series contains a unit root. The alternative hypothesis is that the test variable is generated by a stationary process. Panel A of Table 4.1 shows the results of the unit root tests for the US time series data. Both tests fail to reject the null hypothesis of a unit root for either the level of GDP per capita or the Gini coefficient, but reject the null hypothesis of a unit root for the growth of the two test variables, indicating that the time series data for GDP per capita growth and Gini coefficient growth are now stationary. Similarly, panel unit root tests for 20 advanced economies are shown in Panel B of Table 4.1. Different from the time series, the panel data are demeaned to mitigate the effects of cross-sectional dependence. The Breitung test assumes that all panels have a common autoregressive parameter, while the ADF test assumes that panels are heterogeneous in autoregressive parameters. Both tests have the null hypothesis that panels contain a unit root. The alternative hypothesis of the Breitung test is that panels are stationary while the alternative hypothesis of ADF test is that at least one panel is stationary. As can be seen from the table, both Breitung and ADF tests fail to reject the null hypothesis of a unit root in the level data and reject it in the growth data. Both results indicate stationarity of GDP per capita growth and Gini coefficient growth. Those results are robust when intercept and trend are included.

Table 4.1. Unit root tests

Test	Intercept	Intercept and trend	Intercept	Intercept and trend
A. United States Time Series				
	Gini-level		Gini-growth	
ADF	0.507	-2.663	-5.426	-5.401
	(0.985)	(0.252)	(0.000)	(0.000)
PP	0.240	-9.549	-37.821	-38.755
	(0.978)	(0.220)	(0.000)	(0.000)
	GDPPC-level		GDPPC-growth	
ADF	-0.196	-1.891	-5.357	-5.607
	(0.939)	(0.660)	(0.000)	(0.000)
PP	-0.113	-9.511	-32.728	-34.949
	(0.936)	(0.494)	(0.000)	(0.000)
B. Panel Data				
	Gini-level		Gini-growth	
Breitung	1.311	2.566	-6.672	-7.711
	(0.905)	(0.995)	(0.000)	(0.000)
ADF	62.852	51.545	148.106	123.041
	(0.012)	(0.104)	(0.000)	(0.000)
	GDPPC-level		GDPPC-growth	
Breitung	4.915	3.520	-4.083	-5.472
	(1.000)	(1.000)	(0.000)	(0.000)
ADF	29.148	38.738	197.573	164.192
	(0.898)	(0.527)	(0.000)	(0.000)

-Null hypothesis: unit root. Alternative hypothesis: stationary.
-p values in parentheses.

4.3.3 Estimation

A panel VAR approach is used to explore the short-run dynamics of the inequality-growth relationship. The econometric model takes the following form:

$$\begin{aligned} \boldsymbol{X_{it}} =& \boldsymbol{\Gamma(L)X_{it}} + \boldsymbol{\alpha_i} + \boldsymbol{\epsilon_{it}} \\ \boldsymbol{\epsilon_{it}} =& \boldsymbol{\Lambda_i' F_t} + \boldsymbol{u_{it}} \end{aligned} \tag{4.9}$$

where $\boldsymbol{X_{it}}$ is a vector of endogenous variables and $\boldsymbol{\Gamma(L)}$ is a matrix polynomial in the lag operator that $\Gamma(L) = \Gamma_1 L(1) + \Gamma_2 L(2) + ... + \Gamma_p L(p)$. α_i is a vector of country-specific effects and u_{it} is a vector of idiosyncratic errors. The country fixed effects capture all the time-invariant changes in the dependent variable across countries and the common factors capture the aggregate components that are common across countries at year t. In order to investigate interactions between income inequality and economic growth, I estimate the short-run dynamic system of the variables:

$$\boldsymbol{X_{it}} = [\Delta lnGDP_{it}, \Delta lnGINI_{it}, \Delta lnINF_{it}, \Delta lnINT_{it}, \Delta lnEXC_{it}]' \tag{4.10}$$

where $lnGDP_{it}$ is the natural logarithm of real GDP per capita. $lnGINI_{it}$ is the natural logarithm of income inequality measured by Gini coefficients. $lnINF_{it}$ is the natural logarithm of inflation. $lnINT_{it}$ is the natural logarithm of the money market interest rate. $lnEXC_{it}$ is the natural logarithm of the real exchange rate. Δ is the first difference operator. If there are negative values, growth rates will be used instead of log-difference transformation.

For the following estimations, I first lay out a PVAR model with minimal lag orders which involves five endogenous variables. Consider a standard specification of a PVAR model for country i at year t

$$\boldsymbol{X_{it}} = \boldsymbol{\Gamma X_{i,t-1}} + \boldsymbol{\alpha_i} + \boldsymbol{\Lambda_i' F_t} + \boldsymbol{u_{it}} \tag{4.11}$$

Allowing for higher lag orders in the endogenous variables results in

$$\boldsymbol{X_{it}} = \sum_{j=1}^{p_i} \boldsymbol{\Gamma_j X_{i,t-1}} + \boldsymbol{\alpha_i} + \boldsymbol{\Lambda_i' F_t} + \boldsymbol{u_{it}} \tag{4.12}$$

Then the use of common correlated effects (CCE) estimation, originated from (Pesaran, 2006), accounts for unobserved common factors with heterogeneous factor loadings by including cross-section averages of the dependent and independent variables as additional regressors. (Chudik and Pesaran, 2015) extend the CCE estimation, which allows for the dynamic and heterogeneous panel data model. To make the estimation more reliable, the baseline results apply one lag term of all endogenous variables on the right hand side due to the limitation of the degree of freedom in CCE approach. The results for higher order of lags are listed in the Appendix.

4.4 Results

4.4.1 Evidence of US Time Series Analysis

The estimated results start with the US, which is a large open economy. Table 4.2 reports the results for the growth and inequality equations from the panel VAR model up to order two. Neither the coefficient estimate for inequality in the growth equation nor the coefficient estimate for growth in the inequality equation are statistically significant; and is so in all different measures of the variables shown in Table 4.5 in the sensitivity check. Overall, the regressions suggest that the evidence concerning the short-run dynamic relationship between income inequality and economic growth is, at this stage, very limited in the large open economy of the US.

4.4.2 Evidence of Panel Analysis

In the PVAR analysis, cross-country correlations and country-specific heterogeneity in dynamics are allowed. In the case of panel estimates, cross-sectional averages are first computed using all available observations across the 20 advanced economies in the sample to control for unobserved common factors. Additionally, a jackknife bias correction method is used to

Table 4.2. Evidence of US

	US-Lag 1		US-Lag 2	
	Growth Eq.	Ineq Eq.	Growth Eq.	Ineq Eq.
L1.D.lnGDP_NA	0.402***	0.008	0.309**	0.016
	(0.131)	(0.046)	(0.152)	(0.049)
L2.D.lnGDP_NA			-0.022	-0.087*
			(0.150)	(0.049)
L1.D.lnGINI_POST	0.410	0.242*	0.407	0.263**
	(0.377)	(0.132)	(0.386)	(0.125)
L2.D.lnGINI_POST			-0.062	0.004
			(0.391)	(0.127)
L1.G.INF	-0.010	0.002	-0.008	0.004
	(0.009)	(0.003)	(0.010)	(0.003)
L2.G.INF			0.002	-0.007**
			(0.010)	(0.003)
L1.G.INT	-0.012**	-0.001	-0.009	-0.000
	(0.006)	(0.002)	(0.006)	(0.002)
L2.G.INT			-0.006	-0.000
			(0.008)	(0.003)
L1.G.EXC	-0.001	0.027	-0.029	0.050***
	(0.052)	(0.018)	(0.056)	(0.018)
L2.G.EXC			0.068	-0.046**
			(0.059)	(0.019)
Obs	52	52	51	51

mitigate small sample time series bias since jackknife bias correction is more effective than the recursive mean adjustment procedure in dealing with such bias ((Chudik and Pesaran, 2015)). Furthermore, this study investigates both the CCE mean group and pooled estimations to address short-run dynamics. Finally, it examines the robustness of the main findings by introducing different measures of variables, country samples, as well as time spans in the empirical analysis.

Given that this study is working with the growth rates of variables, it relies on a lag order of 1 and 2 as a maximum lag order of 2 should be sufficient to account for the short-run dynamics. The regression results for lag 2 are displayed in the Appendix. Moreover, it is also important to use the same lag order across all variables and countries since it reduces the possible adverse effects of data mining when country or variable specific lag order is selected ((Chudik et al., 2017)).

Similar to the US time series evidence, the panel analysis suggests that when accounting for global factors, the short-run dynamic relationship between income inequality and economic growth becomes statistically insignificant.

Table 4.3. Evidence of panel, 1970-2017

	Panel-Lag 1-CCEMG		Panel-Lag 1-CCEP	
	Growth Eq.	Ineq Eq.	Growth Eq.	Ineq Eq.
L1.D.lnGDP_NA	0.240***	-0.041	0.252***	-0.020
	(0.051)	(0.048)	(0.067)	(0.025)
L1.D.lnGINI_POST	-0.018	0.455***	-0.038	0.381***
	(0.143)	(0.059)	(0.083)	(0.070)
L1.G.INF	0.049	0.032	-0.014	-0.010
	(0.118)	(0.044)	(0.070)	(0.030)
L1.G.INT	0.143	-0.082	0.045	-0.011
	(0.340)	(0.143)	(0.104)	(0.049)
L1.G.EXC	-0.074***	0.006	-0.045**	0.004
	(0.028)	(0.009)	(0.023)	(0.005)
Correction	Jackknife	Jackknife	Jackknife	Jackknife
No. of countries	20	20	20	20
No. of years	46	46	46	46
Obs	834	832	834	832

Specifically, the results are robust in both cross-country and cross-state evidence (Table 4.3 and Table 4.4 respectively). Cross-country heterogeneity substantially affects the short-run dynamics of the relationship between income inequality and economic growth, and that relationship can vary across countries depending on country-specific components.

Table 4.4. Evidence in US states

	States-Lag 1-CCEMG		States-Lag 1-CCEP	
	Growth Eq.	Ineq Eq.	Growth Eq.	Ineq Eq.
L1.D.lnINCOME	-0.203***	-0.008	-0.425***	0.021
	(0.048)	(0.019)	(0.101)	(0.024)
L1.D.lnGINI	0.027	-0.258***	0.071	-0.299***
	(0.038)	(0.028)	(0.047)	(0.030)
Correction	Jackknife	Jackknife	Jackknife	Jackknife
No. of states	49	49	49	49
No. of years	85	85	85	85
Obs	4,165	4,165	4,165	4,165

4.4.3 Sensitivity Analysis

In this section, a number of robustness checks are carried out. First, this study considers alternative measures of both inequality and income variables. Furthermore, it examines different sample periods as well as different choices of sample countries. Finally, other lag orders are investigated.

Alternative Variable Measures

This study considers two types of robustness checks that utilize alternative measures of growth and inequality. First, while $RGDPNA$ is recommended if the object is to compare the growth performance of economies ((Feenstra et al., 2015)), which is the most suitable measure of real GDP per capita for this study, the other two real GDP per capita measures from Penn World Table database, $RGDPE$ and $RGDPO$, have their own advantages. Specifically,

Table 4.5. Evidence of US, different variable measures

	US-Lag1-GINI_PRE		US-Lag 1-RGDPO		US-Lag 1-RGDPE	
	Growth Eq.	Ineq Eq.	Growth Eq.	Ineq Eq.	Growth Eq.	Ineq Eq.
L1.D.lnGDP_NA	0.389***	-0.044				
	(0.132)	(0.046)				
L1.D.lnGDP_O			0.349***	0.013		
			(0.135)	(0.043)		
L1.D.lnGDP_E					0.372***	0.003
					(0.127)	(0.040)
L1.D.lnGINI_PRE	0.108	-0.040				
	(0.375)	(0.131)				
L1.D.lnGINI_POST			0.414	0.244*	0.479	0.241*
			(0.414)	(0.132)	(0.424)	(0.132)
L1.G.INF	-0.010	-0.002	-0.012	0.002	-0.009	0.002
	(0.010)	(0.003)	(0.010)	(0.003)	(0.011)	(0.003)
L1.G.INT	-0.012**	-0.005**	-0.012*	-0.001	-0.015**	-0.001
	(0.006)	(0.002)	(0.006)	(0.002)	(0.006)	(0.002)
L1.G.EXC	0.002	0.017	-0.014	0.028	0.018	0.027
	(0.052)	(0.018)	(0.057)	(0.018)	(0.058)	(0.018)
Obs	52	52	52	52	52	52

$RGDPNA$, which is real GDP at constant national prices, is obtained from the national accounts data for each country. It is therefore used to compare the growth of GDP over time between countries. In contrast, $RGDPE$ is expenditure-side real GDP, which uses prices for final goods that are constant across countries and over time, while $RGDPO$ is Output-side real GDP, which uses prices for final goods exports and imports that are constant across countries and over time. They are used to compare living standards and productive capacity respectively. These two variables are the best-suited to comparisons across time. As a robustness check, this study therefore uses these real GDP per capita measures as endogenous variables. The last four columns of Table 4.5 and Table 4.6 illustrate results for different measures of real GDP per capita. They suggest that the short-run dynamics of the inequality-growth relationship are not unique to specific real GDP per capita measures.

Second, the measure of income inequality is much more controversial since the estimates of income inequality are typically not as comparable as other macroeconomics variables. The Standardized World Income Inequality Database (SWIID) seeks to maximize the comparability of income inequality estimates for the broadest possible coverage of countries and years. Specifically, it provides both a post-tax Gini coefficient (disposable Gini) and pre-tax Gini coefficient (market Gini). Ginis of disposable income are more appropriate for most researchers than those using the other welfare definitions since it depends on income distribution after all direct taxes and government transfers, thereby capturing the distribution of money actually in people's pockets. However, the market Gini is also valuable since it can capture initial inequality before re-distribution. The results are reported in the first two columns of Table 4.5 and Table 4.6, and are very similar to the baseline results.

Alternative Choices of Samples

As a robustness check on timeframe, I first contract the sample period to start at 1980 in order to examine how sensitive results are to the elimination of the oil crises of the 1970's.

Table 4.6. Evidence of panel, different variable measures 1970-2017

	GINI_PRE-CCEMG		RGDPO-CCEMG		RGDPE-CCEMG	
	Growth Eq.	Ineq Eq.	Growth Eq.	Ineq Eq.	Growth Eq.	Ineq Eq.
L1.D.lnGDP_NA	0.286***	-0.010				
	(0.053)	(0.019)				
L1.D.lnGDP_O			0.087	0.043		
			(0.060)	(0.033)		
L1.D.lnGDP_E					0.187***	0.024
					(0.052)	(0.040)
L1.D.lnGINI_POST			-0.378	0.453***	-0.111	0.450***
			(0.289)	(0.066)	(0.253)	(0.066)
L1.D.lnGINI_PRE	0.295	0.447***				
	(0.372)	(0.078)				
L1.G.INF	0.067	0.052	-0.010	-0.004	-0.041	-0.001
	(0.162)	(0.032)	(0.230)	(0.045)	(0.186)	(0.053)
L1.G.INT	0.306	-0.037	0.682	-0.054	0.392	-0.071
	(0.495)	(0.064)	(0.919)	(0.185)	(0.408)	(0.170)
L1.G.EXC	-0.064**	0.022***	0.004	-0.006	-0.081*	-0.008
	(0.028)	(0.006)	(0.046)	(0.012)	(0.046)	(0.014)
Correction	Jackknife	Jackknife	Jackknife	Jackknife	Jackknife	Jackknife
No. of countries	20	20	20	20	20	20
No. of years	46	46	46	46	46	46
Obs	834	832	834	832	834	832

Table 4.7. Evidence of panel, 1980-2017

	Panel-Lag 1-CCEMG		Panel-Lag 1-CCEP	
	Growth Eq.	Ineq Eq.	Growth Eq.	Ineq Eq.
L1.D.lnGDP_NA	0.236***	-0.032	0.263***	-0.034
	(0.053)	(0.050)	(0.050)	(0.025)
L1.D.lnGINI_POST	-0.125	0.427***	-0.081	0.375***
	(0.172)	(0.064)	(0.098)	(0.065)
L1.G.INF	0.017	0.066	0.044	-0.026
	(0.059)	(0.057)	(0.052)	(0.036)
L1.G.INT	-0.226	0.230	-0.003	-0.018
	(0.353)	(0.201)	(0.177)	(0.221)
L1.G.EXC	-0.084***	0.008	-0.035	0.006
	(0.028)	(0.010)	(0.038)	(0.006)
Correction	Jackknife	Jackknife	Jackknife	Jackknife
No. of countries	20	20	20	20
No. of years	38	38	38	38
Obs	745	743	745	743

Additionally, the time span from 1980 to 2017 contains fewer missing values in the panel data. The results in Table 4.7 present similar results to those of the regressions from the 1970-2017 sample. Table 4.8 reports alternative variable measures with shorter time spans. Both tables suggest that the main finding is not specific to the sample period selected.

Another robustness check concerns some alternative choices of sample countries, reducing the 20 advanced economies sample to "Group 10". After comparing different country samples, the short-run dynamics of this relationship in all cases is quite similar.

Alternative Lag Orders

Finally, this study considers whether the estimates of the short-run dynamics are sensitive to a larger lag order, for example, a lag order of two. Results are presented in the Appendix and those results show that the baseline regression is not unique to the first lag order specification.

The maximum lag order of two is not designed as the main specification since a lag order of two would result in a degree of freedom issue, an issue that would be exacerbated by the CCE approach that is used.

4.5 Conclusion

The relationship between inequality and growth is central to the policy debate on redistribution which, as argued by many economists, affects and is possibly affected by growth. Whether the causal direction in this relationship flows from inequality to growth or vice versa remains at the forefront of the discussion. Despite the existing evidence on the inequality-growth relationship, there is little consensus. Hence, as concerns have grown that income inequality might become worse in advanced economies, emerging markets, and less developed countries, this topic has received renewed interest from policymakers. This study thus revisits the inequality-growth relationship with a focus on short-run dynamics that utilizes a panel of advanced economies.

A comparison between commonly used long-run and short-run specifications is first conducted in this paper. The cross-country regression, an augmented Solow model, does not capture short-run dynamics since the growth rate of real GDP per capita is the long-run average within a certain period. Furthermore, other endogenous variables used in this regression are variables that affect the steady state of the economy and hence capture the long-run rather than the short-run relationship. Even the panel analysis, which examines the growth rate within a shorter period of time, does not aim to capture the short-run effect. This study thus constructs a short-run dynamic specification in the New Keynesian framework of the form widely used in the literature.

A regression analysis of the short-run dynamics of the inequality-growth relationship via a panel VAR with Common Correlated Effects illustrates the independence of inequality from growth. Despite the seemingly positive, negative, or nonlinear correlation between inequality

Table 4.8. Evidence of panel, different variable measures 1980-2017

	GINI_PRE-CCEMG		RGDPO-CCEMG		RGDPE-CCEMG	
	Growth Eq.	Ineq Eq.	Growth Eq.	Ineq Eq.	Growth Eq.	Ineq Eq.
L1.D.lnGDP_NA	0.249***	-0.002				
	(0.055)	(0.025)				
L1.D.lnGDP_O			0.144***	0.027		
			(0.050)	(0.030)		
L1.D.lnGDP_E					0.206***	0.026
					(0.049)	(0.039)
L1.D.lnGINI_POST			-0.243	0.415***	0.016	0.420***
			(0.234)	(0.061)	(0.276)	(0.066)
L1.D.lnGINI_PRE	-0.193	0.461***				
	(0.231)	(0.071)				
L1.G.INF	0.008	0.027	0.032	0.025	0.088	0.037
	(0.067)	(0.039)	(0.106)	(0.050)	(0.083)	(0.054)
L1.G.INT	-0.261	0.162	0.593	0.228	0.310	0.226
	(0.355)	(0.140)	(0.676)	(0.178)	(0.480)	(0.176)
L1.G.EXC	-0.071**	0.024***	-0.013	0.000	-0.076*	-0.003
	(0.028)	(0.007)	(0.044)	(0.011)	(0.040)	(0.012)
Correction	Jackknife	Jackknife	Jackknife	Jackknife	Jackknife	Jackknife
No. of countries	20	20	20	20	20	20
No. of years	38	38	38	38	38	38
Obs	745	743	745	743	745	743

Table 4.9. Evidence of panel, Group 10

	Panel-Lag 1-CCEMG		Panel-Lag 1-CCEP	
	Growth Eq.	Ineq Eq.	Growth Eq.	Ineq Eq.
L1.D.lnGDP_NA	0.277***	-0.049	0.287***	-0.008
	(0.086)	(0.063)	(0.101)	(0.064)
L1.D.lnGINI_POST	-0.017	0.466***	0.010	0.418***
	(0.117)	(0.085)	(0.056)	(0.091)
L1.G.INF	0.097	0.000	0.012	0.051*
	(0.170)	(0.086)	(0.069)	(0.030)
L1.G.INT	-0.219	0.114	0.047	-0.034
	(0.226)	(0.133)	(0.194)	(0.117)
L1.G.EXC	-0.040*	0.014	-0.016	0.010
	(0.020)	(0.014)	(0.017)	(0.010)
Correction	Jackknife	Jackknife	Jackknife	Jackknife
No. of countries	11	11	11	11
No. of years	46	46	46	46
Obs	463	462	463	462

and growth in the existing literature, the empirical results presented here unequivocally point to a lack of correlation between inequality and growth in the short-run. This analysis provides results consistent with the long-run identification of the inequality-growth relationship in the previous chapter, which suggests that income inequality in each country depends on country-specific policy. The panel VAR results also show that in the short-run a change in income inequality does not affect economic growth.

As with any other study, this work has many dimensions along which it can be improved such as data quality and estimation technique. While this work answers its main research question, namely the short-run dynamics of the inequality-growth relationship, it does not address how redistribution policies might affect inequality. Future research could thus evaluate redistribution policies that aim to reduce income inequality. Another issue is the length of the time series utilized when using a CCE approach. This is relevant as the data availability of inequality variables restricts the use of high frequency macroeconomic data, which in turn affects estimation.

CHAPTER 5

CONCLUSION

This dissertation comprehensively analyzes the relationship between inequality and growth, both in the long-run and short-run. It contributes to development economics, especially growth literature by focusing on the interdependence of inequality and growth.

Chapter 2 summarizes existing papers that explore both directions of causality in the inequality-growth relationship. From collecting the estimates in the growth literature, I obtain weak evidence of a negative relationship in cross country regressions which has been explained by the existing literature as the long-run effect of inequality on growth. More than 80% of the estimates are negative. However, this consensus disappears in panel regressions and studies interpret the results as the medium- or short-run relationship. Several estimation issues are also provided to express the mixed findings. Therefore, the empirical results from existing studies should be interpreted carefully. The issues in estimation and mixed findings call for the revisit of long-run and short-run relationship between inequality and growth which are discussed in Chapter 3 and Chapter 4 respectively.

Chapter 3 focuses on the long-run relationship between inequality and growth. To avoid the estimation issues of the augmented Solow regression, relative convergence and weak-σ convergence approaches are used to identify this relationship. Income as measured by real GDP per capita is sub-club convergent while inequality as measured by top income shares is divergent. Additionally, no common factor is obtained in inequality while I find one common factor in income. These results indicate that income is highly correlated among countries while inequality is unique to each country. Every country has its own characteristics and policies dealing with inequality. Therefore, there is no long-run relationship between inequality ad growth. Is there any short-run relationship? After controlling the stochastic trends, the short-run dynamics of inequality-growth relationship then can be obtained through panel regressions which is captured in Chapter 4.

To provide a link why short-run dynamics becomes an interest, Chapter 4 starts from issues of the typical growth model in capturing the short-run dynamics, and then constructs a New Keynesian framework from the existing studies. Through a panel VAR approach with Common Correlated Effects addressing the endogeneity as well as common factors, this chapter then obtains consistent results with Chapter 3, suggesting that inequality is not correlated with growth. Similar results can be found in US time series and a panel of advanced economies. In summary, in the cross country analysis, the change of income inequality is attributed to the country specific policy rather than economic growth.

APPENDIX A

SUPPLEMENTAL MATERIALS FOR CHAPTER 2

A.1 Estimation Issues

A.1.1 Issues of Omitted Variables

In the cross-country regression, suppose the truth is:

$$y_i = \alpha + \beta_1 x_i + \beta_2 z_i + e_i$$

For some reason, however, we don't include z_i either because we didn't think of it or because it is difficult to be measured. An example can be viewed as regressing growth (y_i) on inequality (x_i) and z_i is fertility which will be omitted. Therefore we are running:

$$y_i = \alpha + \beta_1 x_i + u_i$$

where $u_i = \beta_2 z_i + e_i$. Then:

$$\hat{\beta}_1 = \frac{\sum \tilde{x}_i \tilde{y}_i}{\sum \tilde{x}_i^2} = \frac{\sum \tilde{x}_i(\beta_1 \tilde{x}_i + \beta_2 \tilde{z}_i + \tilde{e}_i)}{\sum \tilde{x}_i^2} = \beta_1 + \beta_2 (\frac{\sum \tilde{x}_i \tilde{z}_i}{\sum \tilde{x}_i^2}) + \frac{\sum \tilde{x}_i \tilde{e}_i}{\sum \tilde{x}_i^2}$$

where

$$\tilde{y}_i = y_i - \frac{1}{N}\sum y_i,\ \ \tilde{x}_i = x_i - \frac{1}{N}\sum x_i, \tilde{z}_i = z_i - \frac{1}{N}\sum z_i$$

Therefore:

$$plim \hat{\beta}_1 = \beta_1 + \beta_2 \frac{\sigma_{xz}}{\sigma_x^2} \neq \beta_1$$

The bias depends on the relationship between x_i (eg. inequality) and z_i (eg. fertility).

A.1.2 Issues of Measurement Error

Similar to the omitted variable issue of a cross-country example, suppose theoretically the relationship between Y_i and X_i is:

$$Y_i = \alpha + \beta X_i + e_i$$

Due to the data limitation, we cannot fully observe Y_i and X_i or the measures, to our best, are imperfect. For example, a popular proxy for inequality is Gini index. However, Gini index, to some extent, cannot perfectly measure inequality due to the accuracy of household survey or the concealed information by local governments. Therefore we can only observe y_i^* and x_i^* where:

$$y_i^* = y_i + u_i \text{ and } x_i^* = x_i + v_i$$

If the measurement error happens in y_i:

$$y_i^* = \alpha + \beta x_i + e_i,\ plim\beta = \beta$$

If the measurement error happens in x_i:

$$y_i = \alpha + \beta x_i^* + e_i,\ plim\beta = \beta * (\frac{\sigma_x^2}{\sigma_x^2 + \sigma_v^2})$$

A.1.3 Issues of First Difference Regressions

Suppose the true data generating process is:

$$y_{it} = c_i + a_i t + y_{it}^*,\ x_{it} = d_i + b_i t + x_{it}^*$$

where c_i and d_i are the expected initial values y_{i0} and x_{i0}, a_i and b_i are the long-run growth rate of y_{it} and x_{it}, y_{it}^* and x_{it}^* are the mean-zero idiosyncratic terms of y and x respectively. To estimate the effect of x on y, We run the following regression by taking first difference on both sides:

$$\Delta y_{it} = \alpha_i + \theta_t + \beta_{fd}\Delta x_{it} + \Delta u_{it}$$

Then:

$$\hat{\beta}_{fd} = \frac{\sum\sum \tilde{\Delta} x_{it} \tilde{\Delta} y_{it}}{\sum\sum \tilde{\Delta} x_{it}^2}$$

To start with, the first difference is implemented:

$$\Delta y_{it} = a_i + \Delta y_{it}^*,\ \Delta x_{it} = b_i + \Delta x_{it}^*$$

Then:

$$\tilde{\Delta y_{it}} = \tilde{\Delta y_{it}}^*, \ \tilde{\Delta x_{it}} = \tilde{\Delta x_{it}}^*$$

Here the expected long-run growth rate becomes the long-run average. Therefore,

$$\hat{\beta}_{fd} = \frac{\sum\sum \tilde{\Delta x}_{it}^* \tilde{\Delta y}_{it}^*}{\sum\sum \tilde{\Delta x}_{it}^{*2}}$$

and

$$plim\hat{\beta}_{fd} = \frac{\sigma_{xy}}{\sigma_x^2}$$

In the first difference case, intuitively, the effect of Δx on Δy depends only on the temporary variation of Δx^* and Δy^* because the long-run growth rate (a_i and b_i) in the level case becomes the long-run average after taking first difference so that Δx and Δy will not grow infinitely. Therefore, the temporary variation will dominate and the first difference regression cannot reflect the long-run relationship between y and x.

A.1.4 Issues of Dynamic Panel Models

Consider the dynamic panel model:

$$y_{it} = \rho y_{it-1} + \beta x_{it} + \alpha_i + u_{it}$$

Remove the fixed effects α_i by differencing the cross sectional mean:

$$y_{it} - \bar{y}_{i\cdot} = \rho(y_{it-1} - \bar{y}_{i\cdot}) + \beta(x_{it} - \bar{x}_{i\cdot}) + (u_{it} - \bar{u}_{i\cdot})$$

Because $\bar{y}_{i\cdot}$ is correlated with the error term $(u_{it} - \bar{u}_{i\cdot})$, the LSDV estimator is biased. And (Nickell, 1981) characterizes the degree of bias in AR(1) panels with small T:

$$plim_{N\to\infty}(\hat{\rho} - \rho) = \frac{\frac{-(1+\rho)}{T-1} \times [1 - \frac{1}{T} \times \frac{1-\rho^T}{1-\rho}]}{1 - \frac{2\rho}{(1-\rho)(T-1)} \times [1 - \frac{1}{T} \times \frac{1-\rho^T}{1-\rho}]}$$

As noted, the bias is $O(1/T)$ and for reasonably large T is:

$$plim_{N\to\infty}(\hat{\rho} - \rho) \approx \frac{-(1+\rho)}{T-1}$$

Therefore, $\hat{\rho}$ will always be underestimated in dynamic panel model with fixed effects.

A.1.5 Issues of Interval k

Suppose x_{it} follows an AR(1) process, i.e.,

$$x_{it} = \rho x_{it-1} + \epsilon_{it}$$

And we want to compare the coefficients from the following estimation equations:

$$\begin{cases} y_{it} = \beta_1 x_{it-1} + e_{it} \\ y_{it} = \beta_k x_{it-k} + u_{it} \end{cases}$$

Because

$$x_{it-1} = \rho x_{it-2} + \epsilon_{it-1} = \rho(\rho x_{it-3} + \epsilon_{it-2}) + \epsilon_{it-1} = \cdots$$

$$= \rho^{k-1} x_{it-k} + [\rho^{k-2}\epsilon_{it-(k-1)} + \cdots + \rho\epsilon_{it-2} + \epsilon_{it-1}]$$

Plugging this into y_{it} yields:

$$y_{it} = \beta_1 x_{it-1} + e_{it} = \beta_1[\rho^{k-1} x_{it-k} + \rho^{k-2}\epsilon_{it-(k-1)} + \cdots + \rho\epsilon_{it-2} + \epsilon_{it-1}]$$

$$= \beta_1\rho^{k-1} x_{it-k} + [\beta_1\rho^{k-2}\epsilon_{it-(k-1)} + \cdots + \beta_1\rho\epsilon_{it-2} + \beta_1\epsilon_{it-1}]$$

Therefore, if $0 < \rho < 1$ and $k > 1$ which indicates $\beta_1\rho^{k-1} < \beta_1$ and $\beta_k < \beta_1$. The estimated coefficients are decreasing as the interval k increases.

Table A.1. The number of papers in both directions and specifications

		Causality and specification			
		Direction1		Direction2	
Linear	Positive	[8][1]	(Forbes, 2000) (Li and Zou, 1998)	[8][5]	(Roine et al., 2009) (Bergh and Nilsson, 2010)
	Negative	[29][2]	(Deininger and Squire, 1998) (Herzer and Vollmer, 2012)	[8][6]	(Brueckner et al., 2015) (Bumann and Lensink, 2016)
	Mixed/Insig	[15][3]	(Barro, 2000) (Bjørnskov, 2008)	[17][7]	(Ghossoub and Reed, 2017) (Kraay, 2006)
Nonlinear	Quadratic	[3][4]	(Banerjee and Duflo, 2003) (Scholl and Klasen, 2016)	[22][8]	(Ahluwalia, 1976) (Barro, 2000)
	Cubic	[0]	N/A	[3][9]	(Lessmann and Seidel, 2017) (Park and Shin, 2017)
	Nonparametric	[0]	N/A	[1][10]	(Frazer, 2006)

[-]The number in the square bracket indicates the number of studies in corresponding categories.
[-]The representative papers are listed in the table. See footnotes for all papers included.

A.2 Empirical Papers Included in the Survey

[1]Papers include: (Andrews et al., 2011), (Banerjee and Duflo, 2003), (Forbes, 2000), (Galbraith and Kum, 2003), (Iradian, 2005), (Li and Zou, 1998), (Muinelo-Gallo and Roca-Sagalés, 2013), and (Naguib, 2015)

[2]Papers include: (Abida and Sghaier, 2012), (Alesina and Rodrik, 1994), (Bengoa and Sanchez-Robles*, 2005), (Birdsall et al., 1995), (Birdsall and Londoño, 1997), (Bleaney and Nishiyama, 2004), (Castelló and Doménech, 2002), (Castelló-Climent, 2010a), (Castells-Quintana and Royuela, 2017), (Chambers and Krause, 2010), (Clarke, 1995), (De La Croix and Doepke, 2003), (Deininger and Squire, 1998), (Galor and Zang, 1997), (Gründler and Scheuermeyer, 2018), (Herzer and Vollmer, 2012), (Keefer and Knack, 2002), (Knowles, 2005), (Lee and Son, 2016), (Malinen, 2012), (Malinen, 2013), (Odedokun and Round, 2004), (Ostry et al., 2014), (Perotti, 1996), (Persson and Tabellini, 1994), (Sarkar, 2007), (Sylwester, 2000), (Tanninen, 1999), and (Woo, 2011)

[3]Papers include: (Bagchi and Svejnar, 2015), (Barro, 2000), (Barro, 2008), (Bjørnskov, 2008), (Caraballo et al., 2017), (Castelló-Climent, 2010b), (Davis and Hopkins, 2011), (Deininger and Olinto, 2000), (Ferreira et al., 2018), (Halter et al., 2014), (Khalifa et al., 2010), (Lundberg and Squire, 2003), (Scholl and Klasen, 2016), (Thewissen, 2014), and (Voitchovsky, 2005)

[4]Papers include: (Banerjee and Duflo, 2003), (Bengoa and Sanchez-Robles*, 2005), and (Scholl and Klasen, 2016)

[5]Papers include: (Bergh and Nilsson, 2010), (Blau, 2018), (Hamori and Hashiguchi, 2012), (Lessmann, 2013), (Li and Yu, 2014), (Odedokun and Round, 2004), (Roine et al., 2009), and (Rubin and Segal, 2015)

[6]Papers include: (Brueckner et al., 2015), (Bumann and Lensink, 2016), (Chong et al., 2009), (Delis et al., 2014), (Gustafsson and Johansson, 1999), (Janvry and Sadoulet, 2000), (Tan and Law, 2012), and (Zhang and Naceur, 2019)

[7]Papers include: (Beck et al., 2007), (Breen and García-Peñalosa, 2005), (Cabral et al., 2016), (Calderón and Chong, 2001), (Castells-Quintana and Royuela, 2017), (Dobson and Ramlogan-Dobson, 2012a), (Dobson and Ramlogan-Dobson, 2012b), (Ghossoub and Reed, 2017), (Gupta et al., 2002), (Kraay, 2006), (Li et al., 1998), (Li et al., 2000), (Lundberg and Squire, 2003), (Mookerjee and Kalipioni, 2010), (Muinelo-Gallo and Roca-Sagalés, 2013), (Prete, 2013), and (Scheve and Stasavage, 2009)

[8]Papers include: (Agnello et al., 2012), (Ahluwalia, 1976), (Anand and Kanbur, 1993), (Andres and Ramlogan-Dobson, 2011), (Barro, 2000), (Barro, 2008), (Bonfiglioli, 2012), (Carter, 2007), (Clarke et al., 2006), (Davis, 1992), (Galbraith and Kum, 2003), (Hartmann et al., 2017), (Iradian, 2005), (Ivaschenko, 2003), (Jauch and Watzka, 2016), (Li et al., 2000), (Ram, 1997), (Randolph and Lott, 1993), (Reuveny and Li, 2003), (Roser and Cuaresma, 2016), (Seven and Coskun, 2016), and (Van Velthoven et al., 2018)

[9]Papers include: (Lessmann, 2014), (Lessmann and Seidel, 2017), and (Park and Shin, 2017)

[10]Papers include: (Frazer, 2006)

APPENDIX B

SUPPLEMENTAL MATERIALS FOR CHAPTER 4

B.1 Regression Results with 2 Lags

Table B.1. Evidence of panel (lag 2), 1970-2017

	Panel-Lag 2-CCEMG		Panel-Lag 2-CCEP	
	Growth Eq.	Ineq Eq.	Growth Eq.	Ineq Eq.
L1.D.lnGDP_NA	0.102	-0.013	0.254***	-0.010
	(0.076)	(0.059)	(0.086)	(0.039)
L2.D.lnGDP_NA	-0.112	0.014	-0.016	-0.000
	(0.108)	(0.034)	(0.061)	(0.033)
L1.D.lnGINI_POST	0.072	0.425***	-0.062	0.358***
	(0.234)	(0.078)	(0.086)	(0.086)
L2.D.lnGINI_POST	-0.270	0.025	0.018	-0.036
	(0.339)	(0.071)	(0.100)	(0.078)
L1.G.INF	-0.030	0.075	-0.059	-0.023
	(0.128)	(0.065)	(0.151)	(0.078)
L2.G.INF	0.030	-0.084	0.041	-0.046
	(0.162)	(0.078)	(0.143)	(0.046)
L1.G.INT	1.123	0.233	-0.093	-0.006
	(1.223)	(0.185)	(0.385)	(0.202)
L2.G.INT	0.836	-0.131	0.007	-0.043
	(0.954)	(0.333)	(0.442)	(0.056)
L1.G.EXC	-0.147**	-0.004	-0.046	0.002
	(0.071)	(0.012)	(0.049)	(0.011)
L2.G.EXC	0.026	0.021	-0.017	0.007
	(0.036)	(0.017)	(0.053)	(0.016)
Correction	Jackknife	Jackknife	Jackknife	Jackknife
Joint test P-value	0.728	0.908	0.738	0.968
Linear test P-value	0.527	0.993	0.759	0.847
No. of countries	20	20	20	20
No. of years	45	45	45	45
Obs	816	814	816	814

Table B.2. Evidence of panel (lag 2), 1980-2017

	Panel-Lag 2-CCEMG		Panel-Lag 2-CCEP	
	Growth Eq.	Ineq Eq.	Growth Eq.	Ineq Eq.
L1.D.lnGDP_NA	0.187***	-0.081	0.257***	-0.025
	(0.071)	(0.071)	(0.082)	(0.043)
L2.D.lnGDP_NA	-0.096	-0.012	-0.020	-0.017
	(0.064)	(0.046)	(0.056)	(0.032)
L1.D.lnGINI_POST	-0.147	0.370***	-0.097	0.342***
	(0.289)	(0.084)	(0.087)	(0.078)
L2.D.lnGINI_POST	-0.099	-0.015	-0.011	-0.061
	(0.170)	(0.068)	(0.117)	(0.089)
L1.G.INF	0.034	0.064	0.028	-0.039
	(0.104)	(0.114)	(0.051)	(0.043)
L2.G.INF	-0.033	-0.014	0.025	-0.056*
	(0.169)	(0.099)	(0.055)	(0.031)
L1.G.INT	0.242	0.393	-0.099	-0.021
	(0.337)	(0.344)	(0.258)	(0.295)
L2.G.INT	-0.159	-0.139	-0.047	-0.020
	(0.546)	(0.363)	(0.140)	(0.102)
L1.G.EXC	-0.083**	0.008	-0.041	0.008
	(0.032)	(0.024)	(0.051)	(0.015)
L2.G.EXC	0.013	0.026	-0.032	0.006
	(0.026)	(0.018)	(0.049)	(0.014)
Correction	Jackknife	Jackknife	Jackknife	Jackknife
Joint test P-value	0.712	0.515	0.496	0.684
Linear test P-value	0.438	0.299	0.528	0.388
No. of countries	20	20	20	20
No. of years	37	37	37	37
Obs	739	737	739	737

Table B.3. Evidence of panel (lag 2), Group 10

	Panel-Lag 2-CCEMG		Panel-Lag 2-CCEP	
	Growth Eq.	Ineq Eq.	Growth Eq.	Ineq Eq.
L1.D.lnGDP_NA	0.065	0.184**	0.318***	0.040
	(0.103)	(0.079)	(0.076)	(0.078)
L2.D.lnGDP_NA	0.300	-0.024	-0.056	0.062
	(0.309)	(0.126)	(0.167)	(0.094)
L1.D.lnGINI_POST	0.112	0.520***	-0.049	0.347***
	(0.121)	(0.147)	(0.159)	(0.112)
L2.D.lnGINI_POST	0.056	0.157**	0.079	0.107*
	(0.243)	(0.079)	(0.107)	(0.061)
L1.G.INF	0.052	0.059	0.029	-0.000
	(0.151)	(0.108)	(0.071)	(0.059)
L2.G.INF	0.101	0.036	0.046	0.032
	(0.166)	(0.151)	(0.069)	(0.027)
L1.G.INT	-0.353	-0.013	0.010	-0.035*
	(0.295)	(0.113)	(0.286)	(0.018)
L2.G.INT	-0.425	-0.135	0.008	0.024
	(0.313)	(0.329)	(0.412)	(0.203)
L1.G.EXC	-0.018	0.060***	-0.014	0.022
	(0.032)	(0.020)	(0.044)	(0.020)
L2.G.EXC	0.008	0.016	0.028	0.003
	(0.025)	(0.025)	(0.050)	(0.009)
Correction	Jackknife	Jackknife	Jackknife	Jackknife
Joint test P-value	0.527	0.069	0.747	0.602
Linear test P-value	0.453	0.241	0.812	0.314
No. of countries	11	11	11	11
No. of years	45	45	45	45
Obs	454	453	454	453

Table B.4. Evidence in US states (lag 2)

	States-Lag 2-CCEMG		States-Lag 2-CCEP	
	Growth Eq.	Ineq Eq.	Growth Eq.	Ineq Eq.
L1.D.lnINCOME	-0.203***	-0.014	-0.443***	0.013
	(0.051)	(0.024)	(0.118)	(0.021)
L2.D.lnINCOME	-0.085**	-0.004	-0.039	-0.044*
	(0.035)	(0.024)	(0.067)	(0.023)
L1.D.lnGINI	0.054	-0.303***	0.099**	-0.343***
	(0.035)	(0.031)	(0.046)	(0.034)
L2.D.lnGINI	0.096***	-0.071***	0.095***	-0.088***
	(0.031)	(0.023)	(0.034)	(0.028)
Correction	Jackknife	Jackknife	Jackknife	Jackknife
Joint test P-value	0.005	0.811	0.000	0.158
Linear test P-value	0.003	0.554	0.000	0.223
No. of states	49	49	49	49
No. of years	84	84	84	84
Obs	4,116	4,116	4,116	4,116

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