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Income Inequality, Human Capital and Economic Growth in China

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Income Inequality, Human Capital and Economic Growth in China

by

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Author's Declaration

At no time during the registration for the research degree has the author been registered for any other University award, without prior agreement of the Doctoral College Quality Sub-Committee.

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Abstract

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After initially reviewing the existing literature on the inequality-growth nexus, this thesis then conducts empirical studies to explore the spatial dynamics of China's regional income inequality and economic growth, investigates the relationship between inequality and growth, and the influences of human and physical capital, to examine the theoretical mechanisms underlying the inequality-growth relationship. The findings from these studies can offer valuable insights for the policy makers in China.

Using the latest data, the first study in the thesis explores the pattern and evolution of China's regional inequality. In addition, the study depicts the spatial dynamics of the inequality, growth and the human and physical capital within the country, using provincial level data. The results indicate a declining trend in national income inequality in the period from 1980 to 2016, where intra-regional inequality outweighed inter-regional inequality as the main contributor to national inequality. The study also reflects the unbalanced inequality and growth across the provinces. By offering a comprehensive overview of the variables of interest, the study facilitates a better understanding of China's complex and unique background of inequality and growth.

The second study investigates the two-way causality between inequality and growth using the latest provincial-level data together with new empirical methods. It addresses the issues that appear in many previous studies, such as data incomparability, cross-country heterogeneity, sample selection issues and cross-sectional dependence. In particular, a panel vector error correction model (panel VECM) is adopted to estimate the impacts of inequality on growth, and vice versa; a factor that is largely overlooked in existing literature. The empirical results suggest that the long-term relationship between inequality and growth was positive during the period from 1990 to 2003 and negative from 2003 to 2017, and that physical capital plays a more important role in China's economic growth than does human capital.

The third study first examines the one-directional impacts of inequality on growth, using the panel autoregressive distributed lag model (panel ARDL model). Moreover, as most of the existing empirical studies fail to explore the theoretical mechanisms underlying the inequality-growth connection in China, this study fills the gap by examining the mechanisms through which inequality affects growth. The empirical results suggest that income inequality enhances economic growth in the long term, and supports the classical channel and credit market imperfections channel where inequality promotes growth through physical capital and harms growth through human capital.

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List of Abbreviations

3SLS	3-Stage Least Square
AR1	First-order Serial Correlation
AR2	Second-order Serial Correlation
ARDL	Autoregressive Distributive Lag
CHIP	Chinese Household Income Project
CIPS	Cross Sectionally augmented Im-Pesaran-Shin panel unit root test
CHFS	China Household Finance Survey
CHIP	Chinese Household Income Project
CHLR	Human Capital and Labour Market Research
CSD	Cross Sectional Dependence
DCGE	Dynamic Computable General Equilibrium
DOLS	Dynamic Ordinary Least Squares
FE	Fixed Effects
FE-OLS	Fixed-Effect Ordinary Least Squares
FMOLS	Fully Modified Ordinary Least Squares
GDP	Gross Domestic Product
GMM	General Method of Moments
HAC	Heteroskedastic and Autocorrelation-consistent
HAC SE	Heteroskedastic and Autocorrelation Consistent Standard Error
HDI	Human Development Index
IPS	Im–Pesaran–Shin panel unit root test
LLC	Levin-Lin-Chu panel unit root test
MAIC	MMSC-Akaike's Information Criterion
MBIC	MMSC-Bayesian Information Criterion
MG	Mean Group
MQIC	MMSC-Hannan and Quinn Information Criterion
NBS	National Bureau of Statistics of the People's Republic of China
OLS	Ordinary Least Squares
PIL	Polynomial Inverse Lag
PMG	Pooled Mean Group

PURT	Panel Unit Root Tests
RE	Random Effects
SE	Standard Error
UTIP	University of Texas Inequality Project
VAR	Vector Autoregressive
VECM	Vector Error Correction Model
WGI	Worldwide Governance Indicators

Chapter 1. Introduction

Focusing on the income inequality and economic growth in China, this thesis consists of three separate but related studies, and explores three main issues: i) The pattern and evolution of the regional income inequality and growth in China, ii) the relationship between inequality and growth and iii) how they are affected by human capital and physical capital, and the mechanisms that connect inequality and growth.

In recent decades, income inequality has attracted the attention of many scholars. China is an especially interesting case in this regard. Since its economic reform in 1978, the country has seen a transition from a planned economy to a market economy and has subsequently experienced a rapid rate of economic development. The country's process of urbanisation and marketisation is, however, accompanied by uneven economic development, which has led to high levels of urban-rural inequality as well as regional inequality. According to previous research, the income gap between urban and rural areas accounts for a large portion of China's income inequality (Chen and Fleisher, 1996; Kanbur and Zhang, 2005; Liu et al. 2012; Shi et al. 2013). Meanwhile, in general, the higher level of development in the coastal regions than in the inland regions has resulted in wide regional gaps (Tsui, 2007; Fan and Sun, 2008; Akita, 2003). Importantly, exploring the patterns and spatial dynamics of China's income inequality is, can help shed light on China's inequality and growth over the years.

Besides income inequality in itself, the relationship between income inequality and economic growth is also a hot topic that has been discussed both in theoretical and empirical research. One of the most influential studies is the inverted U hypothesis proposed by Kuznets (1955). The hypothesis suggests that growth raises inequality in the early stage of economic development and reduces it in the later stage. The more recent studies mainly explore the influence of income inequality on economic growth, and despite of the abundance of research, this topic remains controversial. While the majority of the theoretical studies argue that inequality is harmful to growth (Alesina and Rodrik, 1994; Barro 2000; Galor and Zeira, 1993; Acemoglu and Robinson, 2001), the empirical studies fail to reach a consensus regarding whether inequality impedes or promotes economic growth. In particular, some empirical papers indicate that inequality has a positive effect of on growth (Forbes, 2000; Frank, 2009), some papers find a negative impact of inequality on growth (Panizza, 2002), while others imply a non-linear relationship between the two variables (Barro, 2000). Given the controversies on the relationship between inequality and growth, this thesis, utilising data from China, attempts to bring greater clarification to the topic.

While a variety of estimation methods and datasets have been adopted by previous empirical studies on inequality and growth, most of the studies adopt international data collected from different countries. Using cross-country data involves several drawbacks, however. First, studies that adopt such data can yield misleading results, as they neglect the potential cross-country heterogeneity that can be caused by many factors, such as the presence of different political and economic structures (Herzer and Vollmer, 2012). Second, cross-country studies are plagued by data incomparability among the countries, resulting in bias in the estimated results (Knowles, 2005). Different countries may adopt different definitions of income and inequality, for instance. Third, the studies may face sample selection problems, such as placing developing and developed countries, democratic and nondemocratic countries into the same sample, making the empirical results less representative. Considering the above problems with using cross-country data, conducting research in a single-country framework is a better choice because the problems can be greatly alleviated by adopting data from a single country (Frank, 2009; Benos and Karagiannis, 2018). Previous studies are mainly based on international data due to the unavailability of data from a single country, whereas this thesis takes advantage of the latest data from China to investigate the relationship between income inequality and growth in the country, as well as the mechanisms behind the inequality-growth relationship.

Because of the country's unique economic background, the findings from previous studies may not be well-suited to the actual situation in China, it is therefore important to explore the relationship between inequality and growth in the specific context of China. Although China has enjoyed a high level of economic growth in the recent decades of economic transition, this has been accompanied by a high level of income inequality. This thesis aims to shed light on three fundamental research questions: i) What is the pattern of China's regional inequality? ii) What is the relationship between income inequality and economic growth in China? iii) Through which mechanisms does inequality affect growth?

Chapter 2 provides a review of literature on the relationship between income inequality and economic growth, the mechanisms through which inequality affects growth, and the roles of human and physical capital in the inequality-growth relationship. Both theoretical and empirical studies are reviewed in this chapter.

Chapter 3 provides descriptive statistics to explore the first research question regarding the pattern of China's regional inequality. Theil-T and Theil-L decompositions are conducted to explore the inequalities within and between the country's four economic regions in the period between 1980 and 2016. In addition, the chapter depicts the spatial dynamics of the country's inequality, its growth and its human and physical capital on the provincial level, during the period from 1990 to 2017. This chapter also calculates and compares three popular measurements of China's provincial income inequality: i) the Gini index, ii) the Theil coefficient and iii) the urban-rural income ratio. Human capital, which is measured by the years of schooling, is also divided into three levels: i) advanced human capital, ii) medium human capital and iii) basic human capital. By providing a comprehensive overview of the patterns and evolution of the variables of interest, this chapter facilitates a better understanding of China's complex and unique inequality and growth background. Following on from the findings of this chapter, the subsequent chapter goes a step further to explore how inequality and growth are connected.

Further to the research in Chapter 3, Chapter 4 conducts an empirical study to investigate the second research question, regarding the relationship between income inequality and economic growth in China. A panel vector error correction model (panel VECM) is adopted to analyse the long- and short-term inequality-growth nexus, based on the provincial level data collected from 30 provinces over 28 years (1990 –2017). According to the findings of Chapter 3, the year 2003 marked a turning point when China's inequality peaked, hence the whole time period is split into two subsamples: 1990–2003 and 2003–2017. A concern with previous literature is that many studies, neglecting the potential cross-sectional dependence (CSD) in the panel data, can give biased results. In order to confront this problem, this chapter carries out Pesaran's cross-sectional dependence test (Pesaran's CD test) to detect any potential CSD, and the empirical study adopts ordinary least squares (OLS) with Driscoll-Kraay standard errors, which can produce heteroskedastic and autocorrelation-consistent robust standard errors (HAC SE) even when CSD is present. For the purpose of comparison, apart from the Driscoll-Kraay estimator, a variety of other estimators are also adopted, including the fixed effects (FE), mean group (MG), the fully modified OLS (FMOLS) and the general method of moments (GMM). To estimate the panel VECM model, the Engle-Granger two-step method is employed. An advantage of the panel VECM is that it tests not only the effect of inequality on growth, but also tests the impacts of growth on inequality; an area largely neglected in previous studies. Besides that, the model tests the effects of the human and physical capital (the exogenous variables) on inequality and growth. The three levels human capital (advanced, medium and basic) are used in the study to test their different effects in the inequality-growth nexus. To the best of my knowledge, this chapter conducts the first study to use panel VECM to examine China's inequality and growth.

Furthermore, while Chapter 4 tests the inequality-growth nexus using panel VECM, Chapter 5 first revisits the inequality-growth nexus using the panel autoregressive distributed lag model (panel ARDL model). The second panel ARDL model with two interaction terms is then constructed to investigate the third research question. regarding the mechanisms underlying the inequality-growth nexus. More specifically, Chapter 4 explores the two-way causality between inequality and growth, while Chapter 5 investigates the one-way effects of inequality on growth, as well as the long- and short-term effects of human capital and physical capital on growth. Considering that most of the previous empirical studies focus on the inequality-growth connection without exploring the theoretical mechanisms underlying the connection, and even fewer studies focus on the context of China, Chapter 5 fills in this gap by testing the theoretical mechanisms used in the unified growth theory, namely the classical mechanism and credit market imperfections mechanism. In addition, in order to test how the inequality-growth nexus varies in different development stages, this chapter also splits the provinces into three subsamples according to their GDP per capita.

Chapter 6 provides the concluding remarks for the whole thesis.

Briefly, this thesis makes three main contributions. First, the studies here are based on the updated data on the provincial level, taking advantage of higher data quality and thereby mitigating the data incomparability, cross-country heterogeneity and sample selection issues in previous studies. Second, the thesis provides the first study to apply panel VECM in the estimation of the inequality-growth relationship in China, and also deals with cross-sectional dependence, which is largely neglected in previous studies. Third, few existing empirical studies examine the theoretical mechanisms behind the inequality-growth connection, and the studies that do examine these mechanisms usually focus on a single channel, neglecting the fact that different channels can take effects simultaneously (Barro, 2000). Inspired by unified growth theory, this thesis fills the gap by combining and examining both the classical mechanism and the credit market imperfections mechanism.

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Chapter 2. Literature review

This chapter reviews the previous literature on how inequality and growth are connected, on the mechanisms behind their connection and on the role of human capital in the inequality-growth nexus, both from the theoretical and empirical perspectives. The relationship between inequality and growth has been explored since mid-1990s, through both theoretical and empirical literature but first, the early works —including the research of Kuznets (1955) and Kaldor (1956) —are introduced. The pioneering work of Kuznets (1955) examines the influence of growth on inequality, whereas the later studies predominately investigate the effects of inequality on growth, but yield no consensus. Secondly, the four main theoretical channels, through which inequality affects growth, are discussed. These are i) the political economy channel, ii) the credit market imperfections channel that highlights the importance of human capital, iii) the socio-political instability channel and iiii) the savings channel. The chapter then reviews the empirical papers, which have evolved from the initial studies in the mid-1990s, the later research starting from the late 1990s and the most recent ones since 2010, including those conducted within a single country, including China.

2.1. Early research

As mentioned, the research on the relationship between growth and inequality can be traced back to the 1950s. Among the initial theories, the inverted-U hypothesis raised by Kuznets (1955) could be the most influential one.

By comparing the income inequality in a group of developed and developing countries, Kuznets (1955, 1963) finds a higher level of inequality in developing countries than in developed countries. If this hypothesis holds in the context of China, the income gap there should widen in the earlier stages of economic development and narrow down later. Specifically, Kuznets stated that the income inequality is low in the early stage of economic development, but as the economy develops, the inequality soars, and then gradually falls back to a lower level in the later stage of development.

As Kuznets explains in the 1955 research, the development is accompanied by the movement of the labour force from the lower to the higher income sectors. The lower sectors are usually made up of the rural agricultural areas with lower productivity, and the higher-income sectors are comprised of the industrial sectors in urban areas with higher productivity. As a result, the income gap is widened as the more skilled workers in the higher productivity sectors earn higher wages than the unskilled less productive workers, while savings and wealth are accumulated by the rich. However, further industrialisation and urbanisation raise the number of skilled workers while reducing the number of unskilled workers, thereby increasing the income level overall. Thus, the income gap gradually diminishes in the later stage of development. This hypothesis suggests that the trend of rising inequality in underdeveloped countries will reverse as the countries become more urbanised and industrialised.

In addition, further supporting this inequality evolution pattern, Kuznets (1963) presents data from additional countries to demonstrate this pattern, the inverted-U curve, which strongly influenced subsequent inequality studies. Repeatedly re-examined by researchers, the inverted-U hypothesis has its own limitations, and has triggered heated discussion in the years that followed, with economists developing new analytical and empirical studies. Chapter 3 of this thesis will provide a general picture of China's income inequality and economic growth during recent decades, and the inverted-U hypothesis will be tested in Chapter 4. By looking at the evolution of inequality and growth over time, I will establish whether evidence of the inverted-U curve was present in China in recent decades.

Further to Kuznets' research, new empirical studies have been conducted, also based on the inverted-U hypothesis. Although the hypothesis was originally regarded as a one-way causal relationship from growth to inequality, the impact of income inequality on growth, which has been explored in later articles, will be reviewed in the following sections. While Kuznets mainly explored the long-term relationship between inequality and growth, later studies also look at the short-term relationship between the two as well as the channels through which inequality and growth are connected. From the empirical perspective, Kuznets' use of cross-country data in his research can present problems such as data incompatibility and specific country effects (Deininger and Squire, 1998), causing some economists to utilise data from a single country instead, in order to avoid such difficulties. Better data availability has also allowed recent researchers to support their studies with higher quality data. Besides, while the inverted-U curve was once supported by many researchers, more and more recent studies have shown evidences against this hypothesis. The details of studies done after Kuznets' hypothesis will be discussed later in this chapter.

Although Kuznets' hypothesis was proved by new empirical evidences in further studies exploring how inequality evolves during the course of development, there was a lack of systematic analyses based on theory. At the same time, Kaldor (1956) combines distribution theory with growth theory to scrutinise the influence of distribution on growth.

Building a model based on Keynesian techniques, Kaldor (1956) proposes there is a trade-off between the profits of capitalists and the workers' wages. This trade-off relationship is expressed by capital-labour ratio (K/L ratio). As investments rely on accumulated profits, increasing investments require higher profits and more capital. The different saving habits between the capitalists and the workers will make the K/L ratio reach its equilibrium. Once the K/L ratio exceeds its equilibrium value, for instance, the wages to profits ratio will go up accordingly. Compared to the workers, the capitalists tend to have a higher marginal propensity to save and a lower propensity to consume, which means the savings from profits is higher than that from wages. As the ratio of wages to profits rises, there will be a slowdown in the capital accumulation process, and then the K/L ratio will fall back to its equilibrium. In short, higher profits and a higher level of inequality can help generate more accumulated capital and higher investments to boost economic growth. From this perspective, a widening income inequality is correlated with a higher growth rate.

2.2. Theoretical research

As the interest in the relationship between distribution and growth gradually increased, new literatures in the 1990s began to explore the theoretical mechanisms through which the two factors are connected rather than merely focusing on the link itself, and the focus of the literature shifted to the causality of growth from inequality. The theoretical mechanisms were examined in empirical studies over the following years. From the perspective of the mechanisms that account for the influence of inequalities on growth, the theoretical literature can be divided into four main strands: political economy, credit market imperfections, socio-political instability and savings. The first three mechanisms claim that inequality hinders economic growth, contrary to the classical view of Kaldor (1956), while the last mechanism claims inequality promotes growth as this mechanism is based on Kaldor's argument that the higher marginal propensity to save among the rich leads to the accumulation of capital and therefore enhances economic growth. This section will review the key works that relate to each strand, along with the unified growth theory that involves both classical channel and the credit market imperfections channel (Galor and Moav, 2004).

2.2.1. The political economy approach

One of the theories on how inequality affects growth is the political economy approach. This theoretical framework is the topic of many studies such as those of Perotti (1993), Alesina and Rodrik (1994), Li and Zou (1998) and Barro (2000), etc. According to this channel, a high level of inequality can lead to a high tax rate that can redistribute income from the rich to the poor, thereby reducing the incentives to invest and hindering economic growth. The political economy approach includes the median-voter theorem and the lobbying model.

Applying the median voter theorem, Meltzer and Richard (1981) construct a model in which individual productivity and thus income are distributed asymmetrically among individuals, and a proportional tax system is implemented by the government to redistribute income from the rich to the poor. Individuals vote on the tax rate, and the median voter is decisive under majority rule. As the median income is normally below the mean income, the median voter prefers redistribution. The higher inequality, the more pre-tax median income is below the pre-tax mean income, and the higher the preferred tax rate of the decisive, median voter. A higher tax, in turn, reduces people's incentives to work and thus reduces the overall income.

The framework of Meltzer and Richard (1981) is later applied in the context of the inequality-growth relationship, and later various further studies explore the link between inequality and growth through redistribution and taxation. One of the essential pieces of research, which also uses the median voter theorem, was carried out by Alesina and Rodrik (1994). Their model includes the two key variables of capital endowment and labour endowment, and voters have different labour and capital endowment ratios. From the economic mechanism perspective, the presence of a higher tax rate to improve public investment results in a lower after-tax return from private investments, and the investment rate will decrease as a consequence, also causing a lower rate of growth. In terms of political mechanism, the larger the proportion of capital return in a person's total income, the more tax the person will have to pay for supporting the public investment. In this situation, a lower tax rate is favoured. Similar to the model of Meltzer and Richard (1981), the model constructed by Alesina and Rodrik (1994) also finds that as the median voters become poorer compared to the voters with an average income level, the preferred tax on capital is higher and the equilibrium tax rate rises, leading to reduced investments and innovation, thus slowing down economic growth. According to the results of this study, a negative relationship between inequality and growth is indicated. The model constructed by Alesina and Rodrik is based on inequality of wealth and income. Wealth inequality is proxied as land ownership. Persson and Tabellini (1994) also explore the inequality-growth nexus within the same framework, based on an overlapping-generations model. The study indicates that in a society with a higher level of inequality, the voters' decisions will lead to economic policies involving higher taxes on capital and investments, patent legislation, property rights, and other growth-promoting activities. As a result, income inequality can reduce the incentives for investment and harm economic growth. This conclusion is in line with the findings of Alesina and Rodrik (1994) that inequality and growth are negatively related.

It should be noted, moreover, that the median voter theorem is applicable in democratic countries where the distributions policies are greatly influenced by the voters. The conclusion that inequality hurts growth is relevant in those countries. Although this theory is more applicable in democratic societies, it can still be applied in nondemocratic societies. Clarke (1995) assumes that inequality harms growth through median voter theorem only in democratic countries, but not in nondemocratic countries. This hypothesis is rejected in the analysis, meaning that in nondemocratic countries, the median voter theorem can also be used, although the mechanism is weaker in nondemocratic countries. In the context of China, even though the tax rate is not directly decided by the 'one person, one vote' system, the median voter theorem is still applicable, as public opinion is widely considered in the policy making process through multiple channels. For instance, the National People's Congress (NPC) is the highest organ in China that legislates and oversees the activities of the government, the supreme court and the other institutions. It is composed of deputies with different provinces and social backgrounds, and some of the deputies are elected directly by the people, such as the deputies of the counties, municipal districts, etc. Citizens can also make suggestions directly to the government through e-mails, letters, the media and other channels. The government is motivated to listen people's opinions to get their support. One example that public opinion plays an important role in decision making in the country is that when people had rising concerns about the air pollution and the potential health risks it may have brought, a series of policies were carried out to reduce the pollution and improve the air quality, such as reducing coal consumption, increasing land greening and controlling the pollution from the industrial sectors, etc. In this sense, the median voter theorem works in China.

While Alesina and Rodrik (1994) and Persson and Tabellini (1994) reach the conclusion that income inequality and economic growth are significantly and negatively linked, Li and Zou (1998) hold a different opinion on the relationship of these factors, stating that previous research considers government spending only as an input in production; however, in addition to production activities, government expenditure also includes consumption activities, which should enter the utility function. The study concludes that income inequality may have a positive effect on economic growth, even though the connection is generally ambiguous.

Perotti (1993) also builds a model to analyse the link between inequality and growth based on voting and focuses on the effects of redistribution on investment in human capital. The paper suggests that in the political equilibrium, the rich pay for the investment in human capital for other classes. When the poor accumulate human capital, the rich benefit from skilled workers. Thus, the rich and poor may both vote for high redistribution. However, when there is public education, both the rich and the poor may vote for a low distribution. The study finds an inverted-U connection between inequality and income in cross-sections.

In short, studies based on median voter theorem have generally found a negative relationship.

Besides the literature based on median voter theorem, the other strand of literature with the political economic channel is based on lobbying behaviour. Bénabou (1996) discusses a scenario where the political decisions and economic policies are decided by the voter at the *p*th percentile rather than the median voter at the 50th percentile because the ideal 'one person, one vote' assumption in median voter theorem studies can be violated by factors such as lobbying, lower voting rates among the poor and vote buying, and the system of voting favours wealthy individuals. The study concludes that inequality has a harmful impact on growth.

Comparable with Bénabou (1996), Barro (2000) also suggests that the rich can exert a disproportionate influence on policy making. Through lobbying and vote buying, the rich can prevent the redistributive policies from going through, resulting in higher inequality, which in turn causes further lobbying and vote purchasing activities. Such activities are accompanied with bribery as well as a waste of resources, which are harmful to economic growth. From this perspective, income inequality and economic growth are negatively related.

2.2.2. Credit market imperfection and human capital

With its emphasis on the role of human capital, the credit market imperfection approach investigates the relationship between inequality and growth in the presence of credit market imperfections. The theoretical framework of this channel derives from the endogenous growth theory proposed both by Romer (1986) and Lucas (1988). This theory emphasises the role of human capital in promoting economic growth and explores factors that can affect human capital. One of the decisive economic factors in the accumulation of human capital is inequality. Thus human capital is a variable through which income distribution affects growth. Here human capital refers to education, training, experience and other intangible assets that can increase productivity.

According to the credit market imperfections mechanism, in an imperfect market, the lenders do not hold full information about the quality of the borrowers due to information asymmetry, and there are difficulties in the enforcement of contracts between the lenders and borrowers. Such imperfections give rise to higher interest rates for borrowers than lenders, as contract enforcement and the supervision over borrowers entail high costs. The imperfections also generate borrowing constraints such as collateral or income requirements. Consequently, poor people with fewer assets and income have limited access to loans, hence lose the opportunities to invest in human capital, which plays a pivotal role in economic growth. Previous studies based on this mechanism have concluded that an unequal distribution of income undermines economic growth.

Additionally, among the numerous studies on the credit market imperfections channel is the pioneering work of Galor and Zeira (1993). Their research demonstrates that income distribution has both short- and long-term effects on human capital, and also influences economic growth. Accordingly, under the assumptions of credit market imperfections and the indivisibility of human capital, the authors construct an inter-generational model where only one type of goods is produced, either by skilled or unskilled workers, and each individual's life is divided into two time periods.

To be specific, in the first period, the individuals can either work as unskilled workers or invest in human capital and receive an education, while in the second, they work as skilled workers or unskilled workers, depending on their level of education, and they can leave bequests to their children. The model assumes that the only difference among the individuals is the initial inheritance they receive. Due to the constraints and costs in borrowing, only those receiving a sizeable inheritance from the previous generation and do not need to borrow much, can afford investments in human capital in the first period. In the second period, they can work as skilled labour with higher incomes and can accumulate additional capital that can boost economic development, while the poor cannot invest in human capital in the first period, and so will accumulate little physical capital in the second period. To sum up, the aggregate investment is decided by the initial wealth of individuals in the short term. In the long term, poor people invest less in human capital and leave fewer and smaller bequests to the next generations. As the pattern is repeated, an equilibrium is eventually reached. Individuals are divided into dynasties of rich and poor; the former invest in human capital from generation to generation, whereas the latter, as unskilled labour, are trapped. The research indicates that a fairer initial distribution of wealth enables countries to achieve faster economic growth and higher income levels in the long term. It is also pointed out that economic growth is determined by the proportion of individuals whose inheritance allows them to invest in human capital, and that a large middle class is crucial for economic growth.

In addition, following on from the findings of Galor and Zeira (1993) that subsequent economic development in the long term depends on the initial wealth distribution, Banerjee and Newman (1993) build a model in which individuals' occupational preferences and the development process are linked, also based on the initial distribution of wealth. As credit market imperfections limit poor people's access to loans, hence further reducing their chances of entering occupations that require high human capital investments, the poor are likely to be employed by the rich. On the other hand, those who possess more substantial initial wealth will become entrepreneurs. From this perspective, the initial distribution of wealth plays a vital role in determining people's occupations. The occupational structure will then influence the individual's propensity to save as well as their level of risk-taking; with both factors associated with economic growth. An unequal distribution of wealth can cause an underinvestment in entrepreneurial production, thus negatively influencing economic growth. Banerjee and Newman's (1993) finding—that the initial wealth distribution and human capital investments have a strong influence on economic development—is in line with the conclusion of Galor and Zeira (1993).

Inspired by the initial research of Galor and Zeira (1993), several other works also examine the inequality and growth nexus based on the credit market imperfections approach. The studies claim that these imperfections cause an inequality that continues from generation to generation through the inequality in inheritance, with the poor underinvesting both in human and physical capital, thereby making economic development slow (Piketty, 1997; Aghion and Bolton, 1997).

To recap, Persson and Tabellini (1994) study the political economy channel, in a world with credit market imperfections. The overlapping-generations model proposed by Persson and Tabellini (1994), in which individuals live for two periods, assumes that tax is proportional to income and is entirely redistributive, in terms of taking from the rich and giving to the poor. When individuals are young, they inherit human capital accumulated by their previous generations, which has a positive influence on the new generation's income. According to the median voter theorem with credit constraints, higher inequality results in higher taxes on capital and investments, therefore discourages investments in human capital and hinders economic growth. Different from Persson and Tabellini (1994), Alesina and Rodrik (1994) assume that individuals have infinite horizons, and that tax revenue is vital for public investments. A too high tax rate leads to lower after-tax capital return, discouraging investments and therefore economic growth.

On a different note, Barro (2000) proposes a fresh perspective on the influence of inequality on economic growth in the presence of credit market imperfections. On the one hand, he agrees with the views given in previous literature that inequality impedes growth as it deprives poor people of the opportunity to invest in human capital, and generate high returns. On the other hand, Barro argues that the high setup costs of investments can impede would-be investors. Just as a certain level of education is required in order to promote economic growth, a business needs to reach a certain scale in order to make profits. In this sense, inequality is beneficial for economic growth as credit market imperfections enhance the accumulation of capital. In a nutshell, the research finds that inequality can influence growth both negatively and positively through the credit market imperfections channel.

Moreover, the credit market theory is also adopted by Galor and Moav (2004) in their unified growth theory. The theoretical framework of this theory combines the classical approach (rich people have a higher marginal propensity to save) with the credit market imperfections approach. The authors opine that a fairer income distribution can enhance economic growth as it enables greater access to the credit needed to accumulate human capital.

2.2.3. Socio-political instability

According to the socio-political instability mechanism, inequality hinders economic growth in two ways. First, extreme income and wealth inequality can result in social discontent among impoverished citizens, causing political instability and social upheaval (Acemoglu and Robinson, 2001; Keefer and Knack, 2002; Alesina and Perotti, 1996; Gupta, 1990). Second, instability impedes investment and growth. Additionally, socio-political instability and uncertainty bring about problems such as volatility in fiscal policy, and in the form of inflation and migration, leading to lower investment levels as well as loss of human capital, therefore hampering economic development. Meanwhile, violence, crime and other destructive activities can affect productive activities by threatening the safety of workers and entrepreneurs, as well as property rights, thereby deterring investment and harming economic growth (Alesina and Perotti, 1996; Benhabib and Rustichini, 1996; Bénabou, 1996).[1] Besides, social and political instability reduce

[1] Secure property rights are essential for investments and economic growth (Glaeser, et al., 2004; Hall and Jones, 1999).

economic growth as resources are wasted on disruptive non-productive activities and corresponding defensive activities (Barro, 2000). Unlike the political economy mechanism that best suits democratic countries, the socio-political instability mechanism is more effective when applied to developing and non-democratic countries.

One of the original works to examine the socio-political instability mechanism is by Alesina and Perotti (1996).[2] The authors argue that income inequality leads to socio-political instability, which lowers the propensity to invest in the private sector and thus hinders economic growth. As for the link between inequality to political instability, the dissatisfaction with the socioeconomic situation among low-income citizens in a highly unequal society heighten the likelihood of crime, coups and rioting. Regarding the link between instability and investment, instability raises the taxation on capital, disturbs productive activities and makes investors put projects on hold or invest in other countries, as investors are risk-adverse. This finding confirms the previous findings of Barro (1991), where political instability and investment are reversely linked. In addition, it is claimed that a large middle class, which represents a low-income inequality, is good for a country's political stability and investment.

Benhabib and Rustichini (1996) build a game-theoretic framework based on socio-political instability, levels of wealth and incentives to save and accumulate. The instability here refers to the conflicts between various social groups over income distribution. In the model of Benhabib and Rustichini (1996), this instability involves a group's appropriative activities and manipulation of the policy system to maximise its own interest. It is claimed that the extent to which economic growth is hampered by socio-political instability depends on the level of wealth in a country. While income inequality harms growth no matter how wealthy a country is, the economic growth of poor countries is affected more severely by inequality. According to the theoretical model, as a result of income inequality, social groups with lower incomes manage to gain larger shares of the output through redistributive and appropriative activities, or by manipulating the redistributive policies. Such activities discourage the incentive to accumulate and invest, and therefore slow down economic growth. Rodrik (1999) builds another game-theoretic model assuming that different income groups can jointly determine income redistribution

[2] There are initial studies on political instability prior to the research of Alesina and Perotti (1996), such as Venieris and Gupta (1986), Gupta (1990), Rodrik (1991) and Barro (1991).

either through cooperative or non-cooperative strategies. Cooperation here refers to activities to alleviate income inequality, such as providing subsidies to the poor. In this model, accumulation and growth decrease if the groups choose non-cooperative strategies instead of cooperative ones.

Bénabou (1996) develops the work of Benhabib and Rustichini (1996) by constructing a model based on the prisoner's dilemma. The author shares the opinion of these researchers that socio-political instability impedes the accumulation of capital by undermining property rights and likewise, believes that a wider income gap creates a stronger motivation for rent-seeking activities. Considering that a wide income disparity is harmful for long-term economic growth, the rich, for their own interests, should keep income disparity at a reasonable level through the redistribution of income.

Furthermore, Benhabib (2003) suggests a nonlinear, hump-shaped relationship between inequality and growth, based on a model assuming the presence of two agents with different productivity levels. The author states that the optimal level of income disparity should be modest, to allow for economic growth, as an excessive disparity leads to socio-instability, which harms sustainable growth. Within this framework, when inequality decreases due to the cooperation of the agents, there is an initial increase in the growth rate. Thereafter, the more productive agent becomes less willing to cooperate when the income gap continues to narrow, resulting in a decline of growth.

2.2.4. The savings and physical capital

In contrast to the aforementioned three theoretical approaches stating that inequality *inhibits* growth, the savings approach implies that income inequality is *beneficial* for economic growth. The core hypothesis of this approach is based on the classical view of Kaldor (1956), that wealthy people's marginal propensity to save is higher than that of the impoverished, hence a higher level of inequality can increase the aggregate savings and formation of capital to promote investment and economic growth. This strand of literature can be regarded as a development of Kaldor's classical theory. The savings mechanism is often applied in combination with other channels rather than alone. The mechanism is discussed in more detail in the context of China in Chapter 4, where China's income-inequality nexus is tested empirically; and in Chapter 5, where an empirical study is conducted based on the combination of the classical theory and the credit market imperfections theory.

Furthermore, Barro (2000) reviews the four theoretical approaches and provides empirical tests based on these approaches. He points out that the theoretical mechanisms are not mutually exclusive, but also tend to have offsetting effects; hence the net effect of inequality on growth is unclear.

From another perspective, by integrating the savings channel with the credit market imperfection channel, Galor and Moav (2004) develop the unified growth theory, in which the inequality-growth nexus evolves over time. According to their theoretical framework, in the initial stage of economic development, the growth mainly depends on the accumulation of physical capital, thus a wide income gap is beneficial for economic growth due to higher marginal propensity of the rich to save. In this stage, the dominant channel is the savings channel. During the later stage of economic development, human capital plays an increasingly important role in the economy, thus a high level of inequality harms economic growth through the accumulation of human capital. In this period, the dominant channel is the credit market imperfections approach.

2.3. Empirical research

In addition to theoretical literature, there is a wide range of empirical research on the relationship between inequality and growth.

The hypothesis of Kuznets implies that in underdeveloped countries, the inequality level keeps rising, but as economic conditions improve, the level of inequality will reach its peak and then gradually fall back to a lower degree. In Kuznets's time, however, empirical studies were limited by problems such as data availability. In the following decades, the empirical studies conducted by economists tested the inequality-growth nexus, and although most of the theoretical studies reach similar conclusions to show that inequality and growth are negatively connected, the conclusions and predictions of empirical literature are not always consistent. The results from economists on this topic, including those that challenge Kuznets' hypothesis, are mixed in fact. Some of the empirical results suggest a negative relationship (e.g., Ostry et al., 2014; Berg and Ostry, 2011; Castelló, 2010; Frank, 2009b; Alesina and Rodrik, 1994; Persson and Tabellini, 1994), while others announce a positive link (Forbes, 2000; Li and Zou, 1998) between inequality and growth. Additionally, it is argued that the impact on growth is positive in the short term, but negative in the long term (Halter et al., 2014; Partridge, 2005; Forbes, 2000), with nonlinear or non-significant causal links from inequality to growth also identified (Banerjee and Duflo, 2003; Chen, 2003; Barro, 2000). The lack of consensus among empirical studies could be explained by data constraints, differences in the samples or the measurements of inequality and model specifications used (Frank, 2009; Deininger and Squire, 1996).

While the theoretical studies discuss the channels through which income distribution and growth are connected, most of the empirical studies largely aim to identify a causal nexus between the two variables, as well as the sign and magnitude of their relationship.[3] Thus, despite the empirical research conducted to test theoretical mechanisms, most of the empirical studies lack a strong theoretical background to support their empirical results.

In this section, the empirical works on the relationship between inequality and growth will be reviewed. Based on the time of the research, the data and methodologies used, and the findings, the empirical literature can be roughly divided into three stages: i) the early empirical studies emerging from the 1990s; ii) the empirical studies in the later stage starting from the late 1990s, which challenge the methodologies and findings of the initial studies; iii) the research since 2010. While many early studies obtain the similar results of a negative inequality-growth connection, studies in the later stage fail to reach a consensus, due to the variation in research methodology, inequality measurement, sample choice and so on. In addition, some studies argue that inequality and growth are connected nonlinearly and that the relationship depends on the phase of economic development.

2.3.1. The measurements of inequality and growth

As aforementioned, there is consensus in the initial empirical research that inequality and growth are negatively linked, while later studies fail to reach a consensus. One of the reasons for the variation of findings is the quality of data and inequality measurement.

The early empirical studies (e.g., Perotti, 1993, 1996; Clarke, 1995; Keefer and Knack, 1995; Alesina and Rodrik, 1994; Persson and Tabellini, 1994; Venieris and Gupta, 1986)

[3] Many empirical studies explore the transmission channels, and even more focus on the relationship between inequality and growth, but these lack a strong theoretical background.

that emerged in the 1990s measured income inequality in many various ways, including the use of the Gini index, the Theil coefficient, the coefficient of variation (CV), the Atkinson measure and the income share of different quintiles.

A higher Gini index represents a larger income gap. A Gini index higher than 0.4 normally indicates a potential of social and political instability and social unrest. The Theil index is also often used. Similar to the Gini index, the Theil coefficient also ranges from 0 to 1, with the value of 0 indicating a situation of perfect equality. The Theil index has a major advantage in allowing the inequalities to be decomposed into inter-group and intra-group inequalities. The drawback of the Theil index, however, is its over-sensitivity to low-income observations. As for CV index, the value is smaller in more equal countries but has no upper bond. Indices like top or bottom percentiles and quartiles also often appear in studies. In recent years, many articles begin to look at the income shares of the top 0.1, 1, or 5 percent.

A problem with the early empirical literature is to use income inequality measurements as the proxies for wealth inequality. Although some theoretical frameworks are based on income inequality, the rest are based on wealth inequality. This anomaly is due to the unavailability of data on wealth distribution for a group of countries over a long time period, as the early empirical studies mainly use cross-sectional data from different countries. Besides that, the data used in the initial research are of a low quality.

Papers from the later stage, from the late 1990s onwards begin to emphasise the importance of data quality and question the inequality measurements used in the initial works. Deininger and Squire (1998), for instance, comment that previous studies do not pay enough attention to data quality and propose three standards to address this drawback. First, the income inequality data should be collected through surveys rather than being estimated based on national accounts statistics; second, the data should cover all sources of income or expenditure; and third, the data should be representative of the whole sample. Some researchers argue that the use of income inequality is inappropriate, thus adopt indicators of wealth/asset inequality in their studies instead. Wealth/asset inequality can be measured by land distribution and human capital inequality.

Furthermore, Alesina and Rodrik (1994) and Deininger and Squire (1998) use both income inequality and wealth inequality to study how economic growth is influenced by the initial inequality. Alesina and Rodrik (1994) use cross-sectional data both from democratic and nondemocratic countries to explore the relationship between initial inequality and growth; finding a significantly negative relationship exist between initial land inequality and economic growth for the whole sample. Similarly, Deininger and Squire (1998) collect a set of high-quality data covering 108 countries for a period from the 1950s to the 90s, and use the land Gini coefficient to measure wealth inequality. The authors believe that land distribution can be measured more accurately than income distribution and the data have better availability, while some theoretical hypotheses on inequality and growth are, at the same time, based on wealth distribution. The empirical results show that inequality harms growth for the whole sample, but there is no significant relationship between inequality and growth in the democratic subsample. Additionally, the same measurement of asset inequality is adopted by Deininger and Olinto (2000), who find that the initial asset inequality has a significant and negative impact on growth. It is worth noting that the land inequality is more suitable for countries where land is a major asset, e.g., in agrarian countries (Deininger and Squire, 1998).

Apart from land distribution, human capital inequality is also used as a proxy for wealth inequality. Castelló and Doménech (2002) claim that neither income inequality nor land distribution are sufficient to measure wealth inequality, as human capital inequality is also a crucial source of wealth inequality. To measure inequality, they use three indices: i) the income Gini coefficient, ii) the human capital Gini coefficient calculated from educational attainments, and iii) the distribution of education by quintiles. Their empirical results show that inequality measured in both income and human capital inequality are negatively related to growth for the whole sample. The same inequality measurements are used by Castelló (2010) and Castelló and Doménech (2021).

Neves and Silva (2014) review both income and wealth inequality measurements and indicate that these factors can influence economic growth through several mechanisms. They explain that income inequality is preferred over wealth inequality in the savings approach, as savings come from people's income. On the other hand, wealth inequality is more important in the credit market imperfections mechanism, because people's decisions on whether to invest in human capital depend on their wealth more than their income. With respect to the other two channels: socio-political instability and political economy channels, income inequality and wealth inequality are equally plausible.

With regards to the measurements of economic growth, the growth rate of the output in particular, or alternatively of the consumption, are generally used as growth-rate indicators. In addition, some studies also use GDP (not GDP growth) as a proxy for growth as it also captures the information of economic growth (e.g., Herzer and Vollmer, 2012; Simões, 2012).

2.3.2. Methodologies and findings of empirical studies

In addition to the quality of data and inequality measurement, methodological issues such as the type of data (panel vs cross-sectional) used and the estimation approaches adopted by empirical research have also led to the variation of findings in the later literature. While the initial empirical studies mainly use cross-sectional methods and Ordinary Least Squares (OLS) estimators, studies in the later stage mainly use panel methods and adopt a wider range of estimators, such as fixed effect (FE), random effect (RE) and general method of moments (GMM).

Since Deininger and Squire (1998) provided their high-quality dataset, many researchers have used this as a basis for their panel data analyses, utilising various estimation techniques but reaching no consensus on the effect of inequality on growth. While the cross-sectional approach used in previous studies can lead to an estimation bias due to country-specific and time invariant omitted variables, panel estimation can control for such unobserved time invariant heterogeneity by taking differences on data, hence reducing the bias on omitted variables.

Additionally, it is worth noting that although panel estimation has the advantage of dealing with the bias caused by unobservable time invariant country characteristics, it does not control for omitted variables that do change over time. Moreover, panel estimation requires observations across both countries and time, thus a larger sample is needed. These factors magnify the problem of limited sampling and data availability (Forbes, 2000).

Furthermore, Li and Zou (1998) use FE and RE estimators based on Deininger and Squire's dataset and find a positive relationship between the changes of income inequality and economic growth, challenging the conclusions of initial studies that inequality is harmful for growth.

Likewise, Forbes (2000) finds this positive relationship when examining the relationship between income inequality and economic growth based on a panel of 45 countries from 1966–1995 using FE, RE and first difference GMM estimators. Similar to Li and Zou's (1998) finding, the paper identifies a significantly positive effect of inequality on growth in the short term, in high- and mid-income countries. This result remains robust when different samples, variable definitions and model specifications are used. Forbes (2000) argues that the negative relationship found in previous studies could be problematic for two reasons. Firstly, the robustness of the negative relationship is questionable, as it becomes insignificant when sensitivity analysis is applied. Secondly, previous studies suffer from bias, caused by measurement errors of inequality and omitted variables.

Contrary to the findings of Forbes (2000), however, Panizza (2002) does not support the existence of a positive relationship. The author collects data of 48 US states from the period between1940 and 1980, adopting pooled OLS, FE and GMM estimators to examine the connection between inequality and growth to find a negative relationship between income inequality and growth. This result is not robust across different model specifications and inequality measurements, however.

At the same time, Barro (2000), relying on the three-stage least squares (3SLS) approach and the dataset of Deininger and Squire, finds no significant relationship in the sample, including in poor and rich countries. However, in poor countries where GDP per capital is below 2079 dollars (with 1985 as the base year), inequality is harmful for growth, while in rich countries, inequality appears beneficial for growth.

Voitchovsky (2005), moreover, tests the relationship between income inequality (measured both by the Gini coefficient and the ratio of income shares between different quintiles) and growth using data from a panel of developed countries and system GMM estimation. It is found that although the aggregate income inequality is insignificantly associated with growth, the inequality at the bottom of the income distribution has a significant and negative impact on subsequent growth, whereas the inequality at the top of the income distribution positively affects growth. Thus, the author argues that the relationship between inequality and growth varies in different income groups.

Partridge (2005), on the other hand, uses data from 48 states in the US between 1960 and 2000, finding that inequality and growth are positively connected in the short term and negatively related in the long term.

In addition, Frank (2009) uses state-level data in the US and finds that in the short term, higher inequality is good for economic growth, thereby supporting the findings of Forbes (2000). In another paper where a panel vector error correction (panel VAR) model is adopted to investigate the interaction of inequality, human capital and economic growth, the same author finds that a top income decile share harms growth (Frank, 2009b).

More recently (since 2010), the findings in empirical studies are more diverse. Some studies examine how income inequality affects economic growth as well as its sustainability, while others emphasise the nonlinear relationship between income inequality and economic growth, arguing that the income-growth nexus varies throughout the economic development process.

In addition, Berg and Ostry (2011) use data from a group of developed and developing countries, and calculate both average growth and the duration of growth spells over five-year horizons; finding that income inequality, along with other variables such as initial income, openness to trade and macroeconomic stability, is an important factor in the sustainability of growth. Specifically, economic growth lasts for a longer period in countries with a lower degree of income disparity. The conclusion is later elaborated by Ostry et al. (2014), who use Gini indices both of market inequality (before taxes and transfers) and net inequality (after taxes and transfers). The authors find that economic growth is lower and less sustainable in countries with higher inequality. The study also finds that although extreme income redistributions, including extreme taxes, subsidies and other transfers from the rich to the poor, can exert a negative impact on the duration of growth, there is no evidence to show that non-extreme redistributions, which reduce income inequality, are harmful for economic growth.

In addition, Halter et al. (2014), using data from 106 countries over the period from 1965 to 2005, find that inequality and growth are positively connected in the short term but negatively connected in the long term, and the total effect on growth is likely to be negative. The authors believe that the mixed results on the inequality-growth relationship yielded in previous studies are due to the different theoretical mechanisms and empirical methodologies adopted. The growth-promoting mechanisms (e.g., savings and incentives for innovation), for example, often have an immediate effect on growth, while the opposite mechanisms (e.g., socio-political instability and human capital accumulation) take longer to affect growth. The article also argues that studies using panel estimation tend to find a positive connection, as the short-term positive impact of inequality on growth is captured by taking differences, while studies using cross-sectional estimation normally find a negative connection as they use averaged growth data based on longer time intervals (of 5 years or more), detecting the long-term negative effects on growth.

Following the work of Frank (2009) (mentioned above), Atems and Jones (2015) are among the authors of empirical works to emphasise the importance of human capital in the inequality-growth relationship. Using state-level data of the US and panel VAR model to explore the relationship between human capital, inequality and growth, they find that shocks to income inequality significantly decrease economic growth.

Further empirical works examine the unified growth theory raised by Galor and Moav (2004). The theory argues that the inequality and growth are connected nonlinearly through human capital and savings, and in the final stage of development, inequality no longer affects growth significantly.

Among these empirical works is that of Khalifa and El Hag (2010), who test the theoretical framework of Galor and Moav (2004) using threshold estimation. The authors use data from 70 countries between 1970 and 1999, and find a significant income per capital threshold, below which income disparity harms growth, while above it there is no significant influence.

Also supporting the unified growth theory, Chambers and Krause (2010) utilise semiparametric methods and data from 54 countries, finding that in less developed countries, inequality and growth are negatively connected, while in more developed countries, mostly OECD countries, there is no significant connection, as such countries are at the later stage of economic development, when credit constraints are no longer binding.

Bhattarai et al. (2015) develop a dynamic computable general equilibrium (DCGE) model for the UK economy to study the dynamic path of income inequality and economic growth in the context of the decentralized open economy. Specifically, the model assumes that households maximize their lifetime utility (derived from consumption and leisure) based on their decisions on how much to work and how much to save. At the same time, the government uses tax revenue to redistribute income among households and pay for goods and services. Meanwhile, firms maximize their profits based on the optimal amount of capital and labour inputs, and the UK conducts international trades with the rest of the world. The model analyses how tax and transfer policies can be designed to achieve the goals of improving growth and reducing inequality, and finds that the labour-leisure and consumption-saving preferences of the low- and high- income households, along with firms' capital and labour inputs, are key to achieving the two goals in the long term. This study considers two types of tax reform, namely replacing the differentiated tax rates by uniform tax rates, and by increasing the income tax rate of the richest 10 percent. The results show that the reforms reduce income inequality in the short term, but may not encourage growth or reduce inequality in the long term.

Furthermore, Bhattarai et al. (2016) propose a dynamic computable general equilibrium (DCGE) model to assess the influences of the U.S. FairTax proposal, a tax reform that would replace all federal direct taxes with a national retail consumption tax. Similar to Bhattarai et al. (2015), this research also incorporates different economic sectors involved in the economy, such as households, producers, the government and the rest of the world. The study finds that FairTax with a demogrant favours the economy by increasing economic output and boosting employment, investment and capital stock, also raising the income of households at most income levels.

On a different note, Bhattarai et al. (2018) discuss the trade-offs between income redistribution and economic growth through different tax plans in the 2016 US presidential election, using a dynamic computable general equilibrium (DCGE) model. While Trump proposed tax relief for corporations and middle-class Americans, Clinton put forward a proposal of modest tax increases in the taxes on the high-income group. The study indicates that through Trump's tax plan, which favoured the rich, income inequality would increase, boosting the incentive of people to work harder and save or /invest more, while fostering economic growth at the same time. The paper also finds that Clinton's tax plan reduced income inequality and would have slightly reduced economic growth.

Returning to unified growth theory, Benos and Karagiannis (2018) test the theory using state-level data of the US and find the effect both of top income inequality and overall income inequality are insignificant in long-term economic growth. This finding is in line with that of Krause (2010), and shows the US in the later stage of economic development.

2.4. Studies in China

Using provincial-level data of China in empirical studies offers advantages over the use of cross-country data in several respects: provincial data within a single country provides better data comparability than international data, it avoids sample selection problems and have better availability. Thus, compared with international studies, studies in the context of China provide more reliable empirical evidence on the relationship between inequality and growth. This section will review the literature in the context of China.

In spite of the drawbacks of cross-country data, most empirical works are based on this form of data due to its wide availability. According to the research reviewed earlier in this chapter, it can be seen that many empirical studies are based on cross-country data. It therefore follows that fewer studies are based on the regional data within a single country (e.g., Panizza, 2002; Partridge, 2005; Frank, 2009; Atems and Jones, 2015; Benos and Karagiannis, 2018).

There are also studies in the context of China, based on provincial-level data. To examine the inequality-growth nexus in China, Wan et al. (2006) tested the relationship between inequality and growth in post-reform China using data collected from each province and the polynomial inverse lag (PIL) model. Their findings show a nonlinear inequality-growth relationship, and that inequality has a negative effect on growth in the short, medium and long terms.

In a further exploration of the interaction between inequality and growth, Chen (2010) uses the vector autoregressive (VAR) model and impulse response functions (IRF), claiming that in the short term, inequality is slightly harmful for growth, while in the long run inequality does not affect growth significantly. On the other hand, growth can lead to a reduced income disparity in both the short and long term.

Emphasising the role of human capital in economic growth, Chi (2008) finds that China's future growth is accompanied by a wide income disparity between the eastern and western area regions. The author finds that human capital can indirectly promote growth by encouraging physical capital investment, and that both physical and human capital accumulate faster in the eastern area, leading to a widening income gap between the eastern and western regions. Fleisher et a1. (2010) also indicate that human capital can influence growth both directly and indirectly, and by generating higher returns in the less-developed regions of China, human capital can also alleviate regional disparity.

To return to the research methodology of Frank (2009), the authors Li et al. (2016) use panel autoregressive distributive lag model (panel ARDL) and data from 27 provinces from between 1984 and 2012 to examine the long-term inequality-growth relationship in China. They find that China's economic growth is primarily driven by physical capital, but the effects of human capital on growth are unclear.

Finally, Zhang (2021) discusses the patterns and trends regarding the income inequality in China. The article finds that since the economic reform in 1978, the country's income inequality first increases and then decreases in recent years, which is in line with the inverted-U hypothesis. Zhang also finds that the urban-rural income inequality and regional income gap play important roles in overall income inequality over the decades, although less important during the last decade than previously. In addition, the research also finds a negative relationship between inequality and intergenerational mobility, supporting the Great Gatsby curve.

2.5. Conclusion

This chapter has reviewed the theoretical and empirical studies that estimate the income-growth nexus and explore the mechanisms behind their connection. The chapter first reviewed the initial studies of Kuznets (1955) and Kaldor (1956), and then reviewed the four main theoretical channels through which inequality affects growth: i) the political economy, ii) credit market imperfections, iii) socio-political instability and iv) the savings channel. While the former three indicate that inequality harms growth, the latter implies that inequality increases growth. The unified growth theory, which emphasises the importance of human capital, combines the classical approach with the credit market imperfections approach, and presents the relationship between inequality and growth as nonlinear, was also discussed in this chapter.

This chapter reviewed the empirical studies in three stages to present the development in data types (panel vs cross-sectional), empirical methodologies and results. In the initial stage, most empirical studies use a cross-sectional approach and the OLS estimator for data of lower quality, while the later studies, conducted from the late 1990s onwards, mainly use the panel data approach and the new estimators such as FE, RE and GMM for higher-quality datasets. No consensus on the inequality-growth nexus was reached, however. In the most recent studies after 2010, some studies find a nonlinear connection between inequality and growth. The variation in the empirical results is due to many factors such as different datasets, model specifications and estimators. Last but not least, this chapter reviewed the data sources and empirical studies of China and their advantages.

In spite of the achievements of empirical research, some limitations and drawbacks exist. The first one is that due to data availability, most studies are based on cross-country data, which raises the problem of data incomparability across countries, as well as difficulties in sample selection. The second problem is that most of the studies focus on the causal relationship between inequality and growth in only one direction: either the impact of inequality's on growth or vice versa. Few studies consider the inequality-growth relationship in both directions. The third problem is that most of the empirical studies test only the inequality-growth relationship, but fail to explore the theoretical mechanisms underlying the relationship.

To better explore the relationship between income inequality and growth, as well as the mechanisms underlying the relationship, Chapter 3 of this thesis will generate a picture of regional inequality of China using Theil decomposition, along with a description of the economic growth and human capital in the country. Chapter 4 will estimate the income-growth nexus in both directions, using provincial level data. Chapter 5 will subsequently explore the mechanisms discussed in this chapter in the context of China.

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Chapter 3. Regional income inequality, economic growth, human capital and physical capital in China

3.1. Introduction

The income inequality and economic growth in China has been a topic of interest among many researchers. The country's economic reform in 1978 marked the beginning of its transition from a planned economy to a market economy. Post-reform China has experienced a high rate of economic development, but despite the fast growth in recent decades, the country's regional development and income distribution are unbalanced. In order to investigate the pattern this inequality in regional income and the country's evolution since the economic reform, this chapter conducts Theil decomposition to decompose the national income inequality into inter-regional and intra-regional income inequalities. In addition to investigating the pattern of regional income disparities, the chapter also explores the income inequalities on the provincial level, using graphs and maps to illustrate these inequalities. The income inequality of each province is measured by the Gini coefficient, the Theil index and the urban-rural income ratio. Moreover, as the uneven distribution of human capital and physical capital across the provinces can contribute to the income inequality among these areas, human and physical capital, and their evolution over time are also discussed. In short, this chapter intends to study the spatial dynamics of China's income inequality and economic growth, as well as human and physical capital, both at the regional and provincial levels.

The studies in this chapter are important for two main reasons. First, the chapter provides a more comprehensive overview than previous studies regarding China's regional inequality, covering all the mainland provinces and a long time span (1980–2016), using Theil-T and Theil-L decompositions. Second, with regards to the uneven distributions of growth and inequality, and of human and physical capital on the provincial level, this chapter depicts the patterns and evolution from 1990 to 2017, which are discussed little in previous studies on China's regional disparities. The study also decomposes human capital into three levels to investigate both the quantitative and qualitative changes of human capital. The contributions of the research will be explained with further details in sections 3.2 and 3.3.

The remainder of this chapter is constructed as follows: section 3.2 briefly reviews the literature on China's regional inequalities, followed by Theil decompositions to investigate the inter-regional and intra-regional inequalities in China between 1980 and 2016. Section 3.3 discusses the measurements of provincial income inequality, economic development, human and physical capital, and depicts the changes from 1990 to 2017 using tables, graphs and maps. Section 3.4 concludes the whole chapter.

3.2. The pattern of regional income inequality in China

Researchers have used a variety of data and methods to explore the pattern of China's regional income inequality. Tsui (2007) focuses on China's inter-provincial income inequality and the contribution of total factor productivity (TFP), human capital and physical capital to the changes of inter-provincial inequality from 1964 to 1999. Using provincial production functions and Theil decomposition, the author finds a large income disparity between the coastal and inland provinces. While an uneven TFP distribution is the main factor to enlarge the inter-provincial gap between the mid-1960s and mid-1970s, both human and physical capital surpass TFP to be the main drivers of regional disparity in the 1980s, and in the 1990s, the disparity is largely caused by the uneven physical capital distribution fostering economic growth in the richer coastal provinces. Some researchers, such as Fan and Sun (2008) and Akita (2003), divide the country into several regions and use Theil decomposition to study the inter-regional and intra-regional inequalities. Specifically, Fan and Sun (2008) divide the country into three economic belts (eastern, central and western) and apply the Theil decomposition method to examine inter-regional and intra-regional inequalities using provincial level data between 1978 and 2006. The findings suggest that the overall inequality is reduced in the 1980s because of the decrease in intra-regional inequality, and the overall inequality rises in the 1990s due to the rise of inter-regional inequality, while from the late 1990s to 2006, the inter-regional and intra-regional disparities change little at first, but then further widen. Akita (2003) defines a three level, region-province-district structure and conducts a two-stage Theil decomposition to investigate the country's income inequalities between-region, between-province, and within-province in the period from 1990 to 1997. Other researchers reach opposite conclusions regarding how the regional disparity changes in China. Herrmann-Pillath et al. (2002) and Huang et al. (2003), for instance, both separate the provinces into seven areas. The former find that inter-regional inequality increases between 1993 and 1998, whereas the latter suggest a decline in the disparity over the period from 1991 to 2001. The two studies are not strictly comparable, however, as they are based on different time periods and datasets. Moreover, conclusions regarding the change of regional inequalities can vary depending on how the inequalities are measured and defined (Tsui, 1993).

The study in this section conducts Theil decomposition to explore the pattern of regional income disparity in China as well as its evolvement since 1980. The contribution of this section is twofold. First, the study provides an updated view regarding China's regional inequality over a long time-span. Most previous studies on the topic have covered a limited number of provinces in a short or early time period, and so can hardly reflect the long-term dynamic of regional inequalities in post-reform China. According to the existing literature, the country's regional inequalities do not always exhibit the same trend through time. On the contrary, the overall, inter- and intra-regional income disparities go upward at some stages, but then move downward or remain stable in the other stages. The conclusions from previous studies can thus be misleading and fail to provide information on China's regional inequalities in recent years. To provide a more comprehensive picture, this research reports the fluctuations in regional inequalities using the latest data covering all the mainland provinces over the 37 years between 1980 and 2016. Additionally, whereas previous studies perform inequality decomposition in different subgroups (e.g., 3 economic belts, 7 regions or coastal and inland areas), which can lead to different conclusions, this study is based on four economic regions, as defined by the 11th Five-Year Plan recently announced by the government. By following this economic plan, this study can provide better regional policy implications based on the research results. In addition to Theil (Theil-T) decomposition, Theil-L decomposition is the second contribution, conducted here for the purposes of comparison, as the former is more sensitive to the income transfer in the upper part of income distribution, while the latter focuses on the lower part.

3.2.1. Theil decomposition

3.2.1.1. Income inequality measurements

The Theil index, together with the Gini coefficient and urban-rural income ratio are the most commonly used measurements of income inequality in the previous research on China, with each type of measurement having its own advantages and limitations. The Theil coefficient proposed by Theil (1967), when compared with the other two measurements, can easily be decomposed into inequality within and between groups, whereas the other inequality measurements are not readily decomposable. Thus, in order to depict the pattern of China's regional inequality, Theil index decomposition is conducted in this study to examine the income inequality among and within the economic regions. Specifically, the Theil T index (also referred to as the Theil index) is sensitive to the changes at the top of the income distribution, while Theil L is more sensitive to the changes in the lower part. Due to the different properties of the two measurements, this study reports the decomposition results both of Theil T and L indices.

3.2.1.2. Four economic regions of China

Due to the unbalanced economic growth across different areas in China, the economic growth on the country level cannot accurately reflect the growth of each area. To better explore the inequality-growth relationship in China and provide more practical implications for policy, it is therefore important to analyse the provinces by groups according to the various levels of development. The 11th Five-Year Plan proposed by the government in 2006, divided the 31 mainland provinces into four economic regions. The north-eastern region consists of 3 provinces, the eastern region includes 9 provinces, the central region has 6 provinces, and the remaining 10 provinces belong to the western region. The details are shown in Table 3-1 below.

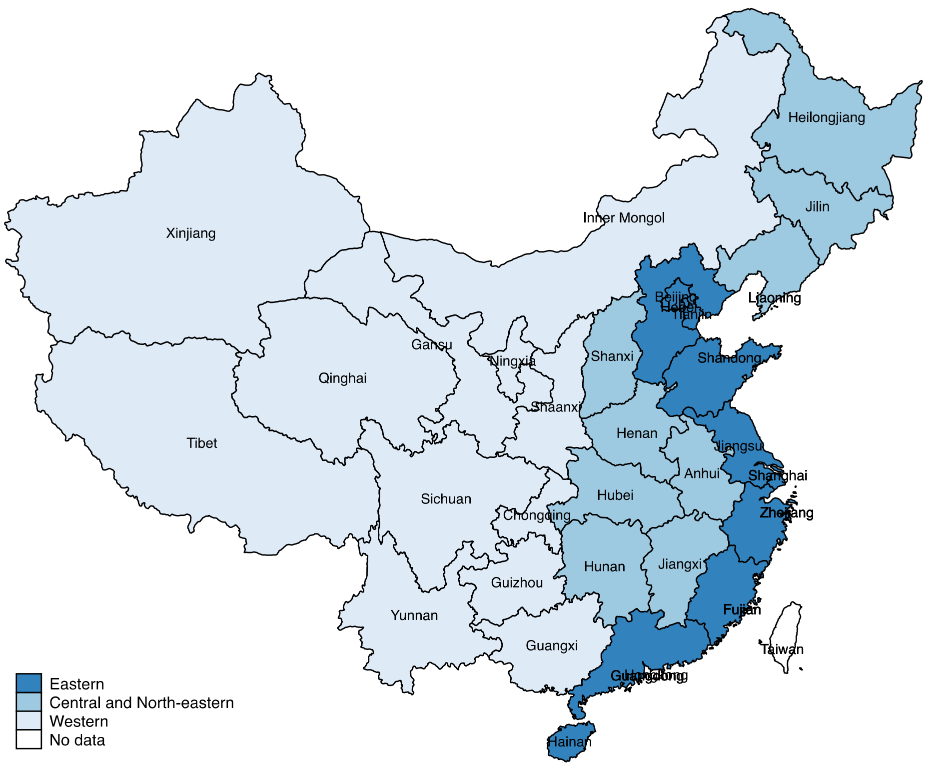
Table 3-1. The four economic regions in China

Regions	Provinces
North-eastern region	Liaoning, Jilin, Heilongjiang
Eastern region	Beijing, Tianjin, Hebei, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong and Hainan
Central region	Shanxi, Anhui, Jiangxi, Henan, Hubei and Hunan

Western region	Inner Mongolia, Guangxi, Sichuan, Chongqing, Guizhou, Yunnan, Tibet, Shaanxi, Gansu, Qinghai, Ningxia and Xinjiang

In addition, Figure 3-1 maps these four economic regions, according to which, the north-eastern and eastern regions are located in the coastal area, whereas the central and western regions consist of the inland provinces.

Figure 3-1. China's four economic regions



These economic regions are divided according to geographical and economic factors. The industrial structure varies across the regions due to historical development, and the coastal provinces in the eastern and north-eastern regions are more highly developed, with higher per capita income, supporting the argument of Tsui (2007). Since the economic reform in 1978, the Chinese government has paid more attention to the development of the eastern region, so this area, with its high labour density, enjoys advanced technologies and also attracts more foreign investments. The eastern region is therefore the most advanced region of the four. The north-eastern region focuses mainly on traditional manufacturing industries, while the central region is rich in mineral and natural resources, with industry and agriculture as the mainstays of its economy. This region is less well-developed than the eastern region, but is more so than the western, which is sparsely populated and has a relatively weak economic foundation, with a poor infrastructure in terms of technology and transport.

3.2.1.3. The data

Previous literature on the income inequality in China employs a variety of data sources, with the macroeconomic data provided by China Statistical Yearbooks from National Bureau of Statistics of China (NBS), as the most commonly mentioned dataset. The NBS supplies data for each year both at the national and regional levels. Akita (2003), for example, uses provincial GDP and population data collected from the yearbooks. Besides these national statistical yearbooks, each province also has its own statistical yearbooks. China Labour Statistical Yearbook is another source of data often referred to in the literature, and the government also provides additional data sources including comprehensive statistical data and materials on 50 years of new China and China Compendium of Statistics 1949–2008, which are utilised by researchers. Fan and Sun (2008), for example, explore China's regional income inequality using data from China Compendium of Statistics 1949–2008 and NBS.

Apart from government databases, the researchers also use data from the surveys conducted by academic institutions. Such databases include the CHIP (Chinese Household Income Project) and CHFS (China Household Finance Survey) datasets. The University of Texas Inequality Project (UTIP) provides Theil indices for China and other countries. These datasets, along with the data provided by the World Bank, are used by Chinese and international researchers, but the data limitations are obvious. The CHIP and CHFS datasets do not provide continuous data; the World Bank database has severe data omission problems, and the data sometimes conflict with that from NBS.

While the micro databases such as CHIP and CHFS may provide more information for the income inequality within households, the NBS database provides data that are more suitable for regional income inequality research, such as the average urban and rural incomes and the provincial GDP. Moreover, the micro databases have their own drawbacks, e.g. the data are not sufficiently representative or are not successive, while the NBS data do not have such problems. Overall, the NBS dataset is ideal for this research, as it provides high-quality data that are successive, and the micro databases can be used as a supplement. More detailed income data are needed on the provincial level for better income distribution calculation.

The study in section 3.2 covers the period from 1980 to 2016 (37 years), with the data collected from the National Bureau of Statistics (NBS) and the China Compendium of Statistics 1949–2008. Among the 31 mainland provinces, Hainan was elevated to a province in 1988, and Chongqing, which used to be part of Sichuan, became independent as a province in 1997, so the data of the two provinces are not available for the start of my research period (1980–2016). Thus, to make the data comparable over time, the study merges Hainan into Guangdong, and Chongqing into Sichuan, while Tibet is removed due to the unavailability of data. Therefore, the study in section 3.3 covers 28 provinces over 37 years.

Because of the lack of provincial-level income data, GDP is used to represent income in this chapter. GDP is adopted here for two main reasons. First, per capita GDP is the most commonly used indicator to reflect the level of economic development, as well as the level of income. Specifically, previous studies on China's regional inequality employ GDP data to measure income inequality (Tsui, 2007; Hermann-Phillath et al., 2002; Fan and Sun, 2008). Besides, Forbes (2000) and Frank (2009) also employ the growth rate of GDP, and Herzer and Vollmer (2012), Risso et al. (2013) and Simões (2012) adopt GDP per capita in their studies on the inequality-growth relationship. As a result, the use of GDP as the income measurement allows this study to be compared with the previous literature. Second, as the research involves a relatively long time-span and a wide range of provinces, the availability of data across years and provinces is important, and therefore, due to its availability and reliability in successive years, GDP is a superior measurement. In this chapter, income is measured by real GDP, which is calculated from nominal GDP and GDP deflator of each province, with 1980 as the base year.

An alternative indicator to GDP is the Gross National Product (GNP), which can also reflect the development of a country. While GDP and GNP are closely related, there are differences between the two. The former refers to the value of finished goods and services produced in a country during a specific time period, including the values produced by non-citizens; whereas the latter is the value of final goods and services produced by a country's citizens, no matter where they are located. As country's GDP and GNP can differ widely, the income measured by the two indices can lead to different empirical results. This study focuses on the income inequality and economic growth of each region and province, so it is based on the income data of the residents of each province within the borders of China. The values produced outside of the border of China are subject to different economic environments from China, and it is hard to tell which provinces those oversea values belong to, which is why the provincial GNP data are unavailable from the databases. From this perspective, GDP is a suitable measurement of income here, while GNP does not fit into my analysis, and it is not possible to tell how the provincial incomes would change if measured by GNP. In short, I use GDP in my study, as it is a more suitable income measurement compared to GNP in the context of this study.

As for the population data used to calculate income inequality, there are mainly two sets of data available in China. The first set is for resident population. According to the NBS, the term *resident* refers to those who live in a province for 6 months or more in any particular year, regardless of their place of birth. The second set of data is on the household registration population, which largely identifies people by their birthplaces, regardless of their residence status. In this study, the former, namely the data of the resident population, is adopted because it takes immigration across provinces into account, and is therefore closer to the real context in China.

3.2.1.4. Theil decomposition method

The country is divided into three levels: country, region and province. According to Akita (2003), China's income inequality can be decomposed into interregional and intraregional inequalities. The equations are shown as follows.

The overall Theil-T index (Theil index) is calculated as below,

$$\mathrm{T}_{China} = \sum_{i}\sum_{j}\left(\frac{Y_{ij}}{Y}\right) log \left(\frac{Y_{ij}/Y}{N_{ij}/N}\right) \tag{3.1}$$

where T_{China} represents the Theil-T index of China; N_{ij} is the total population of province j in region i; N is the sum of the population in all the provinces; Y_{ij} is the total income of province j in region i; Y is the sum of income in all of the provinces.

The interprovincial income inequality within region i can be written as below:

$$T_i = \sum_j \left(\frac{Y_{ij}}{Y_i}\right) \log\left(\frac{Y_{ij}/Y_i}{N_{ij}/N_i}\right) \tag{3.2}$$

Thus the Theil-T decomposition is written as:

$$T_{china} = \sum_i \left(\frac{Y_i}{Y}\right) T_i + \sum_i \left(\frac{Y_i}{Y}\right) log\left(\frac{Y_i/Y}{N_i/N}\right) = T_{within} + T_{between} \tag{3.3}$$

where T_i represents the inequality among the provinces in region i; Y_i represents the total income of region i; N_i is the total population in region i; T_{within} and $T_{between}$ represent the inequality within and between regions respectively. The former is a weighted average of the interprovincial income inequality within each region.

Different from Theil-T index which is weighted by income shares, Theil-L is weighted by population shares so that it is more sensitive to the differences of the poorer provinces (Akita, 2003). The overall Theil-L index is calculated as follows:

$$T_{LChina} = \sum_i \sum_j \left(\frac{N_{ij}}{N}\right) log\left(\frac{N_{ij}/N}{Y_{ij}/Y}\right) \tag{3.4}$$

$$T_{Li} = \sum_j \left(\frac{N_{ij}}{N_i}\right) \log\left(\frac{N_{ij}/N_i}{Y_{ij}/Y_i}\right) \tag{3.5}$$

$$T_{Lchina} = \sum_i \left(\frac{N_i}{N}\right) T_{Li} + \sum_i \left(\frac{N_i}{N}\right) log \left(\frac{N_i/_N}{Y_i/_Y}\right) = T_{Lwithin} + T_{Lbetween} \qquad (3.6)$$

where T_{LChina} represents the Theil-L index of the whole country; T_{Li} represents the inequality among the provinces in region i; $T_{Lwithin}$ and $T_{Lbetween}$ represent the inequality within and between regions respectively, measured by Theil-L.

3.2.2. Theil decomposition results

3.2.2.1. Results of Theil-T decomposition

The results of Theil-T decomposition are reported in Table 3-2. In 1980, the inter-regional income inequality (between-region Theil-T) was 0.044 and the intra-regional inequality (within-region Theil-T) was 0.041, while in 2016, the inter-regional inequality falls to 0.013 and the intra-regional inequality drops to 0.022. The overall trend in China's income inequality is a decrease over the last 37 years, with the Theil-T index decreasing by 58.82% between 1980 and 2016. In addition, the contribution of inter-regional inequality to the overall inequality fell from 51.84% in 1980 to 36.72% in 2016.

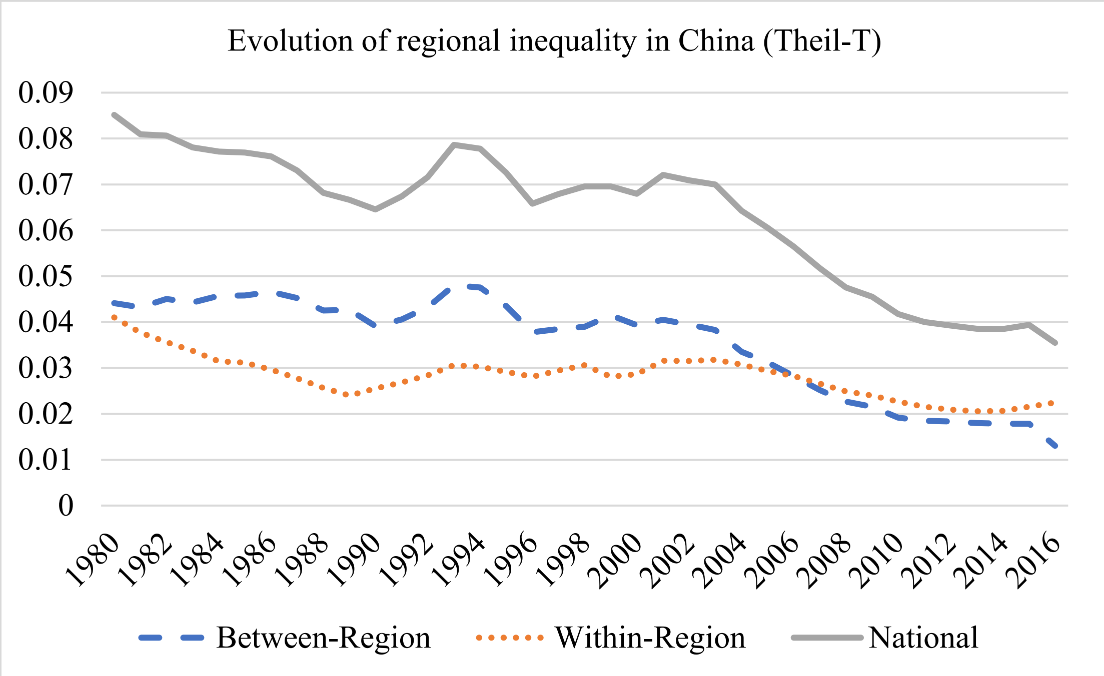
Table 3-2. Regional inequality based on Theil-T decomposition

Year	T_{LChina}	T_{within}	T_{within} Percentage	$T_{between}$	$T_{between}$ Percentage
1980	0.085	0.044	51.84%	0.041	48.16%
1981	0.081	0.043	53.41%	0.038	46.59%
1982	0.081	0.045	55.81%	0.036	44.19%
1983	0.078	0.044	56.73%	0.034	43.27%
1984	0.077	0.046	59.23%	0.031	40.77%
1985	0.077	0.046	59.49%	0.031	40.51%
1986	0.076	0.047	61.11%	0.030	38.89%
1987	0.073	0.045	61.98%	0.028	38.02%
1988	0.068	0.042	62.35%	0.026	37.65%
1989	0.067	0.043	64.04%	0.024	35.96%
1990	0.065	0.039	60.52%	0.025	39.48%
1991	0.067	0.041	60.15%	0.027	39.85%
1992	0.072	0.043	60.38%	0.028	39.62%

1993	0.079	0.048	61.08%	0.031	38.92%
1994	0.078	0.048	61.13%	0.030	38.87%
1995	0.073	0.043	59.91%	0.029	40.09%
1996	0.066	0.038	57.36%	0.028	42.64%
1997	0.068	0.038	56.70%	0.029	43.30%
1998	0.070	0.039	55.99%	0.031	44.01%
1999	0.070	0.041	59.61%	0.028	40.39%
2000	0.068	0.039	57.83%	0.029	42.17%
2001	0.072	0.041	56.21%	0.032	43.79%
2002	0.071	0.039	55.59%	0.031	44.41%
2003	0.070	0.038	54.62%	0.032	45.38%
2004	0.064	0.033	52.15%	0.031	47.85%
2005	0.061	0.031	51.54%	0.029	48.46%
2006	0.056	0.028	50.06%	0.028	49.94%
2007	0.052	0.025	48.68%	0.027	51.32%
2008	0.048	0.023	47.71%	0.025	52.29%
2009	0.045	0.022	47.29%	0.024	52.71%
2010	0.042	0.019	45.85%	0.023	54.15%
2011	0.040	0.018	46.20%	0.022	53.80%
2012	0.039	0.018	46.67%	0.021	53.33%
2013	0.039	0.018	46.70%	0.021	53.30%
2014	0.038	0.018	46.37%	0.021	53.63%
2015	0.039	0.018	45.37%	0.022	54.63%
2016	0.035	0.013	36.72%	0.022	63.28%

Figure 3-2 provides a simple picture of how the inter- and intra-regional inequalities have changed over recent decades.

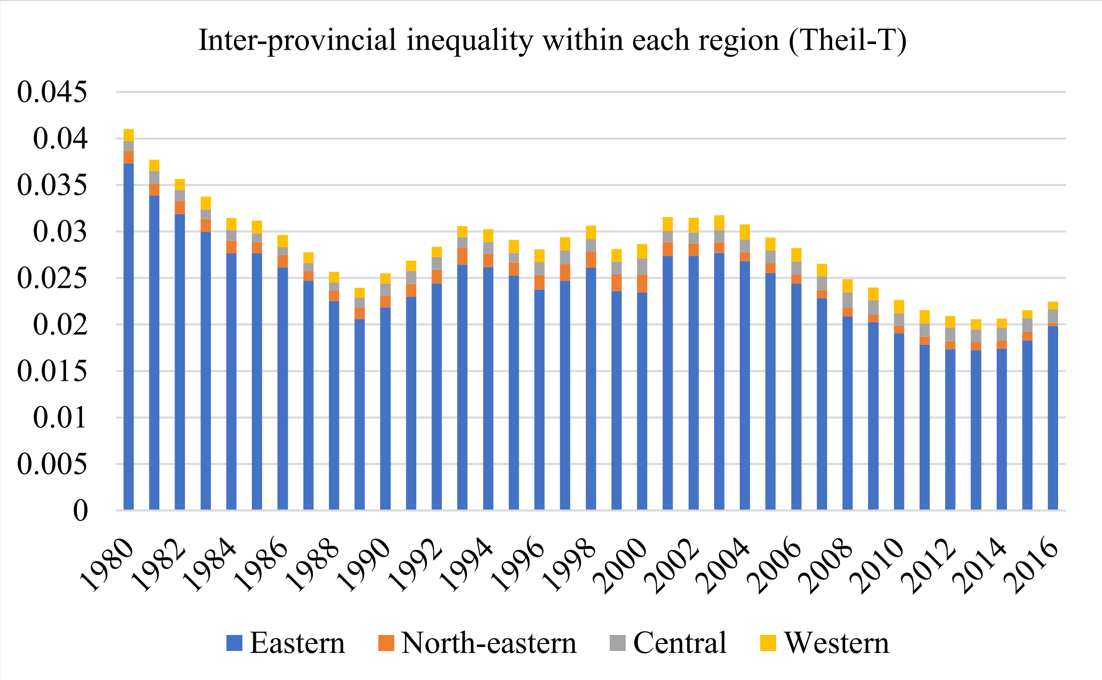
Figure 3-2. Evolution of regional inequality in China (Theil-T)



As shown in Figure 3-2, the whole time period can be roughly divided into three stages. In the first decade (1980–1990), the country's overall income inequality decreased, both in inter- and intra-regional inequalities. In the second period (1990–2003), the national inequality fluctuated, rising slightly between 1990 and 2003. During the last period (2003–2016), the overall, inter-and intra-regional inequalities show decreasing trends. By comparing these inequalities over recent decades, it can be seen that while the overall inequality is mainly inter-regional before 2007, the intra-regional inequality subsequently exceeds the former after that year, to become the main contributor of the overall inequality. This means that the income gaps among the provinces within each region adds up to be larger than the income gap among the four regions. The findings support the conclusion of Fan and Sun (2008) that the overall and intra-regional inequalities decreased during the 1980s and between 2004–2006.

The sharp decline in inter-regional inequality around 2001, in comparison with previous years, is worth noting. A possible explanation is the efficacy of the country's inequality alleviation policies. One of the most important policies, 'China's Western Development Strategy', which was carried out in 2000 in order to boost the economy in the western region, may have been responsible for this welcome decline. Since the implementation of the strategy, the government has made efforts to improve the western region's infrastructure, environmental protection, industrial structure, education and the general opening up of the country. Besides, in 2002, the 'Northeast Area Revitalization Plan' strategy was launched to support the industries in the north-eastern region. Both policies have encouraged a more equal income distribution between the four regions and have led to a decrease of inter-regional inequality since 2001.

Figure 3-3. Inter-provincial inequality within each region (Theil-T)



Additionally, China's intra-regional inequality is further decomposed into the inter-provincial inequalities within the four regions, weighted by income shares (Figure 3.3). Similar to the findings of Fan and Sun (2008), the intra-regional disparity can be largely attributed to the disparity within the eastern region. The inter-provincial income gap in the eastern region is much wider than in the other three regions, showing that the eastern provinces have experienced more uneven economic development. The uneven development within the eastern region has hence been the main contributor to intra-regional inequality. In comparison, the income distribution among the provinces in the other three regions are more equal. Meanwhile, the inter-provincial inequality in the eastern region has slightly risen since 2013. The results are not surprising, and the policies implemented by the Chinese government are the probable explanation. As the eastern region has benefitted most since the opening up of the country in 1978, certain provinces have developed more than the others in this region, leading to a more obvious inter-provincial gap in the east. Besides, as previously mentioned, China's regional inequality is mostly contributed by between-region inequality before 2007, with the eastern region more developed, therefore the policies intended to alleviate inequality mainly focus on balancing the uneven development among regions, rather than on this inter-provincial inequality within the eastern region.

3.2.2.2. Results of Theil-L decomposition

Table 3-3 presents the results of Theil-L decomposition. It can be seen that the national, inter- and intra-regional income inequalities measured by the Theil-L indices in each year are lower than those measured by the Theil-T indices. Moreover, as shown in Table 3-3, the national income disparity in China has declined by a sizeable 47.73% over the last 37 years, falling from 0.044 in 1980 to 0.023 in 2016, with the inter-regional income inequality decreasing by 73.68% from 0.019 to 0.005, while the intra-regional inequality decreased by 28%, from 0.025 to 0.018. Compared to the inter-regional income disparity, the intra-regional income disparity constitutes a larger proportion of the overall income disparity in most of the years.

Table 3-3. Regional inequality based on Theil-L decomposition

Year	T_{LChina}	$T_{Lwithin}$	$T_{Lwithin}$ Percentage	$T_{Lbetween}$	$T_{Lbetween}$ Percentage
1980	0.044	0.019	43.64%	0.025	56.36%
1981	0.042	0.019	44.83%	0.023	55.17%
1982	0.041	0.019	46.95%	0.022	53.05%
1983	0.040	0.019	47.29%	0.021	52.71%
1984	0.040	0.020	49.56%	0.020	50.44%
1985	0.040	0.020	49.96%	0.020	50.04%
1986	0.039	0.020	51.18%	0.019	48.82%
1987	0.037	0.019	52.00%	0.018	48.00%
1988	0.035	0.018	52.21%	0.017	47.79%
1989	0.034	0.018	53.51%	0.016	46.49%
1990	0.034	0.017	49.48%	0.017	50.52%
1991	0.035	0.017	49.22%	0.018	50.78%
1992	0.037	0.018	49.58%	0.019	50.42%
1993	0.040	0.020	50.55%	0.020	49.45%
1994	0.040	0.020	50.18%	0.020	49.82%

1995	0.037	0.018	48.84%	0.019	51.16%
1996	0.035	0.016	45.12%	0.019	54.88%
1997	0.036	0.016	44.35%	0.020	55.65%
1998	0.037	0.016	43.87%	0.021	56.13%
1999	0.036	0.017	47.46%	0.019	52.54%
2000	0.037	0.016	44.03%	0.021	55.97%
2001	0.039	0.017	43.87%	0.022	56.13%
2002	0.038	0.016	43.14%	0.022	56.86%
2003	0.038	0.016	42.20%	0.022	57.80%
2004	0.036	0.014	39.51%	0.022	60.49%
2005	0.034	0.013	38.44%	0.021	61.56%
2006	0.032	0.012	36.51%	0.021	63.49%
2007	0.030	0.010	34.60%	0.020	65.40%
2008	0.029	0.009	32.75%	0.019	67.25%
2009	0.028	0.009	32.30%	0.019	67.70%
2010	0.026	0.008	30.14%	0.018	69.86%
2011	0.025	0.007	29.78%	0.018	70.22%
2012	0.025	0.007	29.88%	0.017	70.12%
2013	0.024	0.007	30.00%	0.017	70.00%
2014	0.024	0.007	29.81%	0.017	70.19%
2015	0.024	0.007	29.43%	0.017	70.57%
2016	0.023	0.005	23.76%	0.018	76.24%

The changes of inter-regional and intra-regional income disparities measured by Theil-L indices are reflected in Figure 3-4. Different from the results of Theil-T decomposition that intra-regional inequality replaces inter-regional inequality as the main contributor of the overall inequality after 2007, the results of the Theil-L decomposition show that during the periods from 1980 to 1985 and 1994 to 2016, the overall inequality is largely explained by intra-regional inequality. Regarding the changes in the overall inequality over these years, Theil-L decomposition provides similar results to Theil-T decomposition, showing that the national income inequality in China decreased between 1980 and 1990, fluctuated in the period from 1990 to 2003, and then declined again after 2003.

Figure 3-4. Evolution of regional inequality in China (Theil-L)

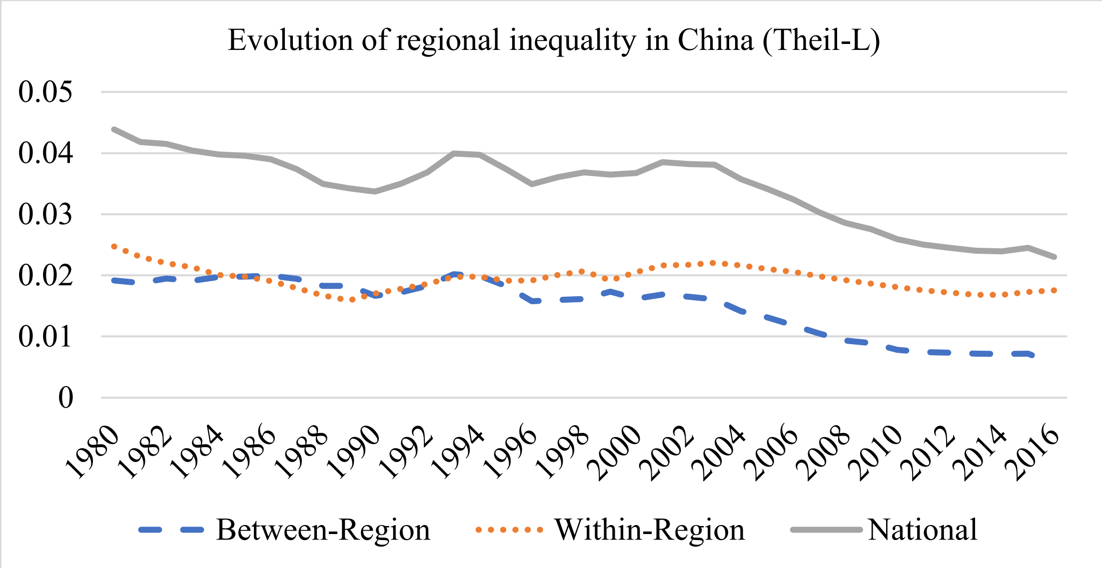
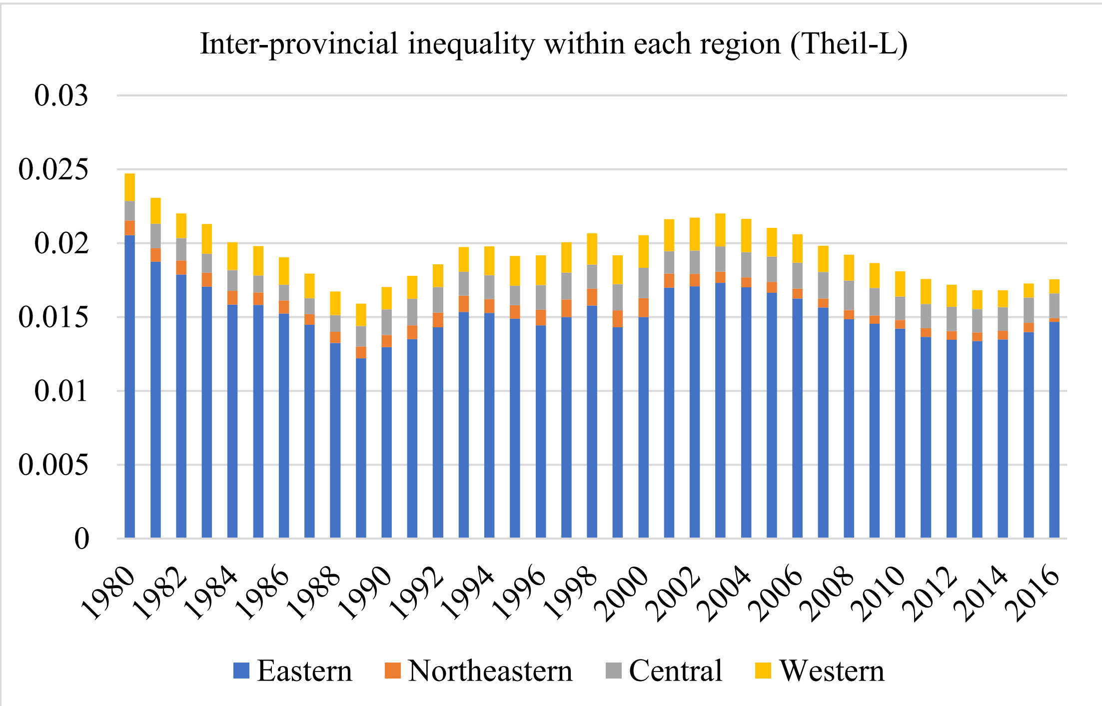


Figure 3-5 depicts the decomposition of intra-regional inequality into inter-provincial inequality within each region, weighted by population shares.

Figure 3-5. Inter-provincial inequality within each region (Theil-L)



At the same time, the results in Figure 3-5 show that the income inequality within the eastern region contributes the largest portion to all intra-regional inequality. This inequality was decreasing until 1990, then it increased between 1990 and 2003, and subsequently decreased again until 2013, beginning to increase again after that. The pattern is similar to that based on Theil-T decomposition.

In summary, section 3-2 investigates the pattern of China's regional income inequality and its evolution during the period from 1980 to 2016, using Theil decomposition methods. Both Theil-T and Theil-L indices are calculated, showing a decline in inequality overall. The intra-regional inequality, which is mainly seen among the provinces in the eastern region, outweighs the inter-regional inequality in recent years, possibly due to the policies implemented to alleviate the disparities. The following section measures and compares the provincial level income inequalities using different inequality indices, including the Theil index, the Gini coefficient and the urban-rural income ratio. China's provincial economic growth, income inequality, human capital and physical capital will also be discussed in more detail, including the measurements and evolvements of these factors over the years.

3.3. China's provincial economic growth, income inequality, human capital and physical capital

Based on the data collected from NBS and the China Centre for Human Capital and Labour Market Research (CHLR) database, this section depicts the economic growth, income inequality, and the human and physical capital in 31 Chinese provinces over the 28 years from 1990 to 2017.[4] This section uses graphs and maps to reflect the development and differences among regions and provinces. The descriptive statistics are not presented here, but are given, together with detailed descriptions of the variables, in Table 4-1 and Table 4-2 in Chapter 4, where the empirical studies on China's inequality and growth are presented. The main contribution of this section is its exploration of the spatial dynamics of China's provincial growth, inequality, human and physical capital. Many studies regarding China's regional income inequality focus on the unbalanced income inequality and growth between and within regions, but do not provide specific information for each province, and tend to neglect the uneven distribution of human and physical capital in the provinces, although these factors are closely related to regional income disparities. This section therefore extends previous studies on China's regional inequality, using tables, graphs and maps, which can reflect the regional and geographical

[4] The urban-rural Gini and Theil indices do not cover Shanghai due to data unavailability, but Shanghai is included under other measurements.

inequality in a clearer way. Moreover, the human capital is decomposed into three levels (basic, medium and advanced), thereby depicting the improvements made through education, not only in terms of quantity, but also of quality.

3.3.1. GDP per capita

GDP per capita is deflated with the GDP deflator (collected from the NBS) for the country and each province, with 1985 as the base year to proxy the average income. The real per capita GDP of the country is presented in Figure 3-6 and the real per capita GDP of the provinces are presented in maps.

Figure 3-6 shows a steady rise of the country's real per capita GDP. China's real GDP per capita has more than tripled during recent decades, rising from 1225 yuan in 1990 to 4391 yuan in 2017, suggesting rapid economic growth. The real per capita GDP increases roughly in a straight line, especially in recent years, meaning the GDP growth rate is stabilized over the years.

Figure 3-6. National real per capita GDP

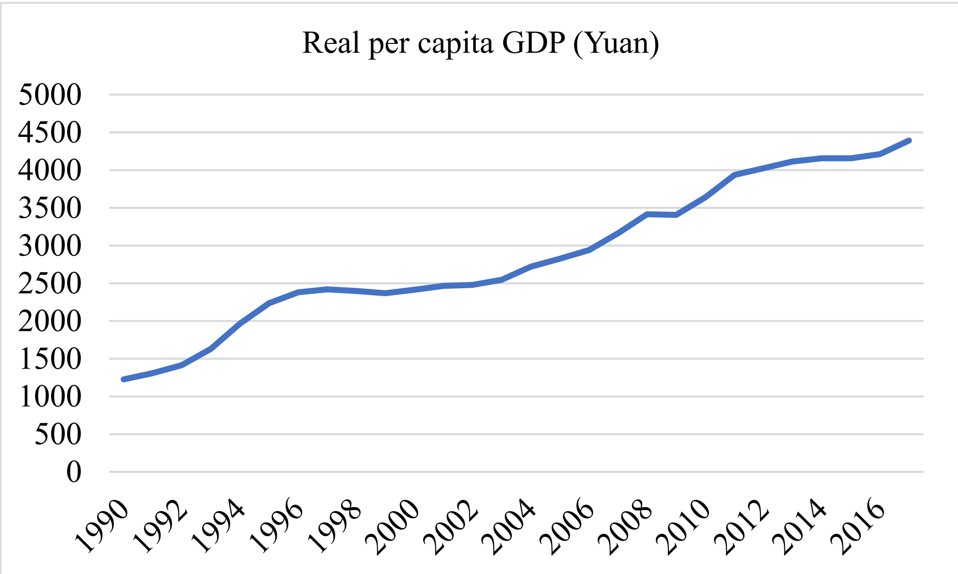


Figure 3-7 and 3-8 depict the provincial real per capita GDP in 1990 and 2017 respectively. The provinces of the north-eastern and eastern regions are mostly located along the coast, whereas the provinces of the central and western regions are located inland. It can be seen from the maps that GDP is distributed unevenly across the provinces. Figure 3-7 shows that in 1990, the coastal provinces, namely the north-eastern and eastern provinces, are more developed than most of those inland. Specifically, the provinces with higher per capita GDP, such as Liaoning, Beijing, Jiangsu, Shanghai, Guangdong, etc., are located in the coastal area, while the provinces with lower GDP are mostly located in the inland area. This finding is in line with Tsui (2007), who finds a disparity between the coastal and inland areas. This disparity, seen in 1990, is possibly related to China's economic reform, especially as the economic reform since 1978 has emphasised the development of the coastal regions, and the geographical location allows the coastal areas to benefit more from international trade, foreign investments and advanced technologies, in contrast with the areas inland.

Figure 3-7. Real GDP per capita 1990 (*gdp*)

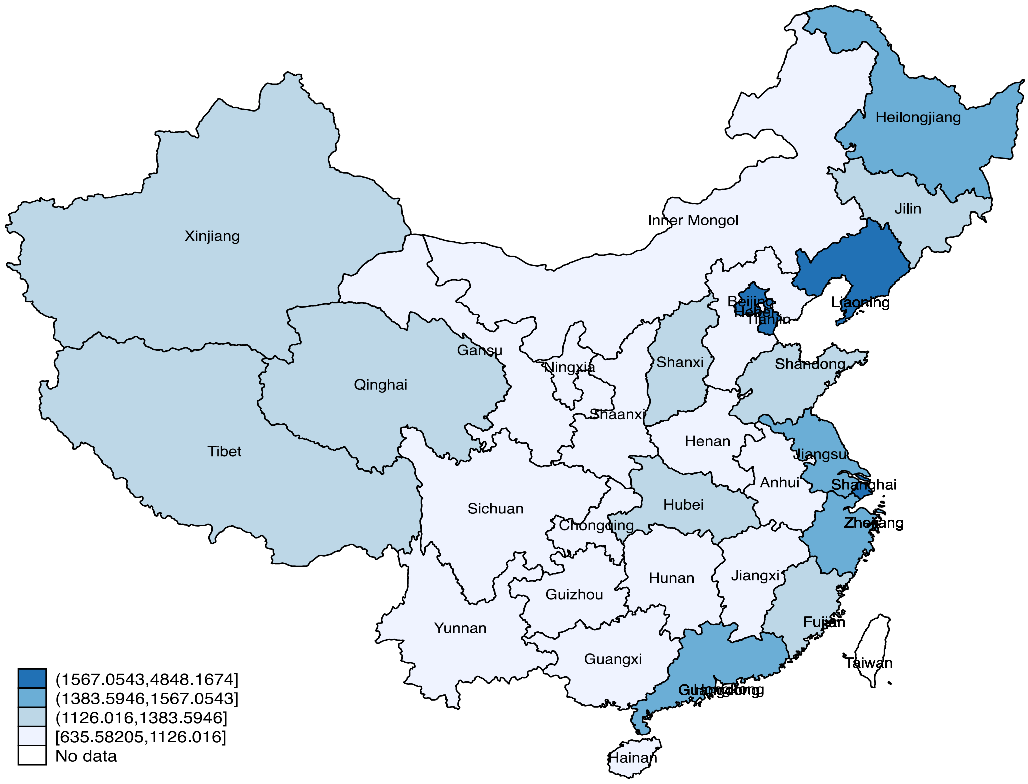
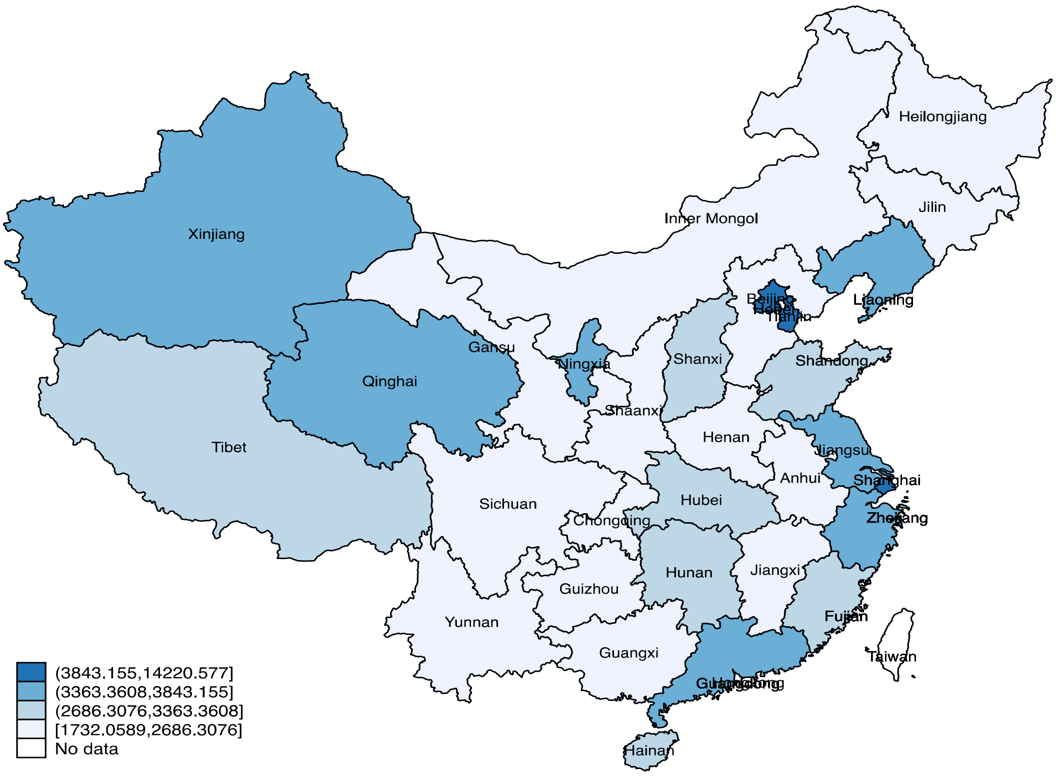


Figure 3-8 reveals a different picture in mapping the real GDP per capita of each province in 2017. Compared to 1990, the gap between the coastal and inland provinces provinces has narrowed by 2017 because the provinces with high per capita GDP are more evenly located. For example, Figure 3-8 shows that among the provinces with relatively high GDP per capita is Liaoning in the north-eastern region. Beijing, Jiangsu, Shanghai, Guangdong, etc. belong to the eastern region, whereas Ningxia, Qinghai and Xinjiang are in the western region. Such changes imply that during the past 28 years, the income inequality between the regions has decreased, in line with the findings in section 2 of this chapter. It is worth noting that some western provinces are seen to be catching up with the more developed provinces, possibly as a result of the country's inequality alleviation policies, such as 'China's Western Development Strategy'. However, the central region does not seem to have improved as much as the western region.

Figure 3-8. Real GDP per capita 2017 (*gdp*)



3.3.2. Income inequality

Due to the unavailability of data for calculating income inequality at the provincial level, the urban-rural inequality of each province is calculated instead. According to previous studies, China's income gap is largely due to the urban-rural income gap (Chen and Fleisher, 1996; Kanbur and Zhang, 2005; Liu et al. 2012; Shi et al. 2013; Li et al. 2016). Using urban-rural inequality measurements guarantees high-quality and successive data in this research and makes my study comparable with previous studies. Moreover, the inequality indices, which are based on two income groups, are consistent with the spirit that individuals are divided into higher and lower income groups (Kuznets, 1955; Galor and Moav, 2004).

Among the income inequality measurements, the Gini coefficient, the Theil index and the urban-rural income ratio are widely adopted in studies on China. As the Gini coefficient is the most commonly used measurement in the literature, the graphs and maps in this subsection are produced based on this coefficient. The Theil index and urban-rural income ratio are also shown in the graph for comparison.

Based on the Lorenz Curve, the Gini coefficient calculates the cumulative income share against the cumulative population share from the bottom to the top income. According to the NBS[5], the Gini coefficient of the country is calculated based on the household incomes:

$$gini = 1 - \sum_{i=1}^{n} P_i(2Q_i - W_i) \tag{3.7}$$

where

$$Q_i = \sum_{k=1}^{i} Wk,$$

so the equation becomes:

$$gini = 1 - \sum_{i=1}^{n} P_i \left(2 \sum_{k=1}^{i} Wk - W_i \right) \tag{3.8}$$

where *i* refers to the *i*th household sorted from low to high according to the household income, W_i is the income ratio of the *i*th household over the total income, and P_i is the population ratio between the *i*th household and the total population.

Based on the general Gini coefficient calculation, the equation of urban-rural Gini coefficient of each province can be written as below (Li et al., 2016):

$$gini = 1 - P_{rural}W_{rural} - P_{urban}(2 - W_{urban}) \tag{3.9}$$

[5] The Gini coefficient calculation is based on the NBS website: http://www.stats.gov.cn/ztjc/ztfx/grdd/201302/t20130201_59099.html

where P_{urban} and P_{rural} represent the population proportions of the urban and rural areas respectively, while W_{urban} and W_{rural} are the income proportions of the urban and rural areas respectively. The value of Gini coefficient is between 0 and 1, and a higher value implies a more unequal income distribution. The population and average incomes of both the urban and rural areas are provided by the NBS. Based on the data, P_{urban}, P_{rural}, W_{urban} and W_{rural} are calculated, and the Gini coefficient of each province is calculated.

Based on the Theil index calculation presented in equation (3.1), the urban-rural Theil index (Theil-T) is calculated as follows (Li et al., 2016):

$$theil = P_{urban}(Y_{urban}/Y)ln(Y_{urban}/Y) + P_{rural}(Y_{rural}/Y)ln(Y_{rural}/Y) \quad (3.10)$$

where P_{urban} and P_{rural} stand for the population proportions of the urban and rural areas respectively, Y_{urban} and Y_{rural} are the average incomes in the urban and rural areas, and Y is the average income of the whole population.

The equation of urban-rural income ratio (*ineq*) is:

$$ineq = Y_{urban}/Y_{rural} \quad (3.11)$$

where Y_{urban} and Y_{rural} are the average net incomes in the urban and rural areas.

Figure 3-9. Urban-rural Gini coefficient of China (*gini*)

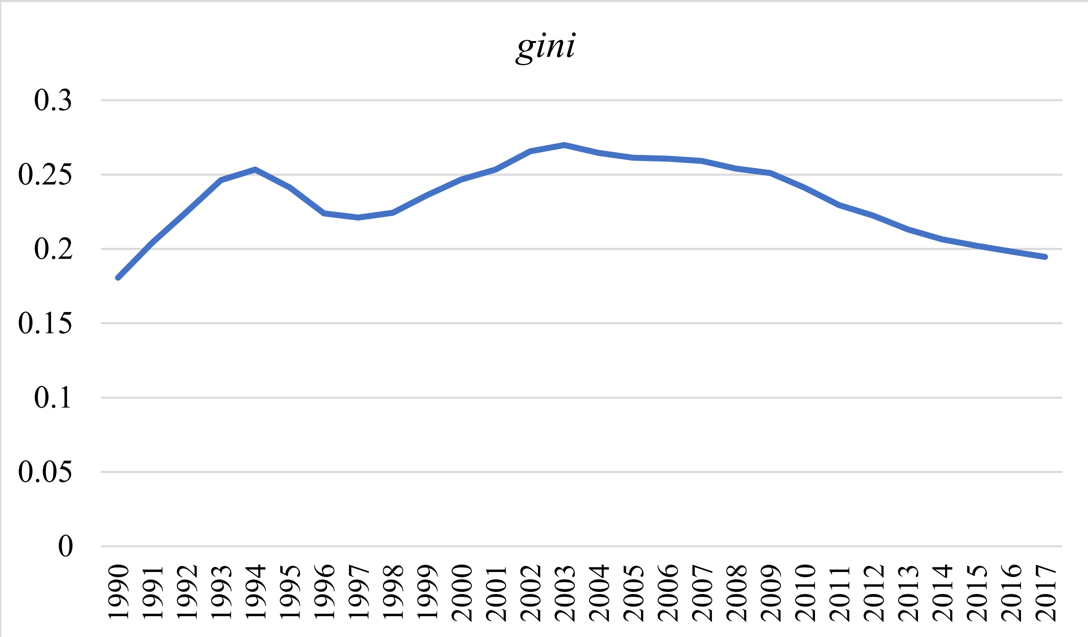


Figure 3-10. Urban-rural income inequalities of China

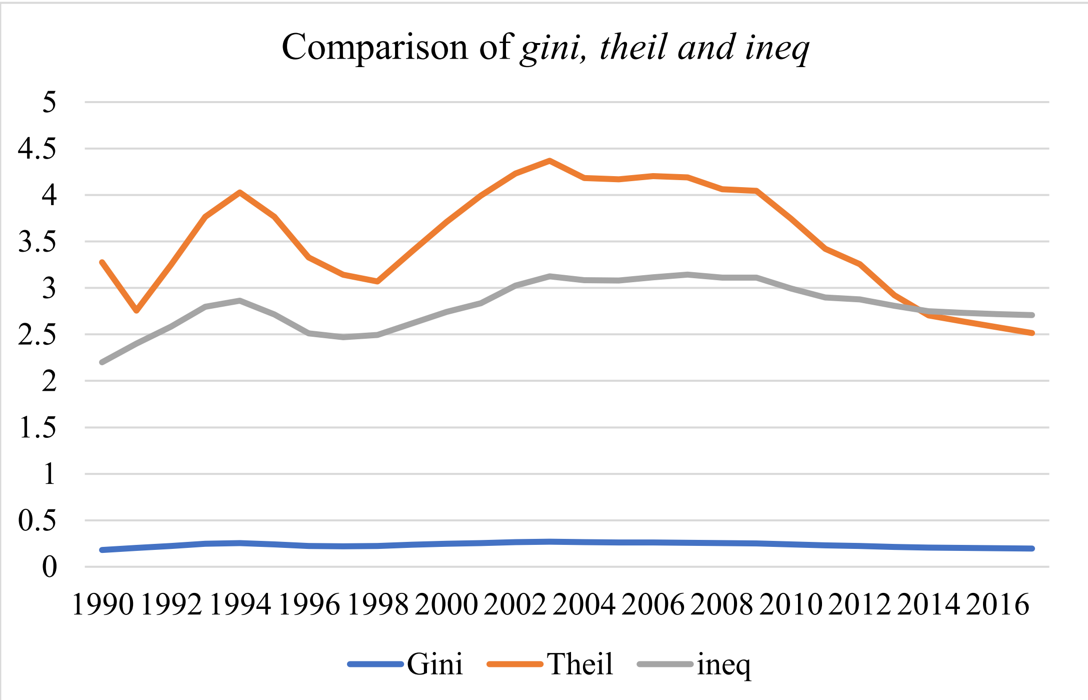


Figure 3-9 shows the change of the Gini coefficient during the specific time period, and Figure 3-10 provides a comparison of the three income inequality measurements. These three indices exhibit similar trends throughout the period. According to each index, a low level of inequality first appears in 1990, then peaks in 2003 and goes down afterwards. The turning point of China's level of income inequality is in 2003, the year the inequality peaks. This is similar to the findings of Zhang (2021) that the national income inequality first increases and then decreases after 1978.

There is another turning point in 1994 where the income inequality is also high, but it is not as obvious as the 2003 one. Overall, between 1990 and 2017, the inequality presents an upward trend first and goes down afterwards. Although the curve does not perfectly match the inverted-U curve proposed by Kuznets, the inequality in China roughly evolves in an inverted-U curve, showing that the inverted-U theory can be valid in the context of China, which will be empirically tested in the following chapters.

According to the inverted-U theory, when the level of industrialisation and urbanisation is low, when the economy grows, the highly skilled workers in the urban areas receive higher incomes, widening the urban-rural income gap. This may explain why the inequality rose higher in 2003 than it did in 1990.

The turning point in 2003 could be due to the political economy theory. The government makes policies in response to the opinions of the poor, who prefer a narrower income gap and wish to improve their incomes. The narrowing of the urban-rural income gap since 2003 can possibly be attributed to the series of poverty alleviation policies launched by the government, as previously stated. Among these policies is the first long-term plan on poverty reduction that was launched in 2001, ‘the Outline for Poverty Reduction and Development of China's Rural Areas (2001–2010)’. Later, in 2011, ‘the Outline for Development-oriented Poverty Reduction for China's Rural Areas (2011–2020)’ was established. Prior to that, in 2004, the project on the reduction or exemption of agricultural tax began, and the agricultural tax was fully abolished in 2006. Direct subsidies were also provided for grain growing farmers in order to supplement their incomes. As the low-income population largely spread in the rural areas, the poverty reduction policies targeting at the rural areas helped to provide more job opportunities and improve education in those areas These measures included developing the local economy, creating new jobs, helping the impoverished to leave their home towns to find jobs in areas that needed more labour, then encouraging people to return to their impoverished hometowns to start new businesses, improving education among the poor by training teachers, providing more internet access, etc. Such actions improved the average income of the people in rural areas, thereby reducing the urban-rural income gap.

Figure 3-11. Urban-rural Gini in 2017

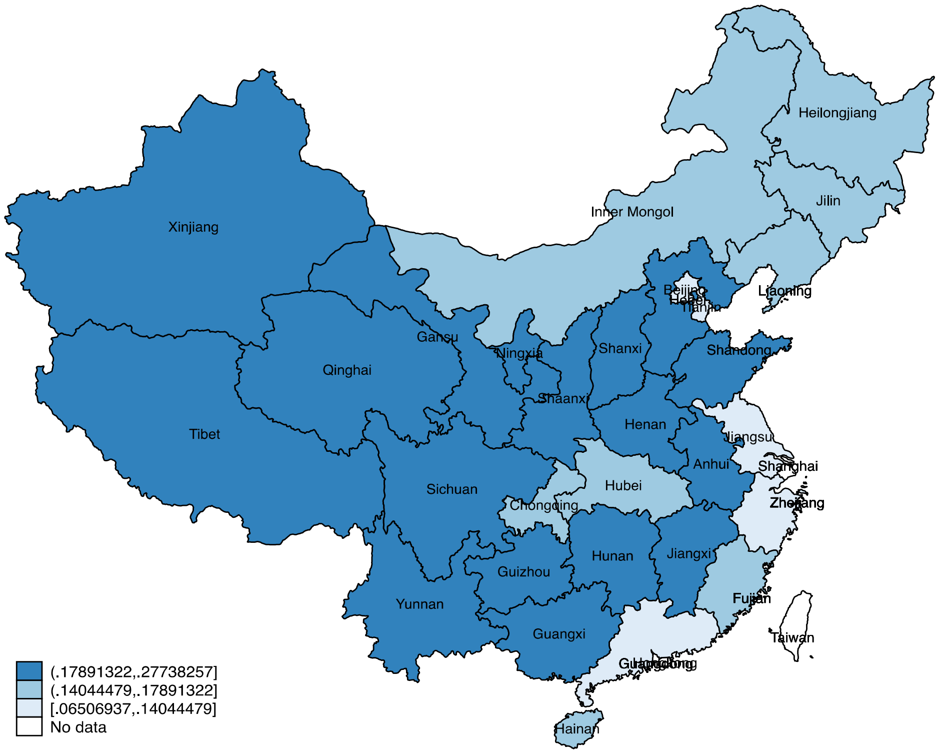


Figure 3-11 maps China's provincial income inequalities in 2017, as measured by the Gini index. The urban-rural inequalities are relatively lower in most of the eastern and north-eastern provinces, while most of the central and western provinces exhibit higher urban-rural inequalities, indicating higher urbanisation levels in the eastern and north-eastern regions.

3.3.3. Human capital

According to existing theoretical studies (Romer, 1990; Solow, 1956, human and physical capital stimulate economic growth. The average years of schooling is often adopted to measure human capital in empirical research (Barro, 2000; Forbes, 2000; Benos et al., 2018). Therefore, in this research, human capital is proxied by this measure (hyrav). Hyrav is further decomposed into three levels: i) Basic human capital (hyr1), measured by the average years of compulsory education, including primary school and junior high school education; ii) medium human capital (hyr2), measured by the average years of high-school education, including senior high school and vocational high-school education; and iii) advanced human capital (hyr3), measured by the average years of tertiary education, including university and college education and above.

The equations are written as follows:

$$hyrav = \sum_{i=1}^{5} \frac{p_i s_i}{p} \tag{3.12}$$

where hyrav is the average years of schooling, p is the population above six years old, p_i is the population with i level of education over six years old, and s_i represents the years of schooling of each level of education. The index $i = 1, 2, 3, 4, 5$, represents no education, primary school education, junior high school education, senior high school education and tertiary education respectively. The years of schooling of each education level is 0, 6, 9, 12 and 16 respectively.

The equations for the decomposed human capital are as follows:

$$hyr1 = \sum_{i=2}^{3} \frac{p_i s_i}{p} \tag{3.13}$$

$$hyr2 = \frac{p_4 s_4}{p} \tag{3.14}$$

$$hyr3 = \frac{p_5 s_5}{p} \tag{3.15}$$

The basic human capital measured by hyr1 includes primary and junior high school education, which are compulsory education in China. The medium human capital includes senior high school and vocational high school education, while the advanced human capital includes college and university education and above.

Table 3-4. National level human capital

Year	hyrav	hyr1	hyr2	hyr3	hyr1 percentage	hyr2 percentage	hyr3 percentage
1990	6.256	4.918	1.091	0.246	78.62%	17.44%	3.94%
1991	6.250	4.921	1.085	0.244	78.74%	17.36%	3.90%
1992	6.250	4.921	1.085	0.244	78.74%	17.36%	3.90%
1993	6.470	5.011	1.092	0.367	77.45%	16.87%	5.68%
1994	6.745	4.833	1.424	0.488	71.65%	21.11%	7.23%
1995	6.715	5.262	1.096	0.358	78.35%	16.31%	5.33%
1996	6.794	5.308	1.129	0.357	78.13%	16.62%	5.25%
1997	7.009	5.326	1.246	0.438	75.98%	17.77%	6.25%
1998	7.088	5.361	1.280	0.447	75.63%	18.06%	6.30%
1999	7.179	5.400	1.285	0.494	75.21%	17.90%	6.89%
2000	7.389	5.489	1.360	0.540	74.28%	18.40%	7.31%
2001	7.598	5.577	1.435	0.586	73.40%	18.88%	7.71%
2002	7.734	5.486	1.495	0.754	70.93%	19.32%	9.75%
2003	7.911	5.429	1.604	0.878	68.62%	20.28%	11.10%
2004	8.010	5.479	1.608	0.923	68.41%	20.07%	11.52%
2005	7.831	5.448	1.493	0.890	69.57%	19.06%	11.36%
2006	8.040	5.494	1.551	0.995	68.33%	19.30%	12.38%
2007	8.186	5.528	1.609	1.049	67.53%	19.65%	12.82%
2008	8.270	5.554	1.643	1.073	67.16%	19.87%	12.97%
2009	8.380	5.558	1.656	1.166	66.33%	19.76%	13.91%
2010	8.613	5.469	1.756	1.388	63.50%	20.39%	16.11%
2011	8.846	5.381	1.856	1.609	60.83%	20.98%	18.19%
2012	8.942	5.313	1.935	1.695	59.41%	21.64%	18.95%
2013	9.048	5.255	1.982	1.811	58.08%	21.91%	20.02%
2014	9.037	5.189	2.004	1.844	57.42%	22.17%	20.41%
2015	9.077	5.022	1.973	2.082	55.33%	21.74%	22.94%
2016	9.078	5.032	2.029	2.017	55.43%	22.35%	22.22%
2017	9.210	4.939	2.107	2.164	53.63%	22.87%	23.50%

Table 3-4 shows the different levels and percentages of human capital. The total average human capital increases over the years, with average years of schooling rising from 6.256

to 9.210. Medium and advanced human capital also increased, and in 2017 advanced human capital surpassed medium human capital to take a slightly larger portion of the total human capital, meaning that more people were receiving tertiary education. In the meantime, basic human capital did not increase as much as the other two.

Figure 3-12 presents the average years of schooling in each province in 2017. Similar to real per capita GDP, education is also distributed unevenly across the provinces. As Figure 3-12 shows, several provinces have the highest level of average education, including Jilin and Liaoning in the north-eastern region; Beijing, Shanghai and Guangdong in the eastern region; Shanxi in the central region and Ningxia, Xinjiang and Inner Mongolia in the western region. Each region has at least one province that is highly ranked.

Figure 3-12. Years of average education in 2017 (*hyrav*)

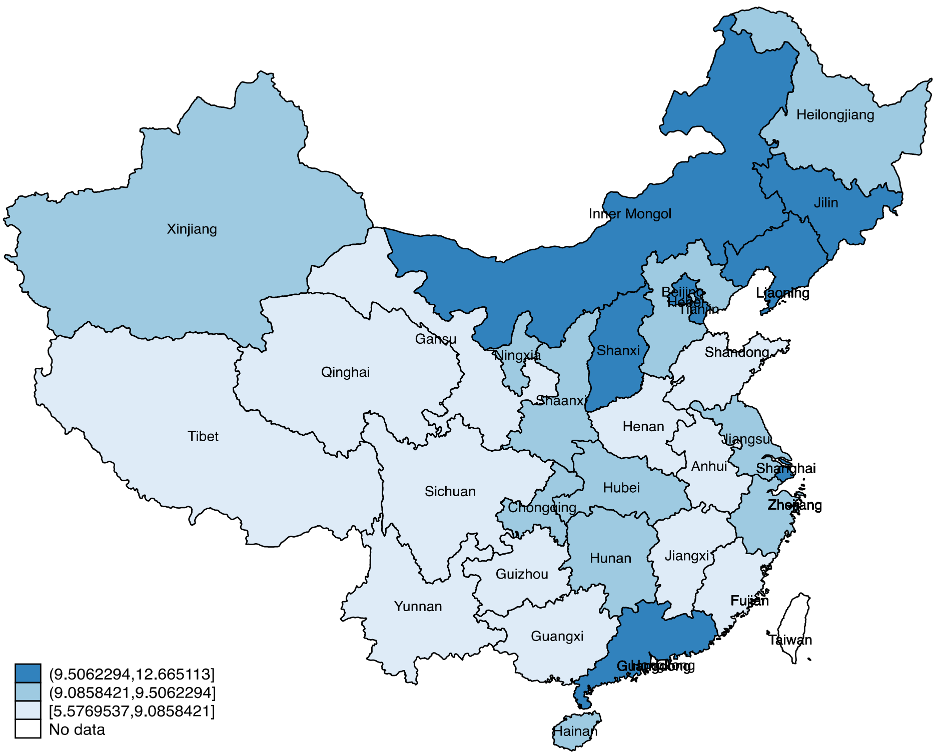
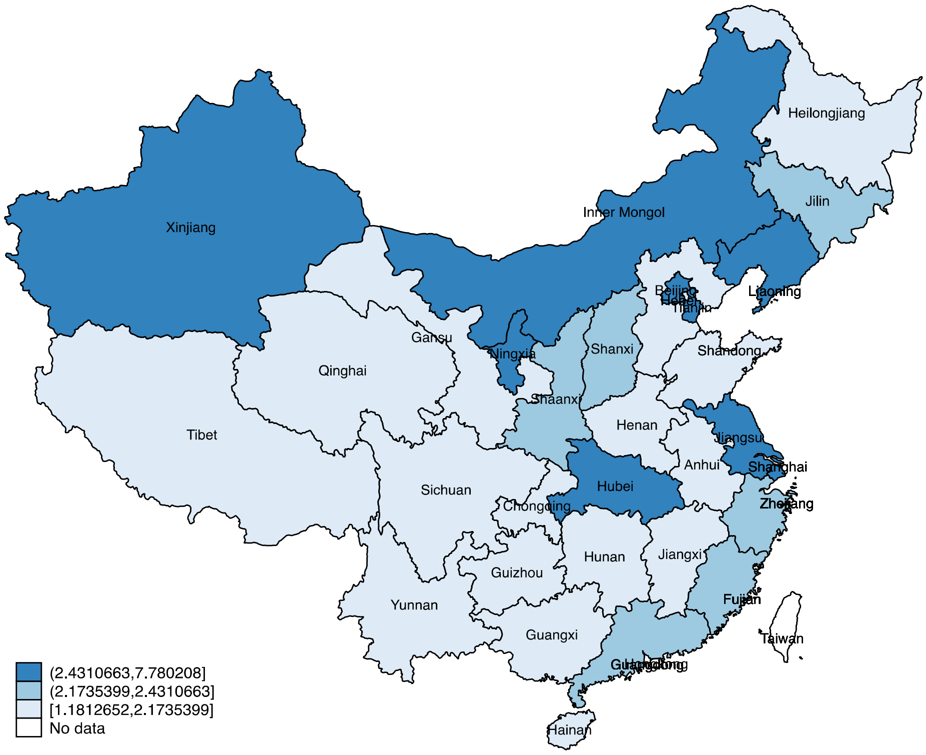


Figure 3-13. Years of tertiary education in 2017 (*hyr3*)



When it comes to the tertiary education in 2017, Figure 3-13 shows a slightly difference pattern from Figure 3-12. Here, the provinces with the highest level of tertiary education include: Liaoning in the north-eastern region; Beijing, Jiangsu, Shanghai in the eastern region; Hubei in the central region and Ningxia, Xinjiang and Inner Mongolia in the western region. From Figures 3-12 and 3-13, it can be seen that the provinces with the highest level of education are, by and large, consistent with the list of provinces with the highest level of per capita GDP. This consistency implies that provinces with higher per capita GDP also have higher level of education and vice versa, revealing a potential connection between education, especially higher education, and GDP.

3.3.4. Physical capital

Besides human capital, physical capital is another vital component of economic growth. A rise in savings and investments contributes to capital stock and therefore leads to a higher rate of economic growth (Solow, 1956). Thus, this study adopts the variable *invest*, which is the fixed asset investment/ GDP ratio, as an indicator of physical capital accumulation.

Figure 3-14 shows the national investment/GDP ratio during 1990-2017. The ratio is not stable, as it has an upward trend with some fluctuations over the years, but it levels out in recent years.

Figure 3-14. Investment-GDP ratio in China

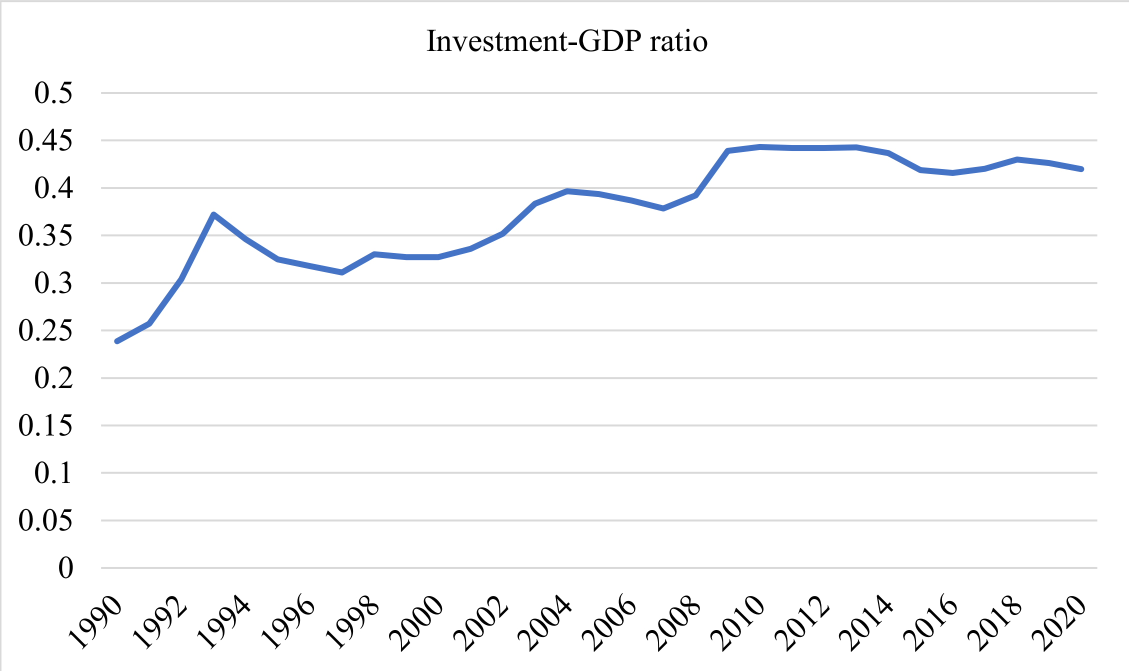


Figure 3-15. Investment-GDP ratio in 1990 (*invest*)

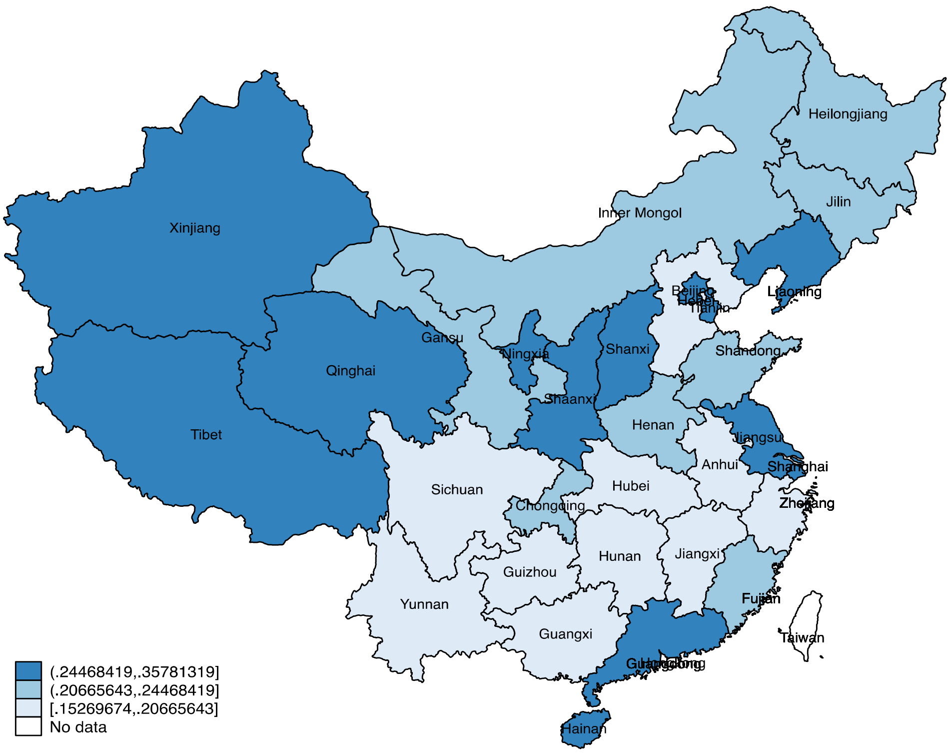
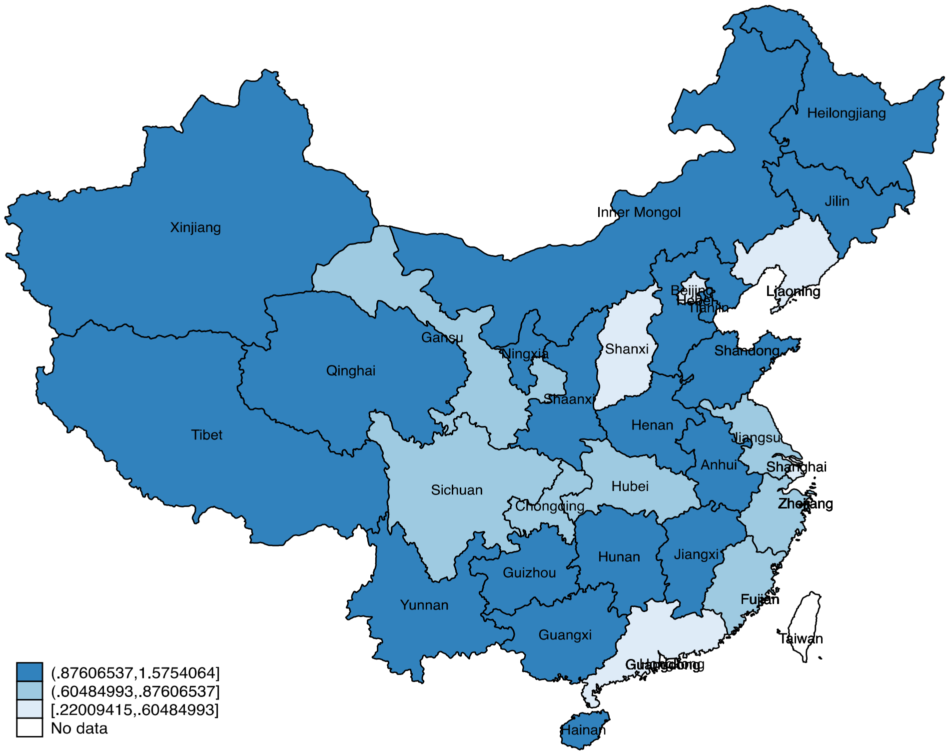


Figure 3-16. Investment-GDP ratio in 2017



Figures 3-15 and figure 3-16 report the patterns of provincial investment-GDP ratio in 1990 and 2017 respectively. Comparing the two figures, while the investment rates of some provinces are higher in 2017 than in 1990, some provinces show the opposite results. Furthermore, the investment-GDP ratios in the western, central and north-eastern regions are higher than those in the eastern region. In some provinces, the ratios are higher than 1.

Table 3-5. Overview of variables

Region	Province	year	*gdp* (yuan)	*gini*	*hyrav* (year)	*hyr3* (year)	*invest*
North-eastern	Liaoning	1990	2014.120	0.150	7.373	0.441	0.247
	Liaoning	2017	3434.687	0.149	9.928	2.717	0.308
Eastern	Beijing	1990	3509.035	0.071	8.588	1.591	0.358
	Beijing	2017	14722.131	0.071	12.665	7.780	0.280
Central	Hubei	1990	1230.971	0.175	6.391	0.277	0.175
	Hubei	2017	3274.971	0.167	9.346	2.533	0.867
Western	Xinjiang	1990	1262.215	0.156	6.518	0.331	0.324
	Xinjiang	2017	3946.567	0.241	9.458	2.797	1.083

Table 3-5 shows one province selected from each region and reports the changes from 1990 to 2017, to provide an overview of the variables.

To summarise, China has seen fast economic development in the recent decades, as the real per capita GDP more than tripled during the period from 1990 and 2017. However, the economic development is unbalanced across the provinces. Comparing the per capita GDP in 1990 and 2017 as presented by the maps, it can be found that although the inland provinces were generally less well-developed than the coastal provinces in 1990, certain inland provinces caught up in 2017. Not only is GDP unevenly distributed, but so are income inequality, together with human and physical capital. The urban-rural income inequality starts from a relatively low level in 1990, peaks in 2003 and is later reduced, with 2003 as the turning point. The coastal provinces, including those in the eastern and north-eastern regions, are more urbanised with lower urban-rural inequalities, compared with the inland provinces.

3.4. Conclusion

This chapter has investigated the patterns and dynamics of China's income inequality, economic growth, and its human and physical capital, on both regional and provincial levels, during the decades since the economic reform. The chapter first conducted Theil decompositions to study the patterns and changes of China's inter- and intra-regional inequalities during the period from 1980 to 2016, then it discussed the selection and measurements of economic growth, income inequality, and human and physical capital, using maps and graphs to depict the unbalanced development across the provinces between 1990 and 2017.

By carrying out the studies, this chapter is intended to facilitate an understanding of China's regional and provincial inequality and growth that is more comprehensive than that in previous studies. The chapter presented some potential explanations underlying the uneven spatial distribution of inequalities as well as the changes over time, and provided some policy implications aiming to reduce income inequality and enhance economic growth.

From the perspective of the patterns of inequality and growth, the results of the Theil decompositions show that China's overall Theil index has been decreasing during the period from 1980 to 2016. The overall regional income inequality is mainly attributed to the income inequality between the four economic regions, and the intra-regional inequality is largely explained by the inter-provincial inequality in the eastern region. Regarding inequality and growth on the provincial level, development and inequality were distributed unevenly among the provinces. Overall, the inland provinces were less well-developed than the coastal provinces in 1990, but this was no longer the case in 2017, when the per capita GDPs in some inland provinces had reached a high level. The urban-rural inequality of the whole country was low in 1990, then reached a peak in 2003 and fell again during the period from 2003 to 2017. On the provincial level, the urban-rural inequalities were generally higher in the inland provinces, compared to those on the coast. In the meantime, the education and investment ratio also changed over the years. The country's average education has been increasing in the previous years, with tertiary education taking a larger portion in 2017 than in 1990, which means that both the quality and quantity of the country's human capital had improved. In addition, the distribution of education across the province was by and large consistent with that of per capita GDP, indicating a possible connection between the two, which will be tested in the following chapters.

In short, this chapter provides four main contributions. First, it presents a more comprehensive overview than previous studies, by using both Theil-T and Theil-L decompositions, and by taking into account all the mainland provinces over a long time period. Second, the study takes a step further than previous studies to illustrate the patterns and evolution of China's provincial inequality, its growth, and its human and physical capital. Third, this chapter not only studies the overall distribution and development of human capital, but also decomposes human capital to investigate how basic, medium and advanced human capitals have changed over the years among the provinces. Lastly, this study divides the provinces into 4 subgroups according to the latest policy, the 11th Five-Year Plan, which divides the provinces into different regions based on their geographic and economic characteristics, thus the results can be more useful for the policy makers.

Having studied the patterns and evolvement of the income inequality and economic growth, how income inequality and economic growth are connected in China remains an interesting question. Empirical studies will be conducted in the next chapter to explore the long- and short-term relationship between China’s inequality and growth, as well as the roles of human and physical capital in this relationship.

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Chapter 4. The inequality-growth nexus in China

4.1. Introduction

It has been over forty years since China's open door policy was first announced in 1978. Over forty years have passed since China's open-door policy was first announced in 1978. During this time, the country has gone through a great economic transformation—from a planned economy to a market economy—that has been accompanied by a high rate of growth. However, despite the country's spectacular growth, its income inequality has also surged dramatically. According to the results in Chapter 3, the regional inequality and urban-rural gap began to widen in 1980, and peaked in 2003. It is natural to see a widening income gap during an economic transition, as a market economy brings both opportunities and uncertainties to individuals, leading to more differentiated income levels in the society. Even though a rising disparity can impede economic growth through various channels, as mentioned in the literature review chapter, it can also encourage factors such as investment, hard work, innovation and risk-taking, which can accelerate economic development. After 2003, the regional and urban-rural income disparity falls gradually, and the economy maintains a rapid rate of growth. Meanwhile, the country also witnessed an increase both in human and physical capital. Due to the unique economic context of China, it is interesting to find the answers to the three questions: i) How are inequality and growth connected in China? ii) What are the roles of human and physical capital in economic growth? iii) Does human capital on each level have a different effect on growth and inequality? Although the relationship between income inequality and economic growth has been long discussed by researchers, the findings of previous studies may not be well-suited to the situation in China. Also, the use of different models and methods can lead to different conclusions. Thus, in this chapter, an empirical analysis based on the panel vector error correction model (VECM) will be described to shed some light on the three questions.

The empirical study in this chapter offers four main contributions. First, as the study uses data from the provincial level rather than cross-country, the data collected from each province within China has better comparability than that collected from different countries, and this also mitigates the cross-country heterogeneity and sample selection issues. Specifically, there are many studies on the relationship between inequality and growth, based on various theoretical approaches, empirical methods and datasets. However, there is no consensus on how the two variables are connected. Controversial results can be found in previous studies. Some studies, for example, argue that income inequality has a negative effect on economic growth (Panizza, 2002), others state that inequality positively affects growth (Forbes, 2000; Frank, 2009), while yet others find that the relationship between inequality and growth is non-linear (Barro, 2000; Benhabib, 2003). A reason for the divided opinions on this topic is related to model constructions, as well as data issues (Frank, 2009). One example of data incomparability is that the definition of *income* varies across different countries, leading to bias in results based on cross-country data (Knowles, 2005). Moreover, as commented by Herzer and Vollmer (2012), cross-country data fails to address the problem of heterogeneity across nations, such as different political and economic structures, policies and technologies, yielding misleading results due to omitted variables. With respect to sample selection, as the inequality-growth nexus changes according to the level of economic development, to estimate a sample consisting of countries in different stages of economic development is problematic. It is also inappropriate to put both democratic and nondemocratic countries, or those with different corruption levels, into one sample, as the empirical evidence for the whole sample may not represent that of a given country. These problems are considerably alleviated by using data from a single country, however (Frank, 2009; Benos and Karagiannis, 2018). The provincial data in China, for example, may have better comparability, as Chinese provinces share many common factors such as the economic and educational policies. Considering that most of the existing studies are done under cross-country frameworks, due to the unavailability of data on regional levels, which leads to the problem of data incomparability caused by structural differences among countries, the study in this chapter takes advantage of provincial level data to better estimate the inequality and growth nexus in China.

The second advantage of this study is that the estimation is done in two time periods. The long time-span (28 years) of the study covers the turning point of urban-rural income inequality in 2003. Thus, by investigating and comparing the results before and after the turning point, this research creates a more comprehensive picture of the evolution of the growth-inequality connection as well as the evolution of the roles of human capital and physical capital. The results suggest a non-linear relationship between income distribution and growth between 1990 and 2017, supporting the conclusion of Barro

(2000), while the variables are positively connected before 2003 and negatively related after. The findings suggest that previous studies on China could be biased by neglecting the turning point.

The third contribution of this chapter is that it not only investigates the role of human capital as a whole, but also evaluates the effects of human capital on three different levels. By taking a closer look at how the education of each level can influence the economy, this chapter combines the empirical results with social background and offers suggestions for each level of education rather than giving general advices.

Another contribution of this study is that by applying panel VECM, the study tests the long-run and short-term relationship between inequality and growth in both directions. As already mentioned in the literature review, the initial research focuses on the influence of economic development on income distribution, while later studies mainly test the impact of inequality on growth. Unlike previous one-direction works, the empirical analysis in this chapter regards both inequality and growth as endogenous variables and inspects their mutual influence on each other under the impact of human capital and physical capital. The study also takes cross-sectional dependence into consideration, and uses the Driscoll-Kraay estimator to address the problem, as the estimator can produce robust standard errors even with the presence of cross-sectional dependence.

The remainder of the chapter is constructed as follows. Section 4.2 describes the variable selection and their measurements, as well as data sources. Section 4.3 presents the preliminary tests such as the cross-sectional dependence test, unit root tests and cointegration tests. Section 4.4 explains the research methods including model specifications and estimating approaches. Section 4.5 shows the empirical results as well as the economic interpretation of the results. Section 4.6 analyses the panel VECM with decomposed human capital and gives policy suggestions based on the results. Section 4.7 is the robustness check with two additional income inequality measurements. Section 4.8 is the conclusion of the whole chapter.

4.2. Data and variables

The empirical study in this chapter uses provincial-level panel data of 30 Chinese provinces over the period from 1990 to 2017 (28 years), including 840 observations.

Specifically, when estimating the inequality-growth nexus using Gini and Theil coefficients, 30 provinces are included, as there are no Gini and Theil coefficients for Shanghai due to data unavailability. Whereas in the robustness check section, 31 provinces, including Shanghai, are included in the estimation where the urban-rural income ratio is used as the proxy for income inequality and the number of observations is 868. The study in this chapter has a long time-span compared with previous studies in China, covering 28 years, and utilising the latest available data. The data are collected from the National Bureau of Statistics (NBS) and the China Centre for Human Capital and Labour Market Research (CHLR) database.

4.2.1. Economic growth measurement

In some studies, the growth rate of per capita real GDP is adopted to measure economic growth (Benos, 2018), while the natural log of GDP per capita is regarded as the level of economic development. On the other hand, some literature uses GDP in its level form. For example, Herzer and Vollmer (2012) and Simões (2012) test the cointegrating relationship between inequality and growth using DOLS estimator, Risso et al. (2013) use the natural logarithm per capita GDP in their model, and they also test both the long- and short- term relationship between income and inequality, based on the FMOLS estimator and panel VECM.

In this chapter, the natural logarithm of real GDP per capita is adopted in order to investigate the long- and short- term relationship between inequality and growth through panel VECM. Real GDP per capita on the provincial level in each year is calculated from GDP per capita and its deflator collected from NBS, with the base year of 1985.

4.2.2. Income inequality measurements

The inequality measures used in this chapter are urban-rural inequality, as China's income inequality is largely explained by the income gap between urban and rural areas (Chen and Fleisher, 1996; Kanbur and Zhang, 2005; Liu et al. 2012; Shi et al. 2013).

In the empirical study of this chapter, the Gini coefficient between urban and rural areas is used as the primary proxy for income inequality, as this is one of the most commonly used measurements for income disparity. The Theil index and urban-rural income ratio are also used in the robustness checks. The data of average per capita income in rural and urban areas were collected from NBS, while the population data were collected from CHLR database.

Using urban-rural inequality indices offers four main advantages. Firstly, the quality of data used to calculate these indices is higher and more reliable than other inequality measurements. The income-gap data in China have two main sources: the NBS database, which is used in this chapter, and the micro databases provided by other organisations. For the NBS database, the per capita income data of urban and rural areas within each province are collected by local statistics departments, based on door-to-door household surveys and sampling surveys, making the official NBS data more accurate and comprehensive compared to those provided by micro databases. For example, according to the micro database provided by the Survey and Research Centre for China Household Finance (CHFS), the Gini coefficient on the national level in 2010 was as high as 0.61. The micro database provided by the China Family Panel Studies (CFPS) also announced a high level of national Gini, equal to 0.51 in 2010. The Gini indices reported by both datasets are much higher than the 0.48 Gini coefficient provided by the NBS. Li and Wan (2013) criticise the CHFS database, stating that the Gini indicators provided in the database are too high, and also mention the presence of bias and statistical problems. For this reason, the provincial Gini coefficients in this chapter are calculated from the urban and rural income data taken from NBS.

Secondly, urban-rural income distribution measurements, including the urban-rural Gini coefficient, the urban-rural Theil coefficient and the urban-rural income ratio, are used in the empirical study due to their data availability. The indicators are calculated from successive data provided by NBS and CHLR databases. Although there are other ways of calculating income inequality, these either lack successive year-by-year data or do not cover sufficient years or provinces. For example, the University of Texas Inequality Project (UTIP) provides Theil indices of industrial sectors from 1987 to 2012. Tian (2012) calculates provincial Gini coefficients for 27 provinces between 1995 and 2010 by calculating the Gini indices within urban and rural areas respectively and taking the weighted mean of urban and rural Gini coefficients. However, the Gini coefficients calculated by this method have many missing values due to data unavailability.

Thirdly, constructing the inequality index based on the two groups is consistent with the economic theory that individuals are divided into two groups—with higher and lower incomes—and that workers flow between the lower and higher productivity sectors (Kuznets, 1955; Galor and Moav, 2004).

Finally, as urban-rural income inequality is widely used in previous studies to investigate the inequality-growth relationship in China, using urban-rural income inequality measurements in this research enables comparability with previous research.

Gini coefficient and Theil coefficient

The Gini coefficient is one of the most widely applied inequality indicators. In this chapter, the urban-rural Gini coefficient is calculated with urban and rural average income and population. The equation is based on the Lorenz curve as presented in Chapter 3. Similar to the Gini coefficient, the provincial Theil coefficients are also calculated based on urban and rural income groups.

Urban-rural income ratio (*ineq*)

Due to the lack of urban and rural population data for Shanghai, the Gini coefficient and Theil coefficient are not calculated for this province. However, as the urban-rural income ratio of Shanghai is available, this province is included in the robustness check using the urban-rural income ratio as the income gap measurement. Moreover, the ratio of per capita income between urban and rural areas is widely adopted to measure income inequality in China, e.g. Wei and Wu (2001), Wan et al. (2006), Chen (2010) and Luo et al. (2020). The income ratio between two different income groups has also been used in international studies. For instance, Voitchovsky (2005) adopts the ratio of income shares between different quintiles as a proxy for income inequality.

4.2.3. Human capital measurements

When considering the factors that can influence economic development and income distribution, human capital and physical capital are two vital variables according to both theoretical and empirical literature.

Human capital and physical capital play important roles in economic growth, according to endogenous growth theory (Romer, 1990; Barro and Sala-i-Martin, 1997) and neoclassical growth theory (Solow, 1956). Human capital in this chapter is measured by the average years of schooling (*hyrav*) as mentioned in Chapter 3. In addition, human capital is decomposed into the three levels of advanced, medium and basic human capital. The details on calculating the variables are given in Chapter 3.

4.2.4. Physical capital measurements

Physical capital is another main factor that influences inequality and growth. Solow (1956) points out that the accumulation of physical capital in the current period depends on savings and investment. The proportion of output that is saved and invested provides information on how much physical capital is generated. Thus, in this chapter, physical capital is captured by the ratio of fixed-assets investment over GDP, similar to the method followed by Herzer and Vollmer (2012). The detailed descriptions of each variable are shown in Table 4-1.

In addition to human and physical capital, other variables are also adopted in previous studies when estimating the inequality and growth nexus. The article by Kanbur and Zhang (2005), for instance, claims that the degree of openness (measured as the ratio of trade volume to GDP) correlates with the regional inequality in China. Urbanisation contributes both to inequality (Kuznets, 1955) and growth (Perotti, 1996). Barro (2000) emphasises the role of government expenditure in economic growth. The influences of further factors, such as political instability and infrastructures, are also estimated in some literature. Nevertheless, the panel VECM in this chapter includes variables only for growth, inequality, human and physical capital. The reasons are similar to those given by Forbes (2000) and Perotti (1996). Firstly, it keeps the model simple and straightforward to better focus on the relationship between inequality and growth, and secondly, including fewer regressors helps retain a sufficient degree of freedom, as panel data analysis requires a large number of observations (Forbes, 2000).

4.3. Preliminary tests

To study the long- and short-term relationship between economic growth and inequality, Engle-Granger two-step method is applied. Before carrying out further estimations, the preliminary tests described below are carried out.

4.3.1. Cross-sectional dependence test

One of the assumptions in panel data study is that the cross-sectional units (in my study, provinces) are independent from each other. However, in real economic scenarios, the assumption may not hold. A growing number of studies has indicated the likely presence of cross-sectional dependence (CSD) in panel data. The correlation across the units can result from common shocks such as macroeconomics and sociological shocks (Andrews, 2005), unobserved components that end up in the error term and spatial dependence. This issue is referred to as cross-sectional dependence (CSD). Overlooking the existence of CSD can lead to biased estimation. The effect of CSD on estimation depends on the level of interdependence across the units or by the nature of CSD itself (De Hoyos and Sarafidis, 2006). One way to deal with this issue is to apply the Driscoll-Kraay estimator (Driscoll and Kraay, 1998) to FE/RE OLS regression. This approach produces heteroskedastic and autocorrelation-consistent (HAC) robust standard errors, even with presence of CSD.

To detect the presence of CSD of residuals in the panel data, Pesaran's cross-sectional dependence test (Pesaran's CD test) is used in this chapter. This approach calculates pairwise correlation coefficients of the cross-sectional units and takes the average of them. The test is applicable in a wide range of situations, including dynamic panels with unit roots (Pesaran, 2021).

4.3.2. Panel unit root test

Panel data have properties both of cross-sectional data and time series data, so apart from the cross-sectional dependence, the non-stationarity of variables is another issue of panel data. A time-series variable is stationary if its statistical properties such as the mean and variance are constant over time, and the covariance between two values at two time points depends only on the length of time between the two values, not on the location of the time points. First and second generation of cointegration tests are carried out to identify the order of integration of the variables.

There are a couple of first-generation panel unit root tests (PURT). The LLC test introduced by Levin et al. (2002) is based on the assumption of homogeneous panel, while the IPS test introduced by Im et al. (2003) extends the LLC test by permitting heterogeneous coefficients across the units. While the first generation of PURT assumes that the errors are independent in panel data, the second-generation unit-root test, cross-sectionally augmented IPS (CIPS) test proposed by Pesaran (2007), relaxes the restriction by allowing the presence of cross-sectional dependence. According to the result of Pesanran's CD test, the CIPS test will be selected if there is cross-sectional dependence, otherwise IPS and LLC tests will be applied. First the stationarity of each variable in its level form is tested, and if the variable is non-stationary, test is performed again on its first-differenced form. If the variables are I(1), panel cointegration tests will be carried out.

4.3.3. Panel cointegration tests

Panel cointegration tests are used to test if a long-term relationship exists between economic development and inequality. The cointegration of variables indicates a long-term equilibrium relationship between the variables. There are many ways to test for cointegration. In the Engle and Granger two-step method (Engle and Granger, 1987), the variables in their level forms are put into an OLS equation in order to generate a residual. Then unit-root tests will be applied to test if the residual is stationary or not. If it is, this means the variables are cointegrated.

Besides the Engle-Granger method, there are additional panel cointegration tests that have been commonly used in previous studies. In this chapter, three panel cointegration tests, including those by Pedroni (2004), Kao (1999) and Westerlund (2007), are adopted to determine if the variables are cointegrated. The Pedroni and Kao tests are residual-based cointegration tests, whereas the Westerlund is error-correction-based. For each test, if the null hypothesis of no cointegration is rejected, it can be concluded that there is convergence to long-term equilibrium between the tested variables, and panel VECM can be constructed in the next step.

The Pedroni test is the most common panel cointegration test. It is a residual-based (based on Engle-Granger two-step method), heterogeneous panel cointegration test. For panel data of a country with different provinces, this test allows for heterogenous trend parameters and intercepts across the provinces, meaning it allows for the possibility of provincial-specific fixed effects and deterministic trends (Pedroni, 2004). Similar to the Pedroni test, Kao integration test is also based on the Engle-Granger two step method. However, heterogeneity across individuals is not permitted. Instead, it assumes cross-sectional homogeneity (Kao, 1999). Unlike the other two tests, Westerlund test is not a residual-based test. It tests cointegration by examining whether the error-correction term is zero in a conditional panel error-correction model (Westerlund, 2007). Westerlund test has fewer restrictions than the other two tests, allowing for heterogenous trend and intercept as well as for cross-sectional dependence. As mentioned earlier, cross-sectional dependence is likely to exist in the data in this study, as provinces within a country can have impacts on each other. It is thus an advantage that the test can accommodate this issue. The three cointegration tests are conducted in the study to check for robustness.

4.4. Estimation methods

Panel VECM is estimated using the Engle-Granger two-step method and a series of different estimators. Panel VECM is widely adopted in economics research to explore the long-term equilibrium relationships among the variables, and estimate the short-term movements away from the equilibrium. It can be used with non-stationary variables as long as cointegration exists, as the model can examine the joint movement of the variables, with the error correction term to adjust any deviation and bring the variables back to the long-term equilibrium. Panel VECM is an appropriate model for estimating the relationship between inequality and growth, especially considering its advantages in interpreting the inequality-growth relationship both in the long- and short-term, and can be applied to non-stationary variables. Besides, previous theories find that inequality and growth have impacts on each other, making the panel VECM a model that is better suited than many others. Unlike the models that test only one-direction influences between variables, panel VECM can test the inequality-growth relationship in both directions.

As mentioned in the literature review in Chapter 2, although there are theories to explain how growth can affect inequality, and vice versa, the existing empirical research focuses mainly on one-way influence of inequality on growth. Moreover, many studies explore the relationship between the two only in the short term. By using the panel VECM model, this study examines the long- and short-term relationship between inequality and growth in both directions, thereby filling the gap in the existing empirical literature. So far as I am aware, this study is the first to apply panel VECM to explore the inequality-growth relationship in China.

4.4.1. Engle-Granger two step method

To estimate the long- and short-term relationship between economic development and inequality in two directions, the Engle-Granger two-step method can be applied (Engle and Granger, 1987).

The representation theorem proposed by Engle and Granger (1987) argues that with cointegration, the nonstationary time series can be represented by error correction models. For the time series that contain unit roots, the variables are non-stationary, but when the series present the common stochastic trends, their linear combination may become stationary, forming a system with cointegrating relations. In an error-correction model, the cointegrating residuals Granger-causes the future movements of the variables, to prevent them from moving too far away from the equilibrium. Later, Johansen (1991) developed the Johansen-Granger representation theorem, proving that the restrictions under the Granger representation theorem also holds for the vector autoregressive process (VAR) integrated of order 1.

To conduct the cointegration analysis, Engle and Granger (1987) provide a two-step approach. The first step tests the long-term relationship among the variables and generates the residuals, and the error-correction equations in the second step use the residuals to estimate how the disequilibrium can be adjusted to achieve long-term equilibrium.

In my research, the first step of Engle-Granger method is to test the long run elasticity between GDP and Gini:

$$\ln gdp_{i,t} = \alpha_i + \beta_{1i} gini_{i,t} + e_{i,t} \tag{4.1}$$

where $i = 1,2,3,\ldots,N$ are the number of provinces, $t = 1,2,3,\ldots,T$ represent years, ln*gdp* is the log of GDP per capita, *gini* is urban-rural Gini index on provincial level, α is the constant, β is the parameter of *gini* and e is the error term.

The estimated value of the error term is as below:

$$\hat{e}_{i,t} = \ln gdp_{i,t} - \hat{\alpha}_i - \hat{\beta}_{1i} gini \tag{4.2}$$

where $\hat{e}$, $\hat{\alpha}$ and $\hat{\beta}$ are the estimated values of the error term, the constant and the parameter of *gini.* The residual $\hat{e}_{i,t}$ measures the disequilibrium. If $\hat{e}_{i,t}$ is stationary, the variables are regarded as cointegrated. According to the Engle-Granger representation theorem, when the linear combination of the variables is stationary, any deviation from the long-run equilibrium is temporary.

The second step includes two error correction equations which corrects the disequilibrium and estimates short-term coefficients. The equations below present how the variables move in the short term:

$$\Delta \ln gdp_{i,t} = \theta_{1i} + \lambda_{1i} ECT_{i,t-1} + \sum_{k=1}^{m} \theta_{11ik} \Delta \ln gdp_{i,t-k} + \sum_{k=1}^{m} \theta_{12ik} \Delta gini_{i,t-k} + \sum_{k=1}^{n} (\theta_{13ik}, \theta_{14ik}, \dots) \boldsymbol{X}_{i,t-k} + u_{1it} \quad (4.3)$$

$$\Delta gini_{i,t} = \theta_{2i} + \lambda_{2i} ECT_{i,t-1} + \sum_{k=1}^{m} \theta_{21ik} \Delta gini_{i,t-k} + \sum_{k=1}^{m} \theta_{22ik} \Delta \ln gdp_{i,t-k} + \sum_{k=1}^{n} (\theta_{23ik}, \theta_{24ik}, \dots) \boldsymbol{X}_{i,t-k} + u_{2it} \quad (4.4)$$

where Δ is the first difference estimator, $\Delta \ln gdp$ is the economic growth rate, $\Delta gini$ is the change in income inequality, *ECT* is the error correction term, which is the estimated residual $\hat{e}_{i,t}$ in equation (4.2), λ is the parameter of *ECT*, θ represents the constants and the parameters of the variables, the vector ***X*** captures exogenous variables including physical capital and human capital, *m* is the maximum lag of endogenous variables and *n* is the maximum lag of exogenous variables. The coefficients of lagged variables are taken into consideration because in general, human capital and physical capital do not immediately influence income distribution and economic growth. All the variables in the second step equations are stationary. λ, the parameter of *ECT,* can correct deviations from the equilibrium.

The relationship between inequality and growth has been estimated by a range of different methods in previous literature, but no consensus has yet been reached on this topic. One of the reasons for this is that various estimating techniques and data sources can lead to controversial conclusions, and even a small adjustment of a model can result in an enormous change in the results (Panizza, 2002); hence the vital role of robustness checks in empirical research. In this chapter, several methods, such as the fixed-effect Ordinary Least Squares (FE-OLS) with Driscoll-Kraay standard error, the fully modified OLS, the mean group and the generalised method of moments, are adopted to estimate equations (4.1), (4.3) and (4.4) for comparative purposes and to provide checks for robustness.

4.4.2. Hausman test

The Hausman test (Hausman, 1978) is applied to choose between the fixed-effect (FE) model and the random-effect (RE) model. The former is consistent if the independent variables and individual-specific effects are correlated. However, if the independent variables and individual-specific effects are uncorrelated, the latter model is preferred over fixed-effect model. The null hypothesis of the Hausman test is that RE is more consistent than FE, so if the null hypothesis is rejected, FE will be used.

4.4.3. OLS approach

In order to check the robustness of the empirical results, four estimators will be adopted to estimate the model: ordinary least squares (OLS), fully modified ordinary least squares (FMOLS), the mean-group estimator (MG) and the general method of moments (GMM). The approaches are discussed below, in sections 4.4.3 to 4.4.6.

The traditional OLS is one of the most widely used methods in previous studies for testing the relationship between inequality and growth (e.g., Benabou, 1996; Perotti, 1996; Forbes, 2000; Ghosh and Pal, 2004; Cialani, 2013). However, the traditional OLS does not account for any cross-sectional dependence problem that is induced by unobserved common factors. If the unobserved common factors and the independent variables are uncorrelated, OLS can still estimate consistent coefficients, but the standard errors are no longer valid. To deal with this issue, the Driscoll and Kraay estimator, which can calculate heteroskedastic and autocorrelation consistent (HAC) standard errors, can be used (Driscoll and Kraay, 1998). To determine whether Driscoll and Kraay estimator is needed, diagnostic tests for cross-sectional dependence (Pesearan, 2004), autocorrelation (Wooldridge, 2002) and heteroskedasticity (Greene, 2018) are carried out for OLS estimator. If the tests show the presence of such issues, the Driscoll and Kraay estimator will be applied.

4.4.4. FMOLS procedure

Besides the traditional OLS, the FMOLS technique proposed by Philips and Hansen (1990) is also frequently chosen by researchers to estimate the cointegrating relationship between I(1) variables, as it addresses the problem of serial correlation and endogeneity bias and makes a consistent and efficient estimation. In this sense, the FMOLS approach can give a better estimation than the conventional OLS. In many studies, the FMOLS procedure is applied in the first step of the Engle-Granger two-step method to estimate the long-term elasticities and obtain residuals (Pedroni, 1999, 2000; Apergis and Payne, 2009; Risso et al. 2013). Thus, the panel FMOLS estimator will be applied to estimate equation (4.1) as an alternative approach to OLS.

4.4.5. Mean-group estimator (MG)

Another alternative approach to OLS is the MG estimator (Pesaran and Smith, 1995). Accordingly, the coefficients of the panel data are estimated by calculating a separate equation for each entity (in this research, ‘province’), and by taking averages of individual coefficients. In this way, the estimator allows not only intercept, but also slope heterogeneity and different error variances in cross-sectional data (Frank, 2009). Compared to the strict assumption of fixed-effect OLS that slope coefficients remain the same across the individuals, the MG estimator does not impose such homogenous restrictions on cross-sectional individuals. Specifically, the MG estimator first estimates the coefficients for each province and then calculates the means of the estimated coefficients across the provinces. Hence, if the data do not meet the strict requirements of the FE estimator, the results gained from the MG estimator can be more efficient. The pooled mean group estimator (PMG) is another approach that relaxes the strict assumptions of the FE estimator. PMG assumes that the short-term coefficients vary across the individuals, while the long-term slope coefficients are the same for cross-sectional individuals (Pesaran et al. 1999). In my study, the MG estimator is applied to estimate the panel VECM as there is no theory to support the assumption that the coefficients should vary in the short term while remaining identical in the long term across the provinces.

4.4.6. General method of moments (GMM)

When error correction models are estimated in the second step of the Engle-Granger method, autocorrelation often arises as the error terms and the lagged dependent variables are correlated. The simple OLS estimation method does not mitigate this problem, which leads to less efficient results. On the other hand, the GMM estimator developed by Arellano and Bond (1991) can deal with autocorrelation and heteroskedasticity issues and therefore produce more efficient estimation by including instrumental variables. The GMM estimator often uses lagged independent or dependent variables as its instrumental variables to obtain results free from second-order autocorrelation. Once the long-term cointegration is estimated, GMM can be employed to estimate the error correction model (Costantini and Martini, 2010). The valid GMM instruments should be correlated with the endogenous variable and uncorrelated from the errors in the meantime. In my estimation, all the instruments are variables used in the regression. To assess the validity of instruments, the Hansen test (Hansen, 1982) is used. This approach can be used to test the overidentifying restrictions in GMM. The null hypothesis of the Hansen test is that over-identifying restrictions are valid. Thus, if the null hypothesis of the Hansen test is not rejected, the instrumental variables are valid. In addition, the Arellano-Bond test for first-order (AR1) and second-order (*AR2)* serial correlations can be applied to detect autocorrelation. There is no autocorrelation in the residuals if the null hypothesis of AR(2) is not rejected. In my estimation, two-step GMM with HAC standard errors is applied to correct for heteroskedasticity and autocorrelation in residuals.

For the two-step GMM approach, two steps are taken to get the weighting matrix. In the first step, the identity matrix is used as the initial weighting matrix, and the parameter vector is estimated. Then, based on this parameter, an updated weighting matrix is generated. In the second step, by using the updated weighting matrix, the final parameters of interest can be re-estimated. Its two-step procedure makes this approach computationally simpler than the one-step GMM estimator. In addition, by using heteroskedastic and autocorrelation-consistent (HAC) robust standard error with the GMM estimator, the issues of heteroskedasticity and autocorrelation, which are likely to be found in panel data, are combatted. In other words, robust standard errors can provide unbiased standard errors of coefficients, even when heteroskedasticity and autocorrelation exist.

4.4.7. Optimal lag selection

The optimal lags are reported in appendices 4-B to 4-D, based on the MMSC-Akaike's information criterion (MAIC), the MMSC-Bayesian information criterion (MBIC) and the MMSC-Hannan and Quinn information criterion (MQIC). MMSC is the abbreviation for moment and model selection criteria. The criteria can test how well candidate models with different lags fit the given data and help to determine the best model. Under MAIC, the best model, or the one with the optimal lag, is the one that will explain the greatest variance in the dependent variable using less independent variables. In short, there is a trade-off between model fitness and parsimony. Similar to MAIC, MBIC and MQIC also penalize models with more parameters, but they penalize more, especially MBIC. According to the criteria, the VECM optimal lags for the time periods of 1990–2017, 1990–2003 and 2003–2017 are 2, 1 and 2 respectively.

4.4.8. Granger causality tests

Granger causality tests (Dumitrescu and Hurlin, 2012) are performed to investigate the causality relationship between variables. The tests are done with data in their stationary forms, and if the null hypotheses are rejected, it can be concluded that variable *x* has a causal influence on variable *y*, meaning that the past values of *x* can help to improve the prediction of *y*. It should be noted that the Granger causality test is not a cause-and-effect test, but is conducted to show the direction of the causality of variables.

Using the VAR model and state-level data in the US, Frank (2009b) investigates the interaction between income inequality, human capital attainment and economic growth, finding that inequality Granger-causes growth, and growth Granger-causes inequality to a lesser degree.

4.5. Empirical results

Table 4-1 shows the descriptions of the variables. The calculation of the variables have been mentioned in chapter 3.

Table 4-1. Definitions of variables

Variable	Description	Data source
growth	Growth rate of GDP per capita (Δlngdp)	NBS
gdp	Real GDP per capita in ten thousand Chinese Yuan (1985 prices)	NBS
gini	Provincial urban-rural Gini index	NBS and CHLR database

theil	Provincial urban-rural Theil index	NBS and CHLR database
ineq	Urban-rural per capita income ratio	NBS
invest	Fixed asset investment/ GDP ratio	NBS
hyrav	Average years of schooling	NBS
hyr1	Average years of compulsory schooling	NBS
hyr2	Average years of senior high school and vocational high school education	NBS
hyr3	Average years of tertiary education	NBS

The descriptive statistics for the variables of interest are summarised in Table 4-2 below.

Table 4-2. Descriptive statistics

Variables	Mean	Std. Dev.	Min	Max
growth	0.034	0.049	-0.096	0.217
gdp	0.268	0.205	0.064	1.472
gini	0.221	0.062	0.065	0.389
theil	0.116	0.057	0.131	0.328
ineq	2.784	0.641	1.241	5.275
invest	0.537	0.286	0.153	1.597
hyrav	7.736	1.507	2.124	12.665
hyr1	5.087	0.667	1.722	6.198
hyr2	1.561	0.592	0.380	3.486
hyr3	1.088	1.009	0.014	7.780

Table 4-3 shows the presence of cross-sectional dependence in the data, as the null hypothesis of no cross-sectional dependence is rejected at 1% significance level. With presence of CSD, the second generation of unit root test (PURT) is employed to test the stationarity of each variable, as the first generation of PURT does not take CSD into consideration.

Table 4-3. Cross-sectional dependence test

Pesaran's test		
	coefficient	p-value
CSD statistic	102.243	0.000***

The results of the cross-sectionally augmented IPS (CIPS) test for unit root is reported in Table 4-4 below. The variables are firstly tested in their level forms both for intercept and intercept with time trend, and if the variables are nonstationary at levels, they will be tested with first difference. In addition to the CIPS test, the IPS and LLC tests are also employed.

The Gini coefficient roughly presents an inverted U shape over time, while each of the other variables displays an upward time trend. It can be seen that lngdp, gini and lninvest fail to reject the null hypothesis of unit root in the three tests, but their first-differenced forms significantly reject the hypothesis at a significance level of 1%. All the human capital variables, however, reject the null hypothesis in their level forms. In short, lnhyrav, lnhyr1, lnhyr2 and lnhyr3 are I(0) variables while the rest are I(1) variables.

Table 4-4. CIPS, IPS and LLC tests for the variables

	CIPS		IPS		LLC	
Variable	Intercept	Intercept & trend	Intercept	Intercept & trend	Intercept	Intercept & trend
Variables in their level forms						
lngdp	0.320	2.051	1.235	-2.040	0.764	-3.090***
gini	-0.072	-2.285**	-2.554***	-0.451	-2.355***	-0.987
lninvest	1.395	2.921	0.346	-2.311**	2.253	0.986
lnhyrav	-7.957 ***	-7.583 ***	-5.594***	-7.026***	-5.659***	-8.108***
lnhyr1	-0.433	-6.254***	-3.509***	-7.159***	-2.805***	-5.053***
lnhyr2	-9.037***	-7.313***	-2.816***	-10.196***	-3.728***	-10.969***
lnhyr3	-9.037***	-7.758***	-8.815***	-10.763***	-8.459***	-11.277***
First-differenced variables						
Δlngdp	-13.173***	-11.190***	-14.35***	-12.714***	-13.517***	-11.757***
Δgini	-19.951***	-18.741***	-21.568***	-19.631***	-18.495***	-14.402***
Δlninvest	-10.222***	-7.539***	-13.582***	-10.182***	-6.833***	-4.602***

Note: H_0: Panel contains unit roots. ***, ** and * represent the significance level of 1%, 5% and 10% respectively. Δ is the first difference operator. Lag selection is based on Akaike information criterion (AIC).

Table 4-5 below shows the results of panel cointegration tests to see if lngdp and gini are cointegrated. Pedroni, Westerlund and Kao tests provide mostly significant results to reject the null hypothesis of no cointegration. Only Phillips-Perron *t* is insignificant. Thus it can be concluded that lngdp and gini are cointegrated at I(1), meaning that there is a long run relationship between lngdp and gini.

Table 4-5. Panel cointegration test 1990-2017

Panel cointgration test	Intercept	Intercept & trend
Pedroni		
Modified Phillips-Perron t	2.921***	2.961***
Phillips-Perron t	2.385***	1.120
Augmented Dickey-Fuller t	3.495***	1.374**
Westerlund		
	2.530***	1.971**
Kao		
ADF	2.144**	

Note: H_0: No cointegration between lngdp and gini. ***, ** and * represent the significance level of 1%, 5% and 10% respectively. Lag selection is based on Akaike information criterion (AIC).

Knowing that lngdp and gini are cointegrated as I(1), and the exogenous variables lnhyrav and lninvest are I(0) and I(1) respectively, equation (4.3) and (4.4) of the error correction model can be written as:

$$\Delta\ln gdp_{i,t} = \theta_{1i} + \lambda_{1i}ECT_{i,t-1} + \sum_{k=1}^{m} \theta_{11ik}\,\Delta\ln gdp_{i,t-k} + \sum_{k=1}^{m} \theta_{12ik}\Delta gini_{i,t-k} + \sum_{k=1}^{n} \theta_{13ik}\,\Delta\ln invest_{i,t-k} + \sum_{k=1}^{n} \theta_{14ik}\ln hyrav_{i,t-k} + u_{1it} \quad (4.5)$$

$$\Delta gini_{i,t} = \theta_{2i} + \lambda_{2i}ECT_{i,t-1} + \sum_{k=1}^{m} \theta_{21ik}\Delta gini_{i,t-k} + \sum_{k=1}^{m} \theta_{22ik}\,\Delta\ln gdp_{i,t-k} + \sum_{k=1}^{n} \theta_{23ik}\,\Delta\ln invest_{i,t-k} + \sum_{k=1}^{n} \theta_{24ik}\ln hyrav_{i,t-k} + u_{1it} \quad (4.6)$$

The result of Hausman test as reported in Appendix 4-A shows that the null hypothesis is rejected on 1% significance level, thus equations FE estimator will be used instead of RE estimator in the data analysis.

In a fixed-effect model, the heterogeneity of the provinces can be captured by the intercept of each province. For instance, the long run elasticity between GDP and Gini with fixed-effect estimator can be written as:

$$\ln gdp_{i,t} = \alpha_i + \beta_{1i} gini_{i,t} + e_{i,t} \quad (4.7)$$

where i and t represent entity (in my case, province) and time respectively, α_i is the intercept/fixed effect of each province, β_{1i} is the coefficient for $gini$, and $e_{i,t}$ is the error term.

Table 4-6. Long-run coefficients 1990-2017

1990-2017	FE-OLS D&K SE	FMOLS	MG
Gini	0.435	-3.807**	0.191
	(2.458)	(1.694)	(0.677)
constant	7.586***	8.593***	7.589***
	(0.611)	(0.277)	(0.161)

Note: Equation (4.1) is estimated. ***, ** and * represent the significance level of 1%, 5% and 10% respectively.

Table 4-6 shows how income inequality and economic growth are associated in the long term between 1990 and 2017 by estimating equation (4.1) with FE-OLS with Driscoll-Kraay SE, FMOLS and MG approaches.

The coefficients are not significant according to the results of FE-OLS with D&K SE and MG estimations, meaning there is no long-term relationship between lngdp and gini. However, the FMOLS estimation suggests the opposite. The coefficient is significantly negative in the FMOLS estimation, showing a negative long-term relationship between the two variables. As mixed results are presented with the coefficients varying from -3.807 to 0.435 across different estimations, the long-term relationship between income inequality and economic growth cannot be determined. With respect to the results, the relationship between the two variables could be non-linear in the period from 1990 to 2007. This result supports the conclusion of Barro (2000) and Benhabib (2003) that the connection between inequality and growth is non-linear.

It is not surprising to find that from 1990 to 2017, the relationship between inequality and growth is non-linear. From the evolution of China's inequality, described in Chapter 3, it can be seen that during the growth of the economy, the income gap between the rich and poor started from a relatively low level in 1980 and reached a peak in 2003, before starting to fall after that year. China has been going through a process of transition since its opening up in 1978, and according to Kuznets' hypothesis, the way that inequality and growth are associated can change during the course of economic development. With 2003 marking the turning point in China's inequality, the following analysis will split the sample into the time periods of 1990–2003 and 2003–2017, in order to estimate the relationship in subsamples and compare the results from before and after 2003[6].

According to the tests presented in Table 4-7, the variables lngdp and gini are cointegrated in the period from 1990 to 2003.

Table 4-7. Panel cointegration test 1990-2003

Panel cointgration test	Intercept	Intercept & trend
Pedroni		
Modified Phillips-Perron t	2.858***	4.307***
Phillips-Perron t	-0.149	0.442***
Augmented Dickey-Fuller t	-2.655***	-3.324***
Westerlund		
	0.733	3.524***

[6] Some previous studies have found that inequality's impact on growth changes throughout the development process of a country and split the data into subsamples. The theoretical work of Galor and Moav (2004) proposes that inequality and growth are positively related in the early stage and negatively related in the later stage of development. This hypothesis has been tested by Khalifa and El Hag (2010), Chambers and Krause (2010) and Benos (2018).

Kao (1999)	
Test statistic (AIC)	T-statistic
ADF	-2.129**

Note: H_0: No cointegration between lngdp and gini. ***, ** and * represent the significance level of 1%, 5% and 10% respectively. Lag selection is based on Akaike information criterion (AIC).

According to table 4-7, the null hypothesis of no cointegration of Pedroni test, Westerlund test and Kao test are rejected, presenting a long-term cointegration between inequality and growth. Thus, the long-term coefficients can be estimated in the next step.

Table 4-8. Long run coefficients 1990-2003

1990-2003	FE-OLS D&K SE	FMOLS	MG
Gini	3.484**	8.718***	4.546***
	(1.409)	(1.01e-05)	(0.725)
constant	6.706***	6.264***	6.571***
	(0.360)	(1.76e-06)	(0.116)

Note: equation (4.1) is estimated for 1990-2003. ***, ** and * represent the significance level of 1%, 5% and 10% respectively.

Table 4-8 presents the long-term relationship between economic development and income disparity between 1990 and 2003, taking 30 provinces into account, and with 420 observations. Unlike the insignificant relationship during the time period of 1990-2017, this time FE-OLS, FMOLS and MG estimations all generate significant and positive results, indicating a long-term positive relationship between the two variables. Focusing on the results of FE-OLS, the long-term relationship can be shown as below:

$$\ln gdp_{i,t} = 6.706 + 3.484 * gini_{i,t} + e_{i,t} \quad (4.8)$$

The long-term coefficient indicates a positive long run relationship between inequality and growth during 1990-2003.

Table 4-9. Panel VECM 1990-2003 (dependent variable: Δlngdp)

	Fe-ols D&K/ Fe-ols D&K	Fmols/ Fe-ols D&K	MG/MG	Fe-ols D&K/ GMM
Depvar.				
Δlngdp				
$ECT_{i,t-1}$	-0.191***	-0.083***	-0.240***	-0.230**
	(0.025)	(0.018)	(0.036)	(0.110)
$\Delta lngdp_{i,t-1}$	0.384***	0.415***	0.164*	0.250
	(0.059)	(0.059)	(0.097)	(0.166)
$\Delta Gini_{i,t-1}$	-0.002	0.294*	-0.430	-0.136
	(0.117)	(0.136)	(0.296)	(0.611)
$lnhyrav_{i,t-1}$	-0.036	-0.110***	-0.198	0.234
	(0.029)	(0.033)	(0.140)	(0.310)
$lnhyrav_{i,t-2}$	-0.017	-0.067**	0.096	-0.300
	(0.026)	(0.029)	(0.155)	(0.298)
$\Delta lninvest_{i,t-1}$	0.019	0.055	0.024	-0.144
	(0.027)	(0.031)	(0.035)	(0.100)
$\Delta lninvest_{i,t-2}$	0.064***	0.070***	0.136***	0.197**
	(0.014)	(0.020)	(0.033)	(0.077)
constant	0.130*	0.295***	0.234	0.153
	(0.058)	(0.053)	(0.202)	(0.158)

Diagnostic results:

Conventional FE-OLS Modified Wald test chi2 = 182.42***

Conventional FE-OLS Wooldridge test F-statistic = 0.285

Hansen test chi2 =7.81, P = 0.167

AR(1) z = -2.38**

AR(2) z = 1.24

Note: Equation (4.5) is estimated for 1990-2003 with m=1 and n=2.

***, ** and * represent the significance level of 1%, 5% and 10% respectively.

Table 4-9, furthermore, shows the results of panel VECM estimated by four different methods: FE-OLS with D&K SE in both steps, FMOLS and FE-OLS with D&K SE in first and second step, MG in both steps and FE-OLS with D&K SE with GMM in first and second step. As can be seen from the diagnostic results at the bottom part of the table, for conventional FE-OLS estimation without D&K SE, there is heteroskedasticity in the residual, while no autocorrelation is detected, according to Modified Wald test for groupwise heteroskedasticity and Wooldridge test for autocorrelation. Thus FE-OLS with D&K SE is preferrable as it produces a HAC robust estimation. For the GMM estimator (also with the HAC standard error), the null hypothesis of the Hansen J test is not rejected (with p value equals to 0.167), implying that the instruments used in the GMM estimation are valid. The null hypothesis of no autocorrelation in order 2 of the AR(2) test is not rejected, meaning that there is no serial correlation.

If the coefficient of lagged error correction term, $\mathrm{Ect}_{i,t-1}$, is negative, it means that the variables converge in the long term. From the table it can be seen that the coefficients are all significant and negative across the four estimations, implying convergence in the long run. Whenever there is a shock on the growth variable, it will be adjusted back to its long-term equilibrium. The error correction model also indicates that the short-term relationship between inequality and growth is insignificant. Only the second model gives a significantly positive coefficient, whereas the other models all show insignificant and negative results. Thus, it can be concluded that no clear short-term relationship exists between inequality and growth, meaning that it is unclear how growth will change in the subsequent year following a shock on inequality in the current year.

It is surprising to find that for the average years of schooling, lnhyrav, only the second model obtains significant coefficients, while the other models estimate statistically insignificant coefficients with mixed signs both for a 1- and 2- years lag. Thus, average human capital does not have a significant impact on growth, as it is hard to predict how human capital affects economic growth. With regards to physical capital, the coefficients of $\Delta \mathrm{lninvest}_{i,t-1}$ are insignificant across all the estimations, and three out of four estimations give positive coefficients, while the coefficients of $\Delta \mathrm{lninvest}_{i,t-2}$ appear to be robust across all four models. The coefficients are significant and positive at either a 1% or 5% significance level, and the magnitudes range from 0.064 to 0.197 in different models. This result, that physical capital can boost economic growth, is in line with previous studies. To conclude, in the period of 1990 to 2003, analysis provides evidence that China's growth mainly relies on the accumulation of physical capital, while human capital does not appear to have a significant effect on growth. Moreover, one of the four short-term coefficients of gini is significant and positive, while the other coefficients are insignificant, meaning that inequality either does not affect growth or enhances growth in the short term. This finding supports the unified growth theory, which states that during the initial stage of economic development, economic growth is primarily driven by physical capital rather than human capital, because the marginal returns on physical capital are high due to a relatively lower capital-labour ratio (Galor and Moav, 2004).

Table 4-10. Panel VECM 1990-2003 (dependent variable: Δgini)

	Fe-ols D&K/ Fe-ols D&K	Fmols/ Fe-ols D&K	MG/MG	Fe-ols D&K/GMM
Depvar. Δgini				
$ECT_{i,t-1}$	0.002	0.015**	0.015	-0.018
	(0.011)	(0.006)	(0.022)	(0.012)
$\Delta lngdp_{i,t-1}$	-0.115***	-0.085***	-0.206***	-0.135***
	(0.011)	(0.013)	(0.040)	(0.029)
$\Delta Gini_{i,t-1}$	0.191**	0.291***	-0.052	0.103
	(0.079)	(0.070)	(0.048)	(0.094)
$lnhyrav_{i,t-1}$	-0.033*	-0.027	-0.039	-0.073
	(0.017)	(0.018)	(0.051)	(0.051)
$lnhyrav_{i,t-2}$	0.006	0.010	0.037**	0.064
	(0.013)	(0.011)	(0.015)	(0.062)
$\Delta lninvest_{i,t-1}$	0.034***	0.038***	0.021	0.055***
	(0.007)	(0.006)	(0.022)	(0.017)
$\Delta lninvest_{i,t-2}$	0.005	0.008	-0.001	-0.007
	(0.009)	(0.009)	(0.115)	(0.026)
Constant	0.058**	0.048	0.190***	0.027
	(0.025)	(0.030)	(0.053)	(0.043)

Diagnostic tests:

Conventional FE-OLS Modified Wald test chi2 = 278.41***

Conventional FE-OLS Wooldridge test F-statistic = 0.05

Hansen test chi2 = 21.51, P = 0.204

AR(1) z = -3.52***

AR(2) z = 1.05

Note: Equation (4.6) is estimated for 1990-2003 with m=1 and n=2.
***, ** and * represent the significance level of 1%, 5% and 10% respectively.

Table 4-10 is the panel error correction model with Δgini as the dependent variable. The heteroskedastic and autocorrelation-consistent robust standard errors (HAC SE) estimators are adopted in the models so there are no heteroskedasticity or autocorrelation in the residuals.

ECT represents the error correction term:

$$ECT_{i,t-1} = \hat{e}_{i,t} = \ln gdp_{i,t-1} - 3.484 * gini_{i,t-1} - 6.706 \quad (4.9)$$

A positive sign of $ECT_{i,t-1}$ coefficient is expected as it implies that following any shock on inequality, the disequilibrium will be corrected and inequality and growth will achieve their long-term equilibrium in the subsequent time period. The coefficient of the second model is 0.015, which is significant at a 5% significance level as expected. It is worth noting that even though the rest of the models get insignificant coefficients, which indicates no convergence of inequality and growth, this does not necessarily mean that the variables are diverged. As mentioned earlier, the FMOLS approach achieves better estimation than the conventional OLS, as the former accounts for serial correlation and endogeneity bias. Considering the significant and positive $ECT_{i,t-1}$ coefficient given by the second model estimated by FMOLS, it is therefore reasonable to conclude that there is a convergence in the long run. Also, adding further stationary variables to the model is helpful in dealing with insignificant error-correction coefficients (Antzoulatos, 1996), and this can be done in the future when more data are available. In this study, I focus only on the four variables in order to estimate a parsimonious model and to retain a sufficient degree of freedom.

The signs of $\Delta lngdp_{i,t-1}$ coefficients predicted by all the models are identical, with the magnitude ranging from -0.206 to -0.085, implying that economic growth can narrow down the income gap in the short term.

In addition, the effect of human capital on inequality is not clear, as different results are presented by the estimations. For average human capital with a one-year lag, the first model obtains a significant and negative result, showing that human capital accumulation is helpful in reducing income disparity, which supports previous studies. The other models also predict negative coefficients, even though these are not significant. The negative coefficient is consistent with existing theories and studies that a higher level of education and skills enables individuals to gain access to higher paying jobs and maximize their income, thus reduce income inequality. However, when it comes to human capital with a two-year lag, the MG estimation generates a significant and positive coefficient with 5% significance, plus three other estimations also give positive coefficients, showing a tendency that $\ln \text{hyrav}_{i,t-2}$ has a positive impact on inequality.

With regard to physical capital with a one-year lag, $\Delta \text{lninvest}_{i,t-1}$, the parameters are all positive, most of which are significant at 1% or 10% significance levels, implying a positive effect of investment on income disparity. The coefficients of $\Delta \text{lninvest}_{i,t-2}$ are not significant, so physical capital with a two-year lag no longer affects inequality. Thus, physical capital contributes to China's income inequality, supporting the findings of Chen (2007).

In addition to the analysis based on the subsample of 1990 to 2003, the subsample of 2003 to 2017 is also estimated. The cointegration tests in Table 4-11 below show a long-term correlation between inequality and economic development.

Table 4-11 Panel cointegration test 2003-2017

Panel cointegration test	Intercept	Intercept & trend
Pedroni		
Modified Phillips-Perron t	4.056***	4.713***
Phillips-Perron t	-0.757	0.735
Augmented Dickey-Fuller t	-2.264**	-2.452***
Westerlund		
	1.795**	3.222***
Kao (1999)		
Test statistic	T-statistic	
ADF	-4.235***	

Note: H_0: No cointegration between lngdp and gini. ***, ** and * represent the significance level of 1%, 5% and 10% respectively. Lag selection is based on Akaike information criterion (AIC).

According to table 4-11, the null hypothesis of no cointegration has been rejected based on each test, except for the PP test, so it can be concluded that lngdp and gini are cointegrate.

Table 4-12. Long-run coefficients 2003-2017

03-17	Fe-ols D&K/ Fe-ols D&K	Fmols/ Fe-ols D&K	MG/MG
Gini	-3.654***	-4.356***	-4.019***
	(0.653)	(0.157)	(0.573)
constant	8.693***	8.817***	8.762***
	(0.132)	(0.0239)	(0.114)

Note: equation (4.1) is estimated for 2003-2017. ***, ** and * represent the significance level of 1%, 5% and 10% respectively.

Table 4-12 shows the long-term relationship between GDP per capita and Gini index from 2003 to 2017 (15 years), with 30 provinces and 450 observations. According to the result of fixed-effect OLS, during this period, Gini index has significantly negative impact on GDP per capita, which is opposite to the result of 1990-2003. The long-term relationship between the two variables is as below:

$$\ln gdp_{i,t} = 8.693 - 3.654 * gini_{i,t} + e_{i,t} \quad (4.10)$$

The FMOLS and MG estimators generate similar results as FE-OLS. The findings are in line with the conclusions of previous literature that income inequality can be harmful to economic development in the long term (Forbes, 2000). The long-term elasticity is 3.654, suggesting that a change of 1% in the Gini coefficient would reduce lngdp by 3.654%.

By combining lngdp and gini's long-term relationship from 1990 to 2003 and from 2003 to 2017, it can be seen that the evolution of their relationship verifies Kuznets inverted U hypothesis in general. In the earlier stage of China's economic development, the income gap and development were positively connected, which implies that the income gap widens during the course of economic growth. However, their connection changes to the opposite in the later stage of development, when income gap narrows while the economy grows.

Table 4-13. Panel VECM 2003-2017 (dependent variable: Δlngdp)

03-17	Fe-ols D&K/ Fe-ols D&K	Fmols/ Fe-ols D&K	MG/MG	Fe-ols D&K/ GMM
Depvar. Δlngdp				
$ECT_{i,t-1}$	-0.095***	-0.074**	0.117	0.162
	(0.029)	(0.028)	(0.136)	(0.132)
$\Delta lngdp_{i,t-1}$	0.065	0.056	-0.508**	-0.284*
	(0.214)	(0.218)	(0.253)	(0.169)
$\Delta lngdp_{i,t-2}$	-0.159*	-0.172*	-0.596***	-0.498**
	(0.088)	(0.0902)	(0.165)	(0.205)
$\Delta Gini_{i,t-1}$	0.224	0.262	1.614	2.061**
	(0.305)	(0.310)	(1.414)	(0.809)
$\Delta Gini_{i,t-2}$	1.207***	1.226***	3.574***	1.733
	(0.268)	(0.266)	(1.276)	(1.131)
$lnhyrav_{i,t-1}$	0.071	0.051	0.193	0.088
	(0.090)	(0.088)	(0.285)	(0.376)
$lnhyrav_{i,t-2}$	-0.283**	-0.289**	-0.674***	-0.557**
	(0.124)	(0.123)	(0.241)	(0.264)
$\Delta lninvest_{i,t-1}$	0.020	0.018	-0.075	-0.053
	(0.026)	(0.026)	(0.118)	(0.056)
$\Delta lninvest_{i,t-2}$	0.039	0.036	-0.027	-0.032
	(0.050)	(0.049)	(0.091)	(0.056)
constant	0.480***	0.540***	1.212***	1.068***
	(0.130)	(0.134)	(0.423)	(0.393)
Diagnostic				
Conventional FE-OLS Modified Wald test chi2 = 201.32***				
Conventional FE-OLS Wooldridge test F-statistic = 0.013				

Hansen test chi2 = 21.07, P = 0.223
AR(1) z = -2.51**
AR(2) z = -0.02

Note: Equation (4.5) is estimated for 2003-2017 with m=2 and n=2.

***, ** and * represent the significance level of 1%, 5% and 10% respectively.

Table 4-13 shows the results of error correction models. The models take lag of order 2 for both the endogenous and exogenous variables (the coefficients of exogenous variables are no longer significant when the lag is over 2, which means the influence of exogenous variables on the economy is no longer evident). ECT L1 is the lagged residual from the first step analysis, and the coefficient of $ECT_{i,t-1}$ is significant and negative in model the former two models, which means that GDP per capita adjusts to its equilibrium in the long term. However, the coefficients estimated by the latter two models are insignificant with opposite signs. As mentioned earlier in this chapter, this does not necessarily indicate a divergence (Antzoulatos, 1996).

A change in inequality, ΔGini, with 1-year lag, does not significantly influence economic growth in the former three models, but the last model exhibits a significantly positive result at the significance level of 5%. Meanwhile, ΔGini with A 2-year lag has a positive impact on economic growth in three of the models at the significance level of 1%. The sum of lagged ΔGini shows the short-term elasticity between inequality and growth, which is positive. This result supports previous literature, in that inequality can boost the economy in the short term, even though it can be harmful to the economy in the long term (Forbes, 2000).

Furthermore, the relationship between growth and human capital with lag of order 1 is positive and insignificant. Even though there is no statistically significant connection, human capital tends to positively affect growth. Benhabib and Spiegel (1994) also find an insignificant relationship between human capital and growth when using a Cobb-Douglas production function model. Surprisingly, human capital with a two year lag has a significantly negative impact on the economic growth. This finding differs from previous theories that human capital is beneficial to the economy. In order to find out more about how human capital and economic growth are related, I will decompose the average human capital into three different levels: advanced, medium and basic human capital, and analyse the impact of each level on growth in the next section of this chapter. As for the coefficients of $\Delta lninvest_{i,t-1}$ and $\Delta lninvest_{i,t-2}$, it is hard to predict whether physical capital is positively or negatively connected to lngdp, because the four models provide mixed results with opposite signs. Meanwhile, none of the coefficients is statistically significant for lag=1 or lag=2, showing that if there is a shock on physical capital will not influence the economy significantly.

Table 4-14. Panel VECM 2003-2017 (dependent variable: Δgini)

	Fe-ols D&K/ Fe-ols D&K	Fmols/ Fe-ols D&K	MG/MG	Fe-ols D&K/ GMM
Depvar.				
Δgini				
$ECT_{i,t-1}$	-0.041***	-0.042***	-0.125***	-0.043***
	(0.007)	(0.007)	(0.034)	(0.016)
$\Delta lngdp_{i,t-1}$	0.039**	0.042**	0.133***	-0.062
	(0.016)	(0.015)	(0.044)	(0.049)
$\Delta lngdp_{i,t-2}$	0.018	0.022	0.119***	0.043
	(0.018)	(0.018)	(0.033)	(0.034)
$\Delta Gini_{i,t-1}$	0.129	0.135*	-0.186	-0.002
	(0.077)	(0.073)	(0.171)	(0.101)
$\Delta Gini_{i,t-2}$	-0.020	-0.002	-0.112	-0.034
	(0.033)	(0.033)	(0.168)	(0.066)
$lnhyrav_{i,t-1}$	-0.010	-0.012	0.033	0.004
	(0.009)	(0.009)	(0.045)	(0.039)
$lnhyrav_{i,t-2}$	0.005	-0.001	-0.016	-0.032
	(0.015)	(0.014)	(0.030)	(0.035)
$\Delta lninvest_{i,t-1}$	0.001	0.001	0.018	-0.065**
	(0.004)	(0.004)	(0.018)	(0.031)
$\Delta lninvest_{i,t-2}$	0.004	0.005	0.018	0.011
	(0.005)	(0.005)	(0.016)	(0.024)
Constant	0.005	0.023	-0.067	0.061
	(0.023)	(0.023)	(0.113)	(0.050)
Diagnostic				

Conventional FE-OLS Modified Wald test chi2 = 385.01***
Conventional FE-OLS Wooldridge test F-statistic = 8.664**
Hansen test chi2 = 22.83, P = 0.155
AR(1) z = -1.75*
AR(2) z = 0.30

Note: Equation (4.6) is estimated for 2003-2017 with m=2 and n=2.

***, ** and * represent the significance level of 1%, 5% and 10% respectively.

The four models in table 4-14 generate consistent results for the coefficient of $ECT_{i,t-1}$. The coefficients are negative and significant at 1% significance level, indicating an adjustment to the equilibrium. The coefficient of $ECT_{i,t-1}$ in the first model is -0.041, and taking the long-run coefficient of table 4-11,

$$ECT_{i,t-1} = \hat{e}_{i,t} = \ln gdp_{i,t-1} + 3.654 * gini_{i,t-1} - 8.693 \tag{4.11}$$

suggesting a coefficient of adjustment equals to -0.041*3.654=-0.150. Whenever there is a shock leading to inequality's temporary departure from the equilibrium, it will be adjusted in the next time period at the speed of 0.150.

The coefficients of one-year lag Δlngdp are significant and positive at significance levels of 1% and 5% in model the former three models, implying that economic development positively influences income redistribution. According to the first model, the short-term elasticity between Δgini and $\Delta lngdp_{i,t-1}$ is 0.039, showing that inequality rises when a shock takes place in economic growth. Meanwhile, growth with a 2-year lag does not exhibit a significant impact on income disparity.

When it comes to the connection between human capital and inequality, the signs of the coefficients are mixed, and the estimations are insignificant as well. To summarize, there is no clear evidence to show how human capital and inequality are connected. Similar to human capital, the physical capital coefficients also insignificant in general. GMM estimation presents a negative and significant coefficient, while the rest of the models provide insignificant and positive results. It can be concluded that physical capital does not affect the income gap in the short term.

In summary, by comparing the results of error correction models in two time periods before and after 2003, it can be seen that the long-term relationship between inequality and economic development is positive before 2003 and negative after 2003. This change can be explained from the market perspective and the policy perspective. The first explanation is Kuznets theory (Kuznets,1955) that the income disparity is widened during the initial stages of urbanisation and industrialisation when members of the labour force move from lower-income rural areas to higher-income urban areas. The higher marginal propensity to save among the rich increases the income gap as well. However, the inequality decreases with further development, affected by factors such as lower fertility rate in the higher income group, industrial changes and taxation policies. The second explanation is that China's economic reform since 1978 initially focused more on the urban areas than the rural areas, resulting in a slower transition from the planned economy to a market economy in rural areas, while the urban areas benefitted from more rapid industrialisation. The imbalanced development brought about by the initial economic reform led to an increasing urban-rural disparity in income inequality, which the government has been making great efforts to alleviate. In 2003, the Provisions on Minimum Wages (2003) were adopted to protect the legitimate rights of lower-income groups. In addition, policies such as the abolition of agricultural tax for rural families in 2003 and the grain subsidy policy, introduced in 2004, have succeeded in reducing poverty in rural areas, and have led to fairer income redistribution. As a result, China's economic development and income inequality after 2003 are negatively connected.

In comparison to the insignificant short-term effect of inequality on growth before 2003, during China's marketisation process, the inequality after 2003 has had a significantly positive influence on growth, which is consistent with the argument of Forbes' (2000) argument that the inequality-growth nexus is positive in the short-term. One reason for the positive nexus is that inequality provides the incentives for people to work harder or move to technologically-advanced, growth-enhancing industries with higher rates of return (Galor and Tsiddon 1997b). Besides, according to Kaldor (1955), higher inequality fosters savings and investments which encourages growth.

Therefore, the average human capital correlation with growth was largely insignificant before 2003 and became negative after 2003, violating the expectation that human capital can induce economic growth. Section 4.6 will look more closely at how human capital affects growth by using decomposed human capital variables. On the other hand, physical capital persistently boosted economic growth in both time periods as expected, revealing that physical capital is the primary contributor to China's growth.

With regards to the short term impact of growth on the income gap, the first period exhibits a negative impact while the second period exhibits a positive one. Human capital does not have a significant influence on income distribution in either time period, but physical capital magnified income disparity before 2003, supporting the findings of Chen (2007), but did not significantly influence disparity after 2003.

4.6. Panel VECM with decomposed human capital

The previous section showed how growth and inequality are affected by the average human capital. This section will offer information on how different levels of human capital can affect inequality and growth, using error correction models with decomposed human capital and will compare the effects of each level.

Table 4-15. Panel VECM 1990-2003 with decomposed human capital (dependent variable: Δlngdp)

	Fe-ols D&K SE/ Fe-ols D&K SE (1a)	Fe-ols D&K SE/ Fe-ols D&K SE (1b)	Fmols/ Fe-ols D&K SE (2a)	Fmols/ Fe-ols D&K SE (2b)	Fe-ols D&K SE/ GMM (3a)	Fe-ols D&K SE/ GMM (3b)
Depvar. Δlngdp						
$ECT_{i,t-1}$	-0.193***	-0.195***	-0.076***	-0.072***	-0.075	-0.186
	(0.025)	(0.036)	(0.016)	(0.015)	(0.109)	(0.132)
$\Delta lngdp_{i,t-1}$	0.443***	0.418***	0.488***	0.512***	0.505**	0.241
	(0.072)	(0.083)	(0.058)	(0.082)	(0.216)	(0.334)
$\Delta lngdp_{i,t-2}$	-0.105**	-0.090**	-0.149**	-0.142**	-0.081	-0.007
	(0.047)	(0.038)	(0.060)	(0.058)	(0.080)	(0.064)
$\Delta Gini_{i,t-1}$	-0.085	-0.025	0.179	0.196	0.303	0.169
	(0.101)	(0.117)	(0.116)	(0.136)	(0.416)	(0.402)

$\Delta Gini_{i,t-2}$	-0.162	-0.090	0.022	0.045	0.123	0.059
	(0.126)	(0.121)	(0.143)	(0.134)	(0.189)	(0.247)
$lnhyr1_{i,t-1}$	0.001	-0.005	-0.028	-0.001	0.036	0.204
	(0.043)	(0.017)	(0.041)	(0.026)	(0.179)	(0.276)
$lnhyr1_{i,t-2}$	-0.060	-0.024	-0.103*	-0.054	-0.250**	0.144
	(0.047)	(0.056)	(0.056)	(0.070)	(0.125)	(0.288)
$lnhyr1_{i,t-3}$		-0.073*		-0.098**		-0.230
		(0.033)		(0.041)		(0.315)
$lnhyr2_{i,t-1}$	-0.008	-0.014	-0.003	-0.020	-0.057	-0.053
	(0.011)	(0.019)	(0.014)	(0.014)	(0.047)	(0.197)
$lnhyr2_{i,t-2}$	0.003	-0.001	0.011	7.67e-06	0.060	0.015
	(0.012)	(0.013)	(0.018)	(0.015)	(0.064)	(0.064)
$lnhyr2_{i,t-3}$		0.018**		0.022*		-0.002
		(0.008)		(0.010)		(0.080)
$lnhyr3_{i,t-1}$	7.14e-05	0.004	-0.013	0.001	0.050*	0.003
	(0.005)	(0.007)	(0.008)	(0.009)	(0.030)	(0.066)
$lnhyr3_{i,t-2}$	-0.008	-0.005	-0.019	-0.009	-0.055	-0.034
	(0.008)	(0.007)	(0.012)	(0.007)	(0.042)	(0.050)
$lnhyr3_{i,t-3}$		-0.007*		-0.012*		0.0004
		(0.003)		(0.006)		(0.050)
$\Delta lninvest_{i,t-1}$	0.017	0.005	0.047	0.025	0.034	0.030
	(0.023)	(0.019)	(0.026)	(0.022)	(0.074)	(0.050)
$\Delta lninvest_{i,t-2}$	0.058***	0.053**	0.057**	0.065**	0.170***	0.080*
	(0.016)	(0.020)	(0.024)	(0.025)	(0.047)	(0.046)
$\Delta lninvest_{i,t-3}$		-0.002		-0.007		0.054
		(0.010)		(0.012)		(0.036)
constant	0.120*	0.188***	0.146**	0.190**	0.349	-0.188
	(0.058)	(0.058)	(0.062)	(0.070)	(0.320)	(0.398)
diagnostic						
Hansen test					15.62	20.22
					(0.209)	(0.381)
AR(1)					-2.22**	-0.90
					(0.026)	(0.370)
AR(2)					1.23	-0.13

	(0.219)	(0.896)

Note: Equation (4.5) is estimated for 1990-2003. Model 1a, 2a and 3a are estimated by three different methods with m=2 and n=2. Model 1b, 2b and 3b are estimated with m=2 and n=3. Standard errors are reported in brackets except for the diagnostic tests. For Hansen test, AR(1) and AR(2) tests, p values are reported in the brackets. ***, ** and * represent the significance level of 1%, 5% and 10% respectively.

Table 4-15 reports the results of the error correction models. The MG estimator is not used in this section as the panel is not large enough for the estimation. Three approaches, FE-OLS, FMOLS and GMM are applied to estimate models in case (a) where the maximum lag of exogenous variables n = 2, and case (b) where n = 3. The analysis will focus on the coefficients of human capital variables.

For basic human capital lnhyr1 with a 1-year lag, there is no significant correlation with economic growth in either case (a) or (b). Both models (2a) and (3a) yield significant and negative coefficients for $lnhyr1_{i,t-2}$, and both (1b) and (2b) yield significant and negative coefficients for $lnhyr1_{i,t-3}$. In general, the basic human capital lnhyr1 has a negative effect on growth. In contract basic human capital, although medium level human capital lnhyr2 with 1- and 2- year lags does not have an effect on growth, $lnhy2_{i,t-3}$ has a significant and positive effect on growth in both cases (1b) and (2b). On the other hand, advanced human capital with 3 year's lag, $lnhy3_{i,t-3}$ has a significant and negative impact on growth in case (1b) and (2b) at a 10% significance level, although the magnitudes of the coefficients are very small, ranging from -0.017 to -0.012. Model (3) does not yield a significant coefficient. In conclusion, only medium-level human capital is positively related with growth, but basic and advanced human capital negatively affect growth. The impact of physical capital on growth is consistent under each case that physical capital with a 2-year lag has a significantly positive connection with growth, and physical capital with a 3-year lag no longer influences growth. In general, the magnitude of human capital coefficients at each level is smaller in comparison with physical capital, thus physical capital is the main driver of economic growth.

The positive relationship between medium-level human capital and growth is as expected according to existing theories and studies, while the negative impact of basic and advanced human capital is not. In China, medium-level human capital includes senior high school and vocational high school education. Education at this level focuses on practical knowledge and skills, catering to the demand of the market. Moreover, as many people join the workforce directly after graduating from high schools, thus medium human capital can increase economic growth very quickly. However, for those who just finished their 9 years of basic education, some may go on to pursue education at a higher level, therefore take longer to join the workforce. As a result, the basic-level human capital does not generate sufficient returns in the short term. Tertiary education, by its nature, also takes longer to take effect on economic growth as it is less application-oriented compared to high school education, thus it may not have any positive effects on growth in the short term.

Table 4-16. Panel VECM 1990-2003 with decomposed human capital (dependent variable: Δgini)

	Fe-ols D&K SE/ Fe-ols D&K SE (1a)	Fe-ols D&K SE/ Fe-ols D&K SE (1b)	Fmols/ Fe-ols D&K SE (2a)	Fmols/ Fe-ols D&K SE (2b)	Fe-ols D&K SE/ GMM (3a)	Fe-ols D&K SE/ GMM (3b)
Depvar. Δgini						
$ECT_{i,t-1}$	0.012	0.041***	0.029***	0.036***	-0.006	0.026
	(0.013)	(0.010)	(0.008)	(0.007)	(0.016)	(0.033)
$\Delta lngdp_{i,t-1}$	-0.065**	-0.017	-0.041	-0.011	-0.108***	-0.023
	(0.024)	(0.018)	(0.024)	(0.017)	(0.032)	(0.164)
$\Delta lngdp_{i,t-2}$	-0.079***	-0.096***	-0.073***	-0.082***	-0.072***	-0.152
	(0.019)	(0.016)	(0.019)	(0.019)	(0.021)	(0.186)
$\Delta Gini_{i,t-1}$	0.131	0.117*	0.255***	0.187***	0.062	0.057
	(0.082)	(0.064)	(0.077)	(0.049)	(0.108)	(0.302)
$\Delta Gini_{i,t-2}$	0.098*	0.138**	0.223***	0.221***	0.070	0.078
	(0.050)	(0.058)	(0.052)	(0.046)	(0.094)	(0.207)
$lnhyr1_{i,t-1}$	-0.023	-0.007	-0.007	0.002	-0.021	0.033
	(0.014)	(0.020)	(0.011)	(0.014)	(0.049)	(0.104)
$lnhyr1_{i,t-2}$	0.001	0.013	0.011	0.022	0.036	-0.050
	(0.014)	(0.019)	(0.013)	(0.019)	(0.063)	(0.117)
$lnhyr1_{i,t-3}$		-0.017*		-0.007		-0.030

		(0.007)		(0.005)		(0.143)
$lnhyr2_{i,t-1}$	0.002	-0.006	0.001	-0.005	0.024	-0.018
	(0.004)	(0.006)	(0.004)	(0.004)	(0.027)	(0.031)
$lnhyr2_{i,t-2}$	-0.007	-0.010*	-0.009*	-0.012**	-0.001	-0.024
	(0.005)	(0.005)	(0.004)	(0.004)	(0.015)	(0.031)
$lnhyr2_{i,t-3}$		0.008		0.004		-0.007
		(0.006)		(0.007)		(0.031)
$lnhyr3_{i,t-1}$	-0.006**	-0.001	-0.005	0.0001	-0.017	0.005
	(0.002)	(0.003)	(0.003)	(0.002)	(0.011)	(0.025)
$lnhyr3_{i,t-2}$	0.002	0.006***	0.002	0.007***	-0.005	0.016
	(0.002)	(0.002)	(0.003)	(0.002)	(0.012)	(0.023)
$lnhyr3_{i,t-3}$		-0.005		-0.004		-0.010
		(0.003)		(0.003)		(0.017)
$\Delta lninvest_{i,t-1}$	0.032***	0.034***	0.034***	0.032***	0.043***	0.039**
	(0.006)	(0.006)	(0.004)	(0.004)	(0.015)	(0.019)
$\Delta lninvest_{i,t-2}$	-0.001	0.009	0.001	0.011	-0.008	0.011
	(0.007)	(0.007)	(0.007)	(0.006)	(0.028)	(0.025)
$\Delta lninvest_{i,t-3}$		0.005		0.005		-0.003
		(0.006)		(0.006)		(0.024)
constant	0.0391***	0.021	0.017**	0.007	-0.038	0.098
	(0.008)	(0.016)	(0.007)	(0.016)	(0.066)	(0.282)
diagnostic						
Hansen test					18.42	6.18
					(0.241)	(0.519)
AR(1)					-3.21***	0.22
					(0.001)	(0.824)
AR(2)					0.22	0.66
					(0.824)	(0.512)

Note: Equation (4.6) is estimated for 1990-2003. Standard errors are reported in brackets except for the diagnostic tests. For Hansen test, AR(1) and AR(2) tests, p values are reported in the brackets. ***, ** and * represent the significance level of 1%, 5% and 10% respectively.

According to Table 4-16, the results provided by cases (a) and case (b) of the three models are consistent in general. Basic human capital and growth are not significantly related in most cases, except for in case (1b), where human capital has a significantly negative relationship with inequality. Regarding medium human capital lnhyr2, cases (1b), (2a) and (2b) provide significantly negative coefficients of $lnhyr2_{i,t-2}$. The negative relationship between human capital and income disparity is as expected, showing that a higher level of human capital can give people access to well-paid jobs and enable them to maximise their incomes. However, the connection between advanced human capital and inequality is positive under cases (1b) and (2b), which is surprising. The other cases show mixed and insignificant results of advanced human capital.

Table 4-17. Panel VECM 2003-2017 with decomposed human capital (dependent variable: Δlngdp)

	Fe-ols D&K SE/ Fe-ols D&K SE (1a)	Fe-ols D&K SE/ Fe-ols D&K SE (1b)	Fmols/ Fe-ols D&K SE (2a)	Fmols/ Fe-ols D&K SE (2b)	Fe-ols D&K SE/ GMM (3a)	Fe-ols D&K SE/ GMM (3b)
Depvar. Δlngdp						
$ECT_{i,t-1}$	-0.126***	-0.056*	-0.107***	-0.045*	-0.222	-0.038
	(0.034)	(0.027)	(0.029)	(0.023)	(0.140)	(0.267)
$\Delta lngdp_{i,t-1}$	0.0706	0.077	0.066	0.073	-0.207	-0.172
	(0.193)	(0.193)	(0.196)	(0.196)	(0.306)	(0.392)
$\Delta lngdp_{i,t-2}$	-0.152	-0.151	-0.161	-0.158	-0.518**	-0.197
	(0.088)	(0.096)	(0.090)	(0.098)	(0.206)	(0.399)
$\Delta Gini_{i,t-1}$	0.390	0.486	0.449	0.515	-0.492	0.524
	(0.268)	(0.310)	(0.278)	(0.312)	(1.159)	(3.871)
$\Delta Gini_{i,t-2}$	1.228***	0.793***	1.274***	0.817***	0.752	2.384
	(0.289)	(0.203)	(0.287)	(0.206)	(0.549)	(4.130)
$lnhyr1_{i,t-1}$	0.139**	0.129*	0.136**	0.126*	0.980**	-0.038
	(0.060)	(0.065)	(0.060)	(0.064)	(0.420)	(0.986)
$lnhyr1_{i,t-2}$	-0.055	-0.016	-0.052	-0.016	-0.421	-0.531
	(0.073)	(0.078)	(0.073)	(0.077)	(0.377)	(0.873)
$lnhyr1_{i,t-3}$		0.012		0.013		0.927
		(0.044)		(0.044)		(0.870)

$lnhyr2_{i,t-1}$	0.037*	-0.017	0.032	-0.018	-0.154	0.029
	(0.0198)	(0.025)	(0.019)	(0.025)	(0.168)	(0.232)
$lnhyr2_{i,t-2}$	-0.063**	-0.056**	-0.062**	-0.055**	-0.228**	-0.415**
	(0.023)	(0.021)	(0.023)	(0.021)	(0.111)	(0.177)
$lnhyr2_{i,t-3}$		0.004		0.004		-0.122
		(0.015)		(0.015)		(0.240)
$lnhyr3_{i,t-1}$	0.003	0.003	0.0003	0.001	0.093	0.036
	(0.016)	(0.015)	(0.016)	(0.015)	(0.071)	(0.190)
$lnhyr3_{i,t-2}$	-0.020	8.79e-05	-0.022*	-4.54e-05	0.017	-0.083
	(0.012)	(0.012)	(0.012)	(0.012)	(0.080)	(0.144)
$lnhyr3_{i,t-3}$		0.008		0.006		0.190
		(0.010)		(0.009)		(0.119)
$\Delta lninvest_{i,t-1}$	0.018	0.006	0.017	0.005	-0.010	0.0117
	(0.023)	(0.022)	(0.023)	(0.022)	(0.139)	(0.143)
$\Delta lninvest_{i,t-2}$	0.044	0.043	0.041	0.042	-0.150	-0.014
	(0.049)	(0.043)	(0.049)	(0.042)	(0.112)	(0.153)
$\Delta lninvest_{i,t-3}$		-0.011		-0.011		0.071
		(0.022)		(0.022)		(0.132)
constant	-0.090	-0.144	-0.081	-0.136	-0.701	-0.326
	(0.162)	(0.139)	(0.159)	(0.136)	(0.463)	(2.869)
Diagnostic						
Hansen test					17.57	16.33
					(0.227)	(0.232)
AR(1)					-2.23**	-1.86*
					(0.026)	(0.063)
AR(2)					-0.63	0.73
					(0.527)	(0.468)

Note: Equation (4.5) is estimated for 2003-2017. Standard errors are reported in brackets except for the diagnostic tests. For Hansen test, AR(1) and AR(2) tests, p values are reported in the brackets. ***, ** and * represent the significance level of 1%, 5% and 10% respectively.

As suggested by Table 4-17, between 2003 and 2017, $lnhyr1_{i,t-1}$ and growth were significantly and positively related, while $lnhyr1_{i,t-2}$ and $lnhyr1_{i,t-3}$ have no significant coefficients. In general, basic human capital can foster economic growth, as expected. On the other hand, medium human capital with a 2-year lag is negatively connected with growth for cases (a) and (b) in all three models, contrary to the situation in the period from 1990 to 2003. As mentioned earlier, medium human capital emphasizes practical knowledge and skills that can be applied in the job market, making it sensitive to changes in the market. Following the rapid industrial and technological upgrade after 2003, if the knowledge and skills taught in schools are updated too slowly to satisfy the demands of the market, human capital will be outdated, and will no longer facilitate economic growth effectively. To solve this problem, high schools, especially vocational high schools, should update their teachings more frequently in order to improve the quality of their education and keep up with the pace of the country's development. Despite of the launch of the policies to encourage vocational education, such as Decision of the State Council on Vigorously Developing the Vocational Education (2005), the vocational secondary education in China needs further enhancement including financial supports and teaching trainings. At the same time, advanced human capital does not generally exhibit a significant influence on economic growth, except in case (2a) where there is a negative influence of $lnhyr3_{i,t-2}$. Even though by nature it takes longer for tertiary education to exhibit its influence on the market, leading to an insignificant short-term impact, some improvement can still be made to raise the return on higher education. Universities can promote the quality and efficacy of the education by paying more attention on innovation and adaptability to the market. The differentiated needs of the job market can be better satisfied with more balanced theoretical and practical education.

Table 4-18. Panel VECM 2003-2017 with decomposed human capital (dependent variable: Δgini)

	Fe-ols D&K SE/ Fe-ols D&K SE (1a)	Fe-ols D&K SE/ Fe-ols D&K SE (1b)	Fmols/ Fe-ols D&K SE (2a)	Fmols/ Fe-ols D&K SE (2b)	Fe-ols D&K SE/ GMM (3a)	Fe-ols D&K SE/ GMM (3b)
Depvar. Δgini						
$ECT_{i,t-1}$	-0.038***	-0.028***	-0.039***	-0.029***	-0.063**	-0.014
	(0.006)	(0.005)	(0.006)	(0.005)	(0.025)	(0.037)
$\Delta lngdp_{i,t-1}$	0.045***	0.044***	0.047***	0.046***	0.066	-0.014
	(0.014)	(0.013)	(0.014)	(0.013)	(0.040)	(0.067)

$\Delta lngdp_{i,t-2}$	0.026	0.0237	0.029*	0.0261*	0.054	0.009
	(0.015)	(0.014)	(0.015)	(0.014)	(0.037)	(0.052)
$\Delta Gini_{i,t-1}$	0.088	0.042	0.097	0.048	0.246**	-0.586
	(0.069)	(0.0530)	(0.067)	(0.052)	(0.111)	(0.451)
$\Delta Gini_{i,t-2}$	-0.022	0.044	-0.004	0.051	0.125	-0.398
	(0.035)	(0.047)	(0.034)	(0.046)	(0.088)	(0.509)
$lnhyr1_{i,t-1}$	-0.0108	-0.014	-0.009	-0.013	0.030	-0.122
	(0.014)	(0.008)	(0.013)	(0.008)	(0.045)	(0.164)
$lnhyr1_{i,t-2}$	-0.037**	-0.038***	-0.036**	-0.037***	-0.014	-0.081
	(0.014)	(0.010)	(0.013)	(0.010)	(0.028)	(0.111)
$lnhyr1_{i,t-3}$		0.024***		0.023***		-0.106
		(0.006)		(0.006)		(0.132)
$lnhyr2_{i,t-1}$	-0.001	-0.009**	-0.001	-0.010**	0.017	0.006
	(0.005)	(0.004)	(0.005)	(0.004)	(0.012)	(0.031)
$lnhyr2_{i,t-2}$	0.003	0.004	0.003	0.004	0.003	0.005
	(0.005)	(0.006)	(0.005)	(0.006)	(0.019)	(0.020)
$lnhyr2_{i,t-3}$		0.009**		0.009**		-0.008
		(0.003)		(0.003)		(0.023)
$lnhyr3_{i,t-1}$	-0.002	-0.004**	-0.002	-0.004**	-0.001	-0.017
	(0.002)	(0.002)	(0.002)	(0.002)	(0.006)	(0.018)
$lnhyr3_{i,t-2}$	-0.002	-0.001	-0.003	-0.001	-0.003	-0.018
	(0.002)	(0.002)	(0.002)	(0.002)	(0.007)	(0.025)
$lnhyr3_{i,t-3}$		0.002		0.002		-0.001
		(0.001)		(0.001)		(0.024)
$\Delta lninvest_{i,t-1}$	0.002	0.001	0.003	0.001	-0.001	-0.019
	(0.003)	(0.003)	(0.003)	(0.003)	(0.011)	(0.020)
$\Delta lninvest_{i,t-2}$	0.006	0.001	0.006	0.001	0.007	-0.009
	(0.005)	(0.005)	(0.004)	(0.004)	(0.013)	(0.010)
$\Delta lninvest_{i,t-3}$		0.008**		0.008**		0.001
		(0.004)		(0.004)		(0.013)
constant	0.072***	0.038***	0.070***	0.038***	-0.040	0.507
	(0.016)	(0.013)	(0.015)	(0.012)	(0.091)	(0.370)
Diagnostic						
Hansen test					19.61	17.11

		(0.105)	(0.194)
AR(1)		-2.70***	-0.42
		(0.007)	(0.673)
AR(2)		-0.91	0.32
		(0.362)	(0.749)

Note: Equation (4.6) is estimated for 2003-2017.

Standard errors are reported in brackets except for the diagnostic tests. For Hansen test, AR(1) and AR(2) tests, p values are reported in the brackets.

***, ** and * represent the significance level of 1%, 5% and 10% respectively.

Table 4-18 reports the correlation between inequality and other variables in the period from 2003 to 2017. The coefficients for both cases (a) and (b) of each model are generally robust. While $lnhyr1_{i,t-1}$ does not exhibit a statistically significant effect on the income gap, $lnhyr1_{i,t-2}$ exhibits a positive effect, according to both cases (a) and (b) of the former two models. The magnitude of the coefficients of $lnhyr1_{i,t-1}$ is slightly larger than that of $lnhyr1_{i,t-2}$, so to take the sum of the coefficients of lagged lnhyr1, it can be concluded that lnhyr1 has a negative impact on inequality, meaning that basic human capital can narrow the income gap. On the other hand, by taking sum of lagged coefficients of lnhyr2, a positive relationship can be found between medium human capital and inequality. Advanced human capital has a significantly negative impact on inequality according to (1b) and (2b), and the other coefficients are also negative, even though insignificant. Therefore, advanced human capital can also reduce income disparity.

To conclude, this section has investigated how human capital on different levels can affect economic growth and income distribution. It has compared the changes in their relationships before and after 2003, explaining the reasons behind the results, and giving policy suggestions. To be specific, before 2003, medium human capital could accelerate growth, while basic and advanced human capital have impeded growth. After 2003, basic human capital accelerated growth, while medium human capital harmed growth, and advanced human capital did not have a significant effect. With regards to the relationship between inequality and human capital, basic- and medium human capital can reduce income disparity, but advanced human capital had the opposite effect before 2003. In the years after 2003, both basic and advanced human capital could mitigate income inequality, while medium human capital widened inequality. In order to take full advantage of human capital to benefit growth, knowledge and skills taught in each level of education should be upgraded quickly in accordance with the needs of the market.

Table 4-19. Granger causality test 1990-2003

lag	Δgdp	Z-bar	Δgini	Z-bar
1	Δgini	24.793***	Δgdp	10.177***
2		17.865***		15.110***
1	lnhyrav	8.263***	lnhyrav	0.401
2		13.935***		2.475**
1	Lnhyr1	7.757***	Lnhyr1	0.911
2		14.589***		4.528***
1	Lnhyr2	6.972***	Lnhyr2	-0.080
2		14.061***		9.978***
1	Lnhyr3	7.467***	Lnhyr3	0.843
2		15.352***		5.571***
1	Δlninvest	16.920***	Δlninvest	4.178***
2		15.485***		18.387***

Note: ***, ** and * represent the significance level of 1%, 5% and 10% respectively.

Table 4-19 shows the causal relationship between the variables with 1 and 2 lags (lag of 3 cannot be tested due to the limited time span). It can be seen that both inequality and growth are granger caused by human capital on each level and physical capital. Inequality and growth granger causes each other as well, supporting the finding of Frank (2009b), while the granger causality from growth to inequality is slightly weaker than that of the opposite direction.

Table 4-20. Granger causality test 2003-2017

lag	Δgdp	Z-bar	Δgini	Z-bar
1	Δgini	5.124***	Δgdp	-0.829
2		10.500***		-1.492
3		15.666***		12.678***
1	lnhyrav	7.943***	lnhyrav	4.545***
2		7.810***		10.067***
3		15.343***		8.025***

1	Lnhyr1	2.418**	Lnhyr1	0.121
2		7.787***		2.338**
3		6.304***		5.228***
1	Lnhyr2	5.772***	Lnhyr2	1.813***
2		10.332***		6.800***
3		8.590***		5.573***
1	Lnhyr3	5.836***	Lnhyr3	2.413**
2		8.617***		10.679***
3		6.881***		4.661***
1	Δlninvest	1.607	Δlninvest	3.027
2		1.871*		2.587
3		7.201***		4.060

Note: ***, ** and * represent the significance level of 1%, 5% and 10% respectively.

According to table 4-20, during 2003-2017, growth and inequality granger causes each other, and only weak evidence is found that economic growth granger causes inequality, as Δgdp does not significantly granger causes growth with one and two year's. This finding is in line with the conclusion of Frank (2009). In addition, growth is also granger caused by human capital and physical capital, while inequality is granger caused by human capital but not physical capital.

4.7. Robustness check with different measurements of inequality

In this section, robustness checks are done with Theil index (theil) and urban-rural income ratio (ineq) as the inequality measurements.

4.7.1. Robustness check with Theil index as the inequality measurement

Table 4-21. Long-run coefficients 1990-2017 (with Theil index)

1990-2017	FE-OLS D&K SE	FMOLS	MG
theil	-0.445	-2.918	1.642
	(2.342)	(3.785)	(1.086)
constant	7.734***	8.156***	7.633***
	(0.340)	(0.237)	(0.092)

Note: Equation (4.1) is estimated. ***, ** and * represent the significance level of 1%, 5% and 10% respectively.

Table 4-21 shows the long-run coefficients between inequality and growth with Theil index as the measurement of inequality. Similar to the results estimated with Gini index in table 4-5, the relationship between inequality and growth is insignificant during the period of 1990-2017.

Table 4-22. Long-run coefficients 1990-2003 (with Theil index)

90-03	Fe-ols D&K Fe-ols D&K	Fmols/ Fe-ols D&K	MG/MG
theil	3.054*	14.51***	4.655***
	(1.653)	(1.66e-05)	(1.173)
constant	7.117***	6.848***	7.077***
	(0.245)	(1.08e-06)	(0.085)

Note: equation (4.1) is estimated for 1990-2003. ***, ** and * represent the significance level of 1%, 5% and 10% respectively.

Table 4-22 shows the long-term elasticity between GDP per capita and Theil index. The variables are connected positively, which is robust to the results estimated with Gini coefficient.

Table 4-23. Panel VECM 1990-2003 (with Theil index; dependent variable: Δlngdp)

	Fe-ols D&K/ Fe-ols D&K	Fmols/ Fe-ols D&K	MG/MG	Fe-ols D&K/ GMM
Depvar. Δlngdp				
$ECT_{i,t-1}$	-0.206***	-0.052***	-0.215***	-0.268***
	(0.022)	(0.010)	(0.029)	(0.099)
$\Delta lngdp_{i,t-1}$	0.369***	0.402***	0.211**	0.232
	(0.063)	(0.057)	(0.094)	(0.145)
$\Delta theil_{i,t-1}$	-0.055	0.288**	-0.292	-0.249
	(0.101)	(0.127)	(0.261)	(0.646)
$lnhyrav_{i,t-1}$	-0.018	-0.129***	-0.170	0.174

	(0.029)	(0.033)	(0.136)	(0.283)
$lnhyrav_{i,t-2}$	-0.005	-0.080**	0.091	-0.181
	(0.027)	(0.033)	(0.152)	(0.282)
$\Delta lninvest_{i,t-1}$	0.016	0.074*	0.0381	-0.181**
	(0.027)	(0.035)	(0.035)	(0.085)
$\Delta lninvest_{i,t-2}$	0.065***	0.075***	0.121***	0.170**
	(0.011)	(0.019)	(0.032)	(0.080)
constant	0.075	0.359***	0.183	0.056
	(0.059)	(0.072)	(0.196)	(0.146)
Hansen test				7.56
				(0.182)
AR(1)				-2.15**
				(0.032)
AR(2)				0.032
				(0.273)

Note: Equation (4.5) is estimated for 1990-2003 with m=1 and n=2.
***, ** and * represent the significance level of 1%, 5% and 10% respectively.
Standard errors are reported in brackets except for the diagnostic tests. For Hansen test, AR(1) and AR(2) tests, p values are reported in the brackets.

Table 4-23 presents the results of the error correction model with Δlngdp as the dependent variable. Compared with table 4-9 which shows the results estimated with Gini coefficient, table 4-23 has generated robust results. In general, inequality and growth are insignificantly connected in the short-run, with only the second model showing a significantly positive coefficient.

Similar to table 4-9, it can be concluded from table 4-23 that the average years of schooling does not significantly influence growth, while physical capital is a contributor of economic growth.

Table 4-24. Panel VECM 1990-2003 (with Theil index; dependent variable: Δtheil)

	Fe-ols D&K Fe-ols D&K	Fmols/ Fe-ols D&K	MG/MG	Fe-ols D&K/ GMM
Depvar.				
Δtheil				
$ECT_{i,t-1}$	0.006	0.017***	0.001	0.047
	(0.009)	(0.004)	(0.017)	(0.060)
$\Delta lngdp_{i,t-1}$	-0.110***	-0.057***	-0.196***	-0.049
	(0.010)	(0.014)	(0.049)	(0.108)
$\Delta theil_{i,t-1}$	0.182***	0.325***	-0.088	0.300*
	(0.054)	(0.043)	(0.116)	(0.172)
$lnhyrav_{i,t-1}$	-0.052**	-0.035*	-0.031	0.068
	(0.019)	(0.019)	(0.050)	(0.069)
$lnhyrav_{i,t-2}$	0.0241	0.034**	-0.026	-0.147
	(0.018)	(0.015)	(0.050)	(0.129)
$\Delta lninvest_{i,t-1}$	0.042***	0.046***	0.039**	0.104**
	(0.009)	(0.007)	(0.018)	(0.050)
$\Delta lninvest_{i,t-2}$	0.006	0.008	0.016	0.019
	(0.009)	(0.008)	(0.024)	(0.038)
Constant	0.060*	0.023	0.120***	0.143
	(0.029)	(0.032)	(0.043)	(0.108)
Hansen test				8.83
				(0.116)
AR(1)				-3.16***
				(0.002)
AR(2)				1.48
				(0.138)

Note: Equation (4.6) is estimated for 1990-2003 with m=1 and n=2. ***, ** and * represent the significance level of 1%, 5% and 10% respectively. Standard errors are reported in brackets except for the diagnostic tests. For Hansen test, AR(1) and AR(2) tests, p values are reported in the brackets.

Table 4-24 presents robust results compared to table 4-10, showing that economic growth can reduce income disparity in the short term during 1990-2003. Human capital does not have a significant impact on inequality, while physical capital can widen the income gap.

Table 4-25. Long-run coefficients 2003-2017 (with Theil index)

03-17	Fe-ols D&K/ Fe-ols D&K	Fmols/ Fe-ols D&K	MG/MG
theil	-3.786***	-6.910***	-4.837***
	(0.541)	(0.167)	(1.065)
constant	8.321***	8.567***	8.371***
	(0.048)	(0.010)	(0.092)

Note: equation (4.1) is estimated for 2003-2017. ***, ** and * represent the significance level of 1%, 5% and 10% respectively.

The long-run relationship between Theil index and growth is negative during 2003-2017 according to table 4-25, which is robust to the relationship between Gini coefficient and growth.

Table 4-26. Panel VECM 2003-2017 (with Theil index; dependent variable: Δlngdp)

03-17	Fe-ols D&K/ Fe-ols D&K	Fmols/ Fe-ols D&K	MG/MG	Fe-ols D&K/ GMM
Depvar. Δlngdp				
$ECT_{i,t-1}$	-0.084**	-0.013	0.072	0.156
	(0.035)	(0.028)	(0.143)	(0.147)
$\Delta lngdp_{i,t-1}$	0.056	0.016	-0.520*	-0.290
	(0.217)	(0.224)	(0.304)	(0.177)
$\Delta lngdp_{i,t-2}$	-0.176*	-0.234**	-0.520***	-0.485**
	(0.085)	(0.091)	(0.177)	(0.213)
$\Delta theil_{i,t-1}$	0.251	0.342	1.002	1.891**
	(0.307)	(0.333)	(1.768)	(0.777)
$\Delta theil_{i,t-2}$	1.207***	1.183***	1.889	1.740
	(0.257)	(0.265)	(1.416)	(1.126)
$lnhyrav_{i,t-1}$	0.064	0.007	0.097	0.0730

	(0.093)	(0.083)	(0.307)	(0.383)
$lnhyrav_{i,t-2}$	-0.276*	-0.274**	-0.649***	-0.567**
	(0.126)	(0.123)	(0.244)	(0.253)
$\Delta lninvest_{i,t-1}$	0.016	0.009	-0.129	-0.054
	(0.027)	(0.027)	(0.152)	(0.057)
$\Delta lninvest_{i,t-2}$	0.033	0.022	0.016	-0.029
	(0.049)	(0.047)	(0.099)	(0.058)
constant	0.482***	0.604***	1.304***	1.118**
	(0.137)	(0.134)	(0.458)	(0.458)
Hansen test				21.53
				(0.203)
AR(1)				-2.50**
				(0.012)
AR(2)				-0.10
				(0.922)

Note: Equation (4.5) is estimated for 2003-2017 with m=2 and n=2.
***, ** and * represent the significance level of 1%, 5% and 10% respectively. Standard errors are reported in brackets except for the diagnostic tests. For Hansen test, AR(1) and AR(2) tests, p values are reported in the brackets.

Table 4-26 shows a positive impact of Theil index on growth, a negative impact of human capital and an insignificant impact of physical capital, which is robust to the results estimated with Gini coefficient presented in table 4-13.

Table 4-27. Panel VECM 2003-2017 (with Theil index; dependent variable: Δtheil)

	Fe-ols D&K/ Fe-ols D&K	Fmols/ Fe-ols D&K	MG/MG	Fe-ols D&K/ GMM
Depvar. theil				
$ECT_{i,t-1}$	-0.042***	-0.032***	-0.101***	-0.043***
	(0.007)	(0.005)	(0.020)	(0.015)
$\Delta lngdp_{i,t-1}$	0.038**	0.039***	0.130***	-0.060
	(0.014)	(0.011)	(0.030)	(0.045)

$\Delta lngdp_{i,t-2}$	0.015	0.018	0.095***	0.042
	(0.017)	(0.017)	(0.028)	(0.035)
$\Delta theil_{i,t-1}$	0.136*	0.172**	-0.108	0.018
	(0.073)	(0.061)	(0.175)	(0.099)
$\Delta theil_{i,t-2}$	-0.017	0.038	0.082	-0.025
	(0.033)	(0.036)	(0.186)	(0.062)
$lnhyrav_{i,t-1}$	-0.009	-0.025***	0.025	0.012
	(0.009)	(0.006)	(0.039)	(0.034)
$lnhyrav_{i,t-2}$	0.007	-0.009	-0.022	-0.035
	(0.015)	(0.012)	(0.035)	(0.034)
$\Delta lninvest_{i,t-1}$	-0.0004	-0.0005	0.028	-0.066**
	(0.004)	(0.003)	(0.019)	(0.028)
$\Delta lninvest_{i,t-2}$	0.002	0.001	0.006	0.010
	(0.005)	(0.005)	(0.015)	(0.023)
Constant	-0.001	0.072***	-0.024	0.049
	(0.024)	(0.023)	(0.077)	(0.049)
Hansen test				22.77
				(0.157)
AR(1)				-1.78*
				(0.075)
AR(2)				0.27
				(0.791)

Note: Equation (4.6) is estimated for 2003-2017 with m=2 and n=2.
***, ** and * represent the significance level of 1%, 5% and 10% respectively. Standard errors are reported in brackets except for the diagnostic tests. For Hansen test, AR(1) and AR(2) tests, p values are reported in the brackets.

Table 4-27 also presents robust results as table 4-14. To summarize, the results estimated with Theil index are robust to those estimated with Gini index.

4.7.2. Robustness check with urban-rural income ratio (ineq) as the inequality measurement

From table 4-28 below it can be seen that similar to table 4-6, the FE-OLS estimator generates insignificant inequality and growth nexus for 1990-2017, but FMOLS and MG estimator exhibits significantly positive coefficients that are different from previous results. Considering that urban-rural Gini coefficient and urban-rural income ratio contain different information about inequality, the minor difference in the results are acceptable.

Table 4-28. Long-run coefficients 1990-2017 (with ineq)

1990-2017	FE-OLS D&K SE	FMOLS	MG
ineq	0.176	0.536**	0.258***
	(0.190)	(0.216)	(0.06)
constant	7.239***	6.788***	7.109***
	(0.590)	(0.481)	(0.142)

Note: Equation (4.1) is estimated. ***, ** and * represent the significance level of 1%, 5% and 10% respectively.

Table 4-29. Long-run coefficients 1990-2003 (with ineq)

90-03	Fe-ols D&K Fe-ols D&K	Fmols/ Fe-ols D&K	MG/MG
ineq	0.265*	1.050***	0.265*
	(0.134)	(5.91e-07)	(0.134)
constant	6.808***	5.550***	6.808***
	(0.413)	(1.26e-06)	(0.413)

Note: equation (4.1) is estimated for 1990-2003. ***, ** and * represent the significance level of 1%, 5% and 10% respectively.

Table 4-30. Panel VECM 1990-2003 (with ineq; dependent variable: Δlngdp)

Depvar. Δlngdp	Fe-ols D&K/ Fe-ols D&K	Fmols/ Fe-ols D&K	MG/MG	Fe-ols D&K/ GMM
$ECT_{i,t-1}$	-0.238***	-0.059***	-0.232***	-0.147
	(0.022)	(0.009)	(0.036)	(0.178)
$\Delta lngdp_{i,t-1}$	0.386***	0.404***	0.258***	0.439
	(0.063)	(0.054)	(0.092)	(0.306)
$\Delta ineq_{i,t-1}$	-0.008	0.021*	-0.017	0.0004
	(0.008)	(0.011)	(0.019)	(0.034)
$lnhyrav_{i,t-1}$	0.024	-0.113**	-0.117	-0.106
	(0.028)	(0.044)	(0.146)	(0.681)
$lnhyrav_{i,t-2}$	0.0083	-0.089**	0.058	0.131
	(0.029)	(0.038)	(0.164)	(0.805)
$\Delta lninvest_{i,t-1}$	0.006	0.071*	0.019	0.039
	(0.024)	(0.034)	(0.036)	(0.193)
$\Delta lninvest_{i,t-2}$	0.065***	0.075***	0.139***	0.169
	(0.014)	(0.022)	(0.038)	(0.111)
constant	-0.073	0.353***	0.179	-0.013
	(0.063)	(0.068)	(0.201)	(0.198)
Hansen test				6.83
				(0.234)
AR(1)				-2.66***
				(0.008)
AR(2)				-0.22
				(0.822)

Note: Equation (4.5) is estimated for 1990-2003 with m=1 and n=2.
***, ** and * represent the significance level of 1%, 5% and 10% respectively. Standard errors are reported in brackets except for the diagnostic tests. For Hansen test, AR(1) and AR(2) tests, p values are reported in the brackets.

Table 4-31. Panel VECM 1990-2003 (with Ineq; dependent variable: ΔIneq)

	Fe-ols D&K Fe-ols D&K	Fmols/ Fe-ols D&K	MG/MG	Fe-ols D&K/ GMM
Depvar.				
ΔIneq				
$ECT_{i,t-1}$	0.093	0.206***	-0.205	0.834
	(0.118)	(0.0528)	(0.244)	(0.554)
$\Delta lngdp_{i,t-1}$	-1.33***	-0.837***	-2.533***	-0.439
	(0.144)	(0.186)	(0.470)	(1.254)
$\Delta ineq_{i,t-1}$	0.236***	0.354***	-0.153	0.378**
	(0.064)	(0.0566)	(0.113)	(0.147)
$lnhyrav_{i,t-1}$	-0.446*	-0.285	0.367	0.754
	(0.216)	(0.227)	(0.677)	(1.399)
$lnhyrav_{i,t-2}$	0.073	0.168	-0.813	-1.869
	(0.198)	(0.192)	(0.603)	(1.489)
$\Delta lninvest_{i,t-1}$	0.440***	0.458***	0.213	1.294***
	(0.098)	(0.0875)	(0.133)	(0.433)
$\Delta lninvest_{i,t-2}$	0.006	0.0289	-0.115	0.408
	(0.067)	(0.0643)	(0.251)	(0.382)
Constant	0.791*	0.449	1.019	2.014**
	(0.402)	(0.475)	(0.742)	(0.813)
Hansen test				6.40
				(0.270)
AR(1)				-3.01***
				(0.003)
AR(2)				0.64
				(0.524)

Note: Equation (4.6) is estimated for 1990-2003 with m=1 and n=2. ***, ** and * represent the significance level of 1%, 5% and 10% respectively. Standard errors are reported in brackets except for the diagnostic tests. For Hansen test, AR(1) and AR(2) tests, p values are reported in the brackets.

Table 4-29 to table 4-31 present long run and short run relationship between inequality and growth during 1990-2003. The results are robust between the models estimated with two different inequality measurements, *gini* and *ineq*.

Table 4-32. Long-run coefficients 2003-2017 (with ineq)

90-03	Fe-ols D&K Fe-ols D&K	Fmols/ Fe-ols D&K	MG/MG
ineq	-0.326***	-0.466***	-0.344***
	(0.045)	(0.0612)	(0.0784)
constant	8.862***	9.234***	8.946***
	(0.106)	(0.142)	(0.237)

Note: equation (4.1) is estimated for 1990-2003. ***, ** and * represent the significance level of 1%, 5% and 10% respectively.

Table 4-33. Panel VECM 2003-2017 (with ineq; dependent variable: Δlngdp)

03-17	Fe-ols D&K/ Fe-ols D&K	Fmols/ Fe-ols D&K	MG/MG	Fe-ols D&K/ GMM
Depvar. Δlngdp				
$ECT_{i,t-1}$	-0.087**	-0.048	0.091	0.057
	(0.036)	(0.030)	(0.107)	(0.070)
$\Delta lngdp_{i,t-1}$	0.059	0.042	-0.469**	-0.178
	(0.215)	(0.220)	(0.216)	(0.117)
$\Delta lngdp_{i,t-2}$	-0.192**	-0.218**	-0.619***	-0.386**
	(0.086)	(0.088)	(0.134)	(0.167)
$\Delta theil_{i,t-1}$	0.021	0.024	0.093	0.167**
	(0.020)	(0.021)	(0.071)	(0.067)
$\Delta theil_{i,t-2}$	0.060***	0.061***	0.137	0.147*
	(0.013)	(0.013)	(0.085)	(0.084)
$lnhyrav_{i,t-1}$	0.068	0.029	0.135	0.303
	(0.096)	(0.092)	(0.205)	(0.361)
$lnhyrav_{i,t-2}$	-0.289**	-0.300**	-0.692***	-0.706**
	(0.124)	(0.124)	(0.190)	(0.295)
$\Delta lninvest_{i,t-1}$	0.014	0.011	-0.048	-0.027

	(0.027)	(0.028)	(0.120)	(0.036)
$\Delta lninvest_{i,t-2}$	0.035	0.029	0.041	0.013
	(0.049)	(0.048)	(0.069)	(0.048)
constant	0.499***	0.609***	1.300***	0.910**
	(0.125)	(0.128)	(0.421)	(0.387)
Hansen test				23.69
				(0.128)
AR(1)				-2.85***
				(0.004)
AR(2)				-0.10
				(0.922)

Note: Equation (4.5) is estimated for 2003-2017 with m=2 and n=2. ***, ** and * represent the significance level of 1%, 5% and 10% respectively. Standard errors are reported in brackets except for the diagnostic tests. For Hansen test, AR(1) and AR(2) tests, p values are reported in the brackets.

Table 4-34. Panel VECM 2003-2017 (with ineq; dependent variable: Δineq)

	Fe-ols D&K/ Fe-ols D&K	Fmols/ Fe-ols D&K	MG/MG	Fe-ols D&K/ GMM
Depvar. ineq				
$ECT_{i,t-1}$	-0.582***	-0.547***	-1.065***	-0.542***
	(0.066)	(0.064)	(0.320)	(0.209)
$\Delta lngdp_{i,t-1}$	0.542**	0.559**	0.998**	-0.018
	(0.225)	(0.205)	(0.434)	(0.463)
$\Delta lngdp_{i,t-2}$	0.095	0.167	1.113***	0.920***
	(0.234)	(0.239)	(0.376)	(0.338)
$\Delta theil_{i,t-1}$	0.024	0.042	-0.175	0.079
	(0.084)	(0.076)	(0.131)	(0.082)
$\Delta theil_{i,t-2}$	-0.055	-0.022	-0.026	0.082
	(0.043)	(0.045)	(0.181)	(0.067)
$lnhyrav_{i,t-1}$	-0.020	-0.112	0.391	0.287

	(0.134)	(0.099)	(0.649)	(0.618)
$lnhyrav_{i,t-2}$	0.040	-0.103	-0.291	0.370
	(0.245)	(0.215)	(0.411)	(0.644)
$\Delta lninvest_{i,t-1}$	-0.041	-0.044	-0.193	-0.737***
	(0.052)	(0.047)	(0.304)	(0.260)
$\Delta lninvest_{i,t-2}$	0.014	0.014	-0.040	0.289
	(0.062)	(0.058)	(0.224)	(0.217)
Constant	-0.085	0.434	-0.437	-1.406
	(0.418)	(0.382)	(1.175)	(0.916)
Hansen test				18.91
				(0.334)
AR(1)				-2.79***
				(0.005)
AR(2)				0.19
				(0.849)

Note: Equation (4.6) is estimated for 2003-2017 with m=2 and n=2. ***, ** and * represent the significance level of 1%, 5% and 10% respectively. Standard errors are reported in brackets except for the diagnostic tests. For Hansen test, AR(1) and AR(2) tests, p values are reported in the brackets.

As shown in table 4-32 to table 4-34, the empirical results between 2003 and 2017 are also generally robust with those in section 4.5. To conclude, this section does robustness check with two different income disparity measurements, Theil and Ineq. The analysis done with both measurements have generated robust results to those estimated with Gini.

4.8. Conclusion

The research of Kuznets in 1955 first analyses the evolution of income disparity during the course of economic development. Since then, the relationship between economic growth and income inequality has been evaluated, both in theoretical and empirical studies. Even though there have been heated discussions on the growth and inequality nexus, no consensus has yet been reached so far. This chapter has explored this topic in the context of China, as a country with a unique economic background. Since the economic reform in 1978, the country has experienced the transition from a planned economy to a market economy, and the high growth rate has been accompanied by a high level of inequality. The empirical research presented in this chapter to investigate the long- and short- term connection between inequality and growth in China, the influence of human and physical capital on growth and inequality, and the role of human capital on each level.

The empirical study applied panel VECM to examine the inequality and growth nexus in both directions, thereby improving on previous studies that usually focus on only one direction, either from growth to inequality in earlier research or from inequality to growth in later studies. Various estimators such as FE-OLS with Driscoll-Kraay SE, FMOLS, MG and GMM were applied. Most results show insignificant connections between inequality and growth in the period from 1990 to 2017. The analysis was conducted for two time periods, before and after the turning point of inequality in 2003.

The results of the research support Kuznets curve (Kuznets, 1955) as the long-term relationship between income inequality and growth is positive before 2003 and negative afterwards. In the short term, there is weak evidence to show a positive impact of inequality on growth before 2003, and half of the results show that inequality positively affects growth after 2003, supporting the findings of Forbes (2000) that inequality positively influences growth in the short term. The results also show that compared with human capital, physical capital plays a more important role in China's economic growth, as average human capital affected growth insignificantly before 2003 and negatively after, while physical capital improved economic growth in both time periods. In the short term, growth narrowed the income gap before 2003 and widened the income gap after that year. The average years of schooling did not significantly affect inequality in the two periods, while physical capital enlarged the income gap before 2003, which is consistent with the findings of Chen (2007), and affected inequality insignificantly after 2003.

According to the panel VECM estimated with decomposed human capital, in the first period of time, medium human capital boosted economic growth in the short term, but basic and advanced human capital harmed growth. It was also found that basic and medium human capital reduced income inequality before 2003, while advanced human capital widened the gap. During the second period, basic human capital promoted growth, while medium human capital harmed growth and advanced human capital had no significant effect. The insignificant or negative connection between human capital and income growth is due to the fact that human capital could take longer show its effect on growth, and is not reflected by the short-term coefficients. Also, regarding the quality of education, the skills and knowledge provided by schools and universities can be quickly outdated in view of the fast economic development and technological upgrades; thus education should be updated more frequently. In addition, more emphasis should be given to practical knowledge targeting the needs of the market.

The findings of the empirical research are highly robust across various estimators, model specifications and measurements of income inequality.

As suggested in the Granger causality test, before 2003, inequality and growth Granger-causes each other, and both are granger caused by physical capital as well as human capital on three levels. The results after 2003 are similar, except that physical capital does not Granger-cause inequality in this period. Besides, the evidence that growth Granger-causes inequality is weaker than that that showing how inequality leads to growth.

As for suggestions on policies, because inequality and growth are negatively related over the long term since 2003, China should continue making efforts to alleviate income disparity, especially the urban-rural disparity, in order to improve the economy in the long term. This can be achieved by accelerating urbanisation, applying more balanced resource allocation between urban and rural areas and supporting poor families in rural areas. Furthermore, as the influence of human capital on growth is much less than that of physical capital, there is great potential for human capital to enhance growth. In order to enable human capital to play a more important role in growth, the government can raise its expenditure on education and provide more student loans; universities and schools can place more emphasis on innovation and practical knowledge and need to update their teachings in accordance to market needs; and vocational education that focuses on practical skills should be encouraged.

Briefly, the empirical study in this chapter has investigated the growth-inequality nexus in China with the influence of human and physical capital using panel VECM. The chapter has also compared the empirical findings with those in previous literature and given suggestions on policies. While this chapter examines the direct impact of inequality on growth, the next chapter will test the effect of inequality on growth through different channels. The empirical study presented in the next chapter, will be based on the unified growth theory developed by Galor and Moav (2004), which combines the classical and credit market imperfections approaches.

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Appendix 4-A. Hausman test

	FE	RE
Gini	0.435	-0.326
Constant	7.586	7.754
Chi-square=40.86***		

Note: H_0: RE is more consistent. ***, ** and * represent the significance level of 1%, 5% and 10% respectively. The dependent variable is lngdp.

Appendix 4-B. Selection of optimal lag (1990-2017)

Lag	MAIC	MBIC	MQIC
1	93.333	25.582	66.770
2	6.406*	-44.407*	-13.516*
3	22.352	-11.523	9.071
4	-3.808	-20.746	-10.449

Note: * denotes the optimal lag with the minimum value of each criterion. The lag with the minimum MMSC-Akaike's information criterion (MAIC), MMSC-Bayesian information criterion (MBIC) and MMSC-Hannan and Quinn information criterion (MQIC) is selected as the optimal lag.

Appendix 4-C. Selection of optimal lag (1990-2003)

Lag	MAIC	MBIC	MQIC
1	-9.827	-49.824*	-25.956*
2	-13.032*	-43.03	-25.129
3	-11.799	-31.797	-19.863
4	-4.906	-14.905	-8.938

Note: * denotes the optimal lag with minimum value of each criterion. The lag with the minimum MMSC-Akaike's information criterion (MAIC), MMSC-Bayesian information criterion (MBIC) and MMSC-Hannan and Quinn information criterion (MQIC) is selected as the optimal lag.

Appendix 4-D. Selection of optimal lag (2003-2017)

Lag	MAIC	MBIC	MQIC
1	7.297	-40.873	-12.273
2	-14.887*	-51.015*	-29.565*
3	-8.371	-32.456	-18.156
4	-6.719	-18.761	-11.611

Notes: * denotes the optimal lag with minimum value of each criterion. The lag with the minimum MMSC-Akaike's information criterion (MAIC), MMSC-Bayesian information criterion (MBIC) and MMSC-Hannan and Quinn information criterion (MQIC) is selected as the optimal lag.

Chapter 5. China's inequality-growth nexus and the underlying mechanisms

5.1. Introduction

How inequality and growth are connected is a long standing question. Since the pioneering work of Kuzents (1955), the inequality-growth relationship has been explored by both theoretical and empirical studies, but the relationship between the two still remains inconclusive. As mentioned in the literature review chapter, most of the theoretical studies argue that inequality has a negative impact on growth. For example, researchers such as Perotti (1993), Alesina and Rodrik (1994) and Barro (2000) find that inequality harms growth through the political economy channel; Galor and Zeira (1993) and Banerjee and Newman (1993) conclude that a higher inequality leads to a lower growth through the credit market imperfection channel; Acemoglu and Robinson (2001), Keefer and Knack (2002) as well as Alesina and Perotti (1996) investigate the socio-political instability channel through which inequality impedes economic growth. By contrast, the classical channel, or the savings channel, argues that inequality can stimulate growth by increasing the savings and capital accumulation (Kaldor, 1956). Regarding the empirical studies, the results are mixed. Some researchers find that inequality harms growth, such as Alesina and Rodrik (1994), Frank (2009b) and Ostry et al. (2014), while some announce a favourable effect of inequality on growth (Forbes, 2000; Li and Zou, 1998), and some point out that the inequality-growth relationship is nonlinear (Benos and Karagiannis, 2018; Barro, 2000).

Although plenty of studies investigate the inequality-growth relationship, few of the empirical studies are conducted with a strong theoretical framework to investigate the mechanisms behind the relationship. The studies that do test the theoretical mechanisms mainly focus on a single mechanism. The theoretical mechanisms are not mutually exclusive, however, meaning that inequality can affect growth through different channels at the same time. Due to the offsetting effects of different channels, how inequality and growth are connected still remains unclear (Barro, 2000). Different from the previous studies, the unified growth theory developed by Galor and Moav (2004) merges the classical theory and the credit market imperfections theory, arguing that inequality has different effects on growth throughout the process of economic development. In the early stage of industrialisation, physical capital is the main stimulator of economic growth, hence inequality mainly affects growth through the classical channel; while in the later stage, human capital replaces physical capital to be the main engine of economic growth. Inequality therefore affects growth mainly through the credit market imperfections channel. Unlike many previous studies that consider only a single channel, the unified growth theory explores the inequality-growth nexus in a more comprehensive way by weaving together the classical and the credit market imperfections channels. Thus, inspired by the unified growth theory, this chapter will present an empirical model in which both the classical and credit market imperfections channels will be investigated.

This chapter aims to shed light on three research questions: i) How is economic growth affected by inequality, and by physical and human capital in China, both in the long- and the short-term? ii) What are the mechanisms behind the inequality-growth relationship? iii) How does the relationship vary across different provinces in China?

While the last chapter adopted panel VECM to examine the relationship between inequality and growth in China, this chapter will first revisit the inequality-growth relationship by adopting the panel autoregressive distributed lag model (panel ARDL). Specifically, the previous chapter focused on the long- and short-term causality effects between inequality and growth in both directions, with both inequality and growth as the endogenous variables, and human and physical capital as the exogenous variables. The long-term effects of human capital and physical capital on growth were not tested in the previous chapter. This chapter uses the dynamic models to explore the one-directional effects of inequality, and of physical and human capital on growth, in both the long- and the short-term. After examining the relationship between the variables, this chapter will present a model with two interaction terms in order to investigate the theoretical mechanisms through which inequality affects growth. The chapter will also split the whole sample into three subsamples according to their levels of development, in order to see how the inequality-growth nexus varies during the process of development.

This chapter makes four main contributions: First, it uses panel ARDL models to test the relationship between inequality and growth. The models can predict the long-term coefficients even when the variables have mixed orders of integration (a mixture of I(1) and I(0), but not I(2)). Second, further to the inequality-growth nexus, this chapter combines and examines two mechanisms (the classical and the credit market mechanisms) through which inequality affects growth in China, with the inspiration of the unified growth theory. As mentioned earlier, many previous empirical studies have examined the connection between inequality and growth without focusing on the theoretical mechanisms behind the connection, and even fewer studies have combined different mechanisms in one model. The combination of the classical and the credit market imperfections mechanisms has not been tested by many studies, and even less so in a single country framework. Only Benos and Karagiannis (2018) have tested the unified growth theory using state-level data in the US. This chapter not only investigates the two empirical mechanisms behind the inequality-growth nexus, but also conducts the research using provincial level data of China from 1990 to 2017, thereby allowing for better data comparability. Third, the study in this chapter investigates how the inequality-growth relationship changes for the provinces in different development stages. As mentioned in Chapter 3, the development is unbalanced among the provinces in China. Thus, it is important to conduct the research in subsamples. By splitting the whole sample into three subsamples with the highest, medium and lowest per capita GDP, the study tests which development stage each subsample is in, and explores how the inequality-growth relationship evolves through different economic development stages. In addition, based on the empirical results, the chapter provides policy implications that specifically target each subsample. Last but not least, the study in this chapter is conducted using provincial-level data within China. As mentioned in the literature review chapter, most of the previous studies were conducted in an international framework, and therefore suffer from data incomparability, cross-country heterogeneity and sample selection issues. By using provincial level data, this study alleviates the bias caused by such issues, due to better data comparability and slope homogeneity.

The remainder of the chapter is arranged as follows: Section 5.2 reviews the classical and credit market imperfections channels as well as the arguments of unified growth theory. Section 5.3 discusses the research methods. Two models are constructed in this section. Specifically, the first model is a four-variable model constructed to test the inequality-growth nexus, and the second, six-variable model with two interaction terms will be used to test the mechanisms of the inequality-growth connection. Section 5.4 presents the descriptive statistics for the whole sample and three subsamples. Section 5.5 provides the empirical results estimated by the panel ARDL approach. The robustness check with different inequality measurements is presented in section 5.6. Lastly, section 5.7 concludes the chapter.

5.2. Two mechanisms in the unified growth theory

Proposed by Galor and Moav (2004), the unified growth theory combines the classical theory and the credit market imperfections theory. Specifically, the classical theory argues that inequality is beneficial for growth. People with high incomes have a higher marginal propensity to save, thus inequality can encourage the accumulation of savings and investments, and therefore promote economic growth. On the other hand, the credit market imperfections theory states that due to the credit constraints on the poor, inequality limits people's investments in human capital, thus hindering economic growth, whereas a more equal income distribution is helpful in human capital accumulation, and hence enhances economic growth.

The fundamental hypothesis of the unified growth theory is that human capital and physical capital accumulation are asymmetric. During the accumulation of human capital, its return diminishes on the individual level, due to the physiological constraints. As a result, the total amount of human capital is maximised when it is widely spread among individuals. In contrast, the aggregate productivity of physical capital is unlikely to be affected by its distribution among individuals. Thus, equality is beneficial for human capital accumulation when credit constraints exist, as in a more unequal society. Fewer people have access to education in the presence of credit constraints, whereas inequality favours the accumulation of physical capital due to the higher marginal propensity to save among the rich (Galor and Moav, 2004).

The theory states that the effect of inequality on growth changes in different phases of economic development and argues that physical capital is gradually replaced by human capital as the prime growth stimulator during the process of development. Specifically, in the initial stage of development when the marginal return on physical capital is high due to the scarcity of physical capital, the inequality-growth nexus is dominated by the classical mechanism. Due to the higher marginal propensity of rich people to save, inequality encourages growth through physical capital. While in a more developed economy, the rate of return on physical capital gets lower with a rising capital-labour ratio, while the return on human capital rises because of capital-skill complementarity. As a result, human capital gradually replaces physical capital to be the prime booster of economic growth, and the credit market imperfections channel dominates the inequality-growth nexus. Thus, inequality has a negative impact on growth in this stage. In the final stage of development when income increases to the level that credit constraints are no longer binding and human capital is optimal, inequality no longer has an influence on growth.

An important advantage of the research of Galor and Moav (2004) is that it merges the classical and credit market imperfections mechanisms into one model. Specifically, inequality can affect growth through different channels at the same time, and the channels are not mutually exclusive, thus inequality can affect growth through various channels at the same time (Barro, 2000). This fact is neglected by many of the previous studies, which concentrate only on a single channel, however. In this sense, merging the classical and credit market imperfections mechanisms can better test the inequality-growth nexus. As mentioned in the literature review chapter, the empirical studies to examine the unified growth theory are mainly based on cross-country data (Khalifa and El Hag, 2010; Chambers and Krause, 2010). While Benos and Karagiannis (2018) examine the theory in a single country framework, the research is conducted in the context of the US. Apart from the above studies, few others test the inequality-growth relationship, assuming that inequality affects growth through the classical channel and credit market imperfections channel at the same time. Thus, inspired by the unified growth theory, the work in this chapter aims to fill the gap in previous studies by investigating the inequality-growth nexus through both channels in the context of China, using provincial level data between 1990 and 2017.

5.3. Research methods

To estimate the long- and short-term relationship between income inequality, human capital, physical capital and economic growth, two empirical models are built in this chapter. In the four-variable model, the coefficients are estimated to explore the independent variables' impacts on growth. Based on this model, the six-variable model adds two interaction terms, designed to examine the two theoretical mechanisms adopted by the unified growth theory. After both models are used to estimate the results for the whole sample (including 30 provinces of China), there will be estimations in the subsamples with the highest, medium and the lowest per capita GDP. After analysing and comparing the results of each subsample, the study will provide policy implications for each subsample.

When estimating the models, the panel autoregressive distributed lag (panel ARDL) approach proposed by Pesaran and Smith (1995), which deals with slope heterogeneity and data non-stationarity issues, is adopted. Regarding the estimators, both the fixed effects (FE) estimator and the mean group (MG) estimators are used, similar to in the last chapter. For the FE estimator, the intercept varies across the provinces and the slope of each province is identical, while the MG estimator assumes that the slope coefficient varies across different provinces.

5.3.1. Data and variables

Similar to in the last chapter, the first model includes economic growth (*lngdp*), income inequality (*gini*), human capital (*lnhyrav*) and physical capital (*lninvest*) variables. The dependent variable, *lngdp*, is the natural logarithm of the per capita real GDP of each province, similar to the use of GDP in its level form in previous inequality-growth relationship research (Herzer and Vollmer, 2012; Simões, 2012; Risso et al., 2013). The other variables are independent, with *gini* representing the urban-rural Gini coefficient of each province, *lninvest* as the natural logarithm of fixed asset investment and GDP ratio and *lnhyrav* as the natural logarithm of the average years of schooling. The measurement and calculation of each variable are already given in Chapter 3.

In the second model, in addition to *lngdp, gini, lninvest* and *lnhyrav*, the two further interaction terms *ginilninvest* and *ginilnhyrav* are added, to test the channels through which inequality affects growth. The former interaction term is constructed as *gini* times *lninvest*, to capture the effect of inequality on growth through physical capital based on the classical channel, while the latter interaction term is constructed as *gini* times *lnhyrav*, capturing the impact of inequality on growth through human capital, based on the credit market imperfections channel. By adding both interaction terms to the six-variable model, two theoretical channels are taken into consideration and examined.

In this chapter, the empirical analysis is based on provincial-level data of 30 Chinese provinces covering 28 years, with 840 observations.[7] The data are collected from the National Bureau of Statistics (NBS) and the China Centre for Human Capital and Labour Market Research (CHLR) database.

5.3.2. Panel ARDL model

There are several advantages of using the panel ARDL model. The first is that this approach accounts for many issues, such as slope heterogeneity and data non-stationarity as well as endogeneity. Specifically, by considering slope heterogeneity, the panel ARDL model takes into consideration the potential heterogeneous parameters across the provinces; by allowing for non-stationarity, both I(1) and I(0) variables can be included in the model; the coefficients can also be estimated by the model for both exogenous and endogenous variables (Pesaran and Shin, 1999). The second advantage is that the error correction form of the model (ARDL-ECM) can be used to estimate both the long- and short-term relationship between the independent and dependent variables. Frank (2009), for instance, uses panel ARDL-ECM to investigate the relationship between income inequality and economic growth in the US, with fixed effects (FE), mean group (MG) and pooled mean group (PMG) estimators. Moreover, the statistical significance of the error correction term can reveal whether the variables are cointegrated or not.

The slope heterogeneity issue arises in many cross-country studies because of structural differences among countries. For example, Forbes (2000) and Barro (2000) collect data from countries at different stages of development to investigate the inequality-growth connection, with income inequality, human capital and physical capital variables as the independent variables and economic growth as the dependent variable. These studies estimate the coefficients of inequality by placing developing and developed countries in the same sample as well as assuming that the countries have identical slope coefficients. Such assumptions of strong slope homogeneity across countries ignores the possibility that the coefficients vary across countries due to structural differences, however, and may lead to omitted variable bias. As stated by Pesaran and Smith (1995), ignoring cross-sectional heterogeneity can result in misleading results for the dynamic model.

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[7] Shanghai is not included in the 30 provinces due to the unavailability of the data used to calculate Gini and Theil coefficients. However, in the robustness check with different inequality measurements, Shanghai is included when *ineq* is used as the inequality measurement.

The issue of cross-sectional heterogeneity is addressed by adopting panel ARDL, a dynamic heterogeneous panel data model. In addition, by using the provincial-level data of China, the study in this chapter alleviates the cross-country heterogeneity issue, as data within a single country has greater comparability and homogeneity than international data (Frank, 2009).

Regarding the data non-stationarity issue, the panel ARDL approach is applicable when the variables are I(0) or I(1), or a mixture of both (Pesaran and Smith, 1995; Pesaran, 1997; Pesaran and Shin, 1999). Besides, the model can be used regardless of whether the variables are endogenous or exogenous.

Specifically, the standard panel ARDL (p,q) model can be written as below:

$$lngdp_{i,t} = \sum_{j=1}^{p} \lambda_{i,j} lngdp_{i,t-j} + \sum_{j=0}^{q} \delta'_{i,j} \boldsymbol{X}_{i,t-j} + \varepsilon_{i,t} \tag{5.1}$$

where the number of the provinces i = 1, 2,…, N; the number of years t = 1,2,…, T; $lngdp_{i,t}$ is the dependent variable; $\boldsymbol{X}_{i,t}$ stands for all the explanatory variables, and $\boldsymbol{X}_{i,t}$ = $(gini_{i,t}, \ lninvest_{i,t}, \ lnhyrav_{i,t})'$, while in the six-variable model with interaction terms, $\boldsymbol{X}_{i,t}$ = $(gini_{i,t}, \ lninvest_{i,t}, \ lnhyrav_{i,t}, \ ginilninvest_{i,t}, \ ginilnhyrav_{i,t})'$; $\lambda_{i,j}$ are scalars; $\delta_{i,j}$ is a k × 1 coefficient vector; $\varepsilon_{i,t}$ is distributed independently from $\boldsymbol{X}_{i,t}$; p represents the lag length of the dependent variable and q is the lag length of the independent variables.

The error correction form of equation (5.1) is as below:

$$\Delta lngdp_{i,t} = \alpha_i \left(lngdp_{i,t-1} - \theta_i' \boldsymbol{X}_{i,t} \right) + \sum_{j=1}^{p-1} \lambda^*_{i,j} \Delta lngdp_{i,t-j} + \sum_{j=0}^{q-1} \delta'^*_{i,j} \Delta \boldsymbol{X}_{i,t-j} + \varepsilon_{i,t} \tag{5.2}$$

where

$$\alpha_i = -(1 - \sum_{j=1}^{p} \lambda_{i,j})$$

$$\theta_i = \frac{\sum_{j=0}^{q} \delta_{i,j}}{1 - \sum_{j=1}^{p} \lambda_{i,j}}$$

$$\lambda_{i,j}^* = -\sum_{m=j+1}^{p} \lambda_{i,m}$$

$$\delta_{i,j}^* = -\sum_{m=j+1}^{q} \delta_{i,m}$$

The speed of adjustment to the long-run equilibrium between $\boldsymbol{X}_{i,t}$ and $lngdp_{i,t}$ is captured by α_i; θ_i represents the long run coefficients of $\boldsymbol{X}_{i,t}$, while $\lambda_{i,j}^*$ and $\delta_{i,j}^*$ represent the short run coefficients. $\varepsilon_{i,t}$ is the error term. In the equation, the error correction term is $lngdp_{i,t-1} - \theta_i' \boldsymbol{X}_{i,t}$, while α_i, the coefficient of the error correction term, brings the dependent variable back to the equilibrium. In this way, the model can achieve convergence.

When selecting the lag lengths of the dependent and independent variables, p and q, there should be a balance between the number of observations and sufficient lag order, as extending the lag length leads to a loss of observations. Moreover, when estimating the long term coefficients, underestimating the lag length can result in inconsistent results, while too many lags can induce a loss of efficiency (Chudik et al., 2013). Some previous studies adopt the same lag length for all the variables., Chudik et al. (2013), for example, uses the panel ARDL approach to explore the relationship between growth, debt and inflation in a panel of 40 countries in the period between 1965 and 2010 (46 years). The research uses the same lag order for all the variables, and estimates the empirical results with lag order ranges from 1 to 3. Frank (2009), moreover, explores the inequality-growth nexus for the period from 1945 to 2004, using the panel ARDL model, and adopting the same lag length for all the variables, using 1 year's lag for FE, MG and PMG estimators and 3 years' lag for MG and PMG estimators. Cavalcanti et al. (2015) set a maximum lag of 2 in the panel ARDL model to cover 118 countries over 38 years. Following the previous research, the empirical study in this chapter will adopt the same lag order for all the variables. The optimal lag in this study is selected by the Bayesian information criterion (BIC) with the maximum lag of 2. Based on the BIC, the optimal lag for all the variables is 1. In this sense, the lag length of 1 (p = q = 1) is adopted in this research. In addition, lag lengths of 2 and 3 are also reported in order to make comparisons.

5.4. Data description

The whole sample is split into three subsamples based on the average real per capita GDP of each province during 1990-2017.

Table 5-1. Provinces in the subsamples

Top group		Middle group		Bottom group	
Province	Region	Province	Region	Province	Region
Beijing	Eastern	Shandong	Eastern	Shaanxi	Western
Tianjin	Eastern	Shanxi	Central	Hebei	Eastern
Liaoning	Northeastern	Fujian	Eastern	Jiangxi	Central
Zhejiang	Eastern	Hubei	Central	Anhui	Central
Xinjiang	Western	Hunan	Central	Henan	Central
Guangdong	Eastern	Tibet	Western	Yunnan	Western
Ningxia	Western	Jilin	Northeastern	Sichuan	Western
Heilongjiang	Northeastern	Hainan	Eastern	Guangxi	Western
Jiangsu	Eastern	Inner Mongolia	Western	Gansu	Western
Qinghai	Western	Chongqing	Western	Guizhou	Western

Table 5-1 shows the provinces in each subsample and the region each province belongs to. The top group includes 10 provinces with the highest average real per capita GDP for the years 1990–2017. Among the 10 provinces in the top group, five belong to the eastern region, two are from the north-eastern region, three are from the western region, and there is no province from the central region. In the middle group, there are three provinces from the eastern, central and western parts of China and one from the north-eastern part. As for the lower group, six provinces are from the west and only one province is from the east. The results depict imbalanced regional development in China, with the eastern provinces more developed than the other provinces, and the western region less well-developed than other regions.

Table 5-2. Definitions of variables

Variable	Description	Data source
gdp	Real GDP per capita in ten thousand Chinese Yuan (1985 prices)	NBS
gini	Provincial urban-rural Gini index	NBS and CHLR database
theil	Provincial urban-rural Theil index	NBS and CHLR database
ineq	Urban-rural per capita income ratio	NBS
invest	Fixed asset investment/ GDP ratio	NBS
hyrav	Average years of schooling	NBS
ginilninvest	Interaction term of *gini* and *lninvest*	NBS and CHLR database
ginilnhyrav	Interaction term of *gini* and *lnhyrav*	NBS and CHLR database

The definitions of the variables are provided in Table 5-2.

Table 5-3. Descriptive statistics for the whole sample and subsamples

Panel A: Whole sample					
Variables	Mean	Std. Dev.	Min	Max	Observations
gdp	0.247	0.167	0.064	1.472	840
gini	0.221	0.062	0.065	0.389	840
invest	0.542	0.288	0.153	1.597	840
hyrav	7.668	1.474	2.124	12.665	840
Panel B: Subsample of top 10 provinces					
Variables	Mean	Std. Dev.	Min	Max	Observations
gdp	0.364	0.239	0.107	1.472	280
gini	0.183	0.068	0.065	0.317	280
invest	0.536	0.283	0.207	1.597	280
hyrav	8.240	1.473	4.521	12.67	280
Panel C: Subsample of middle 10 provinces					
Variables	Mean	Std. Dev.	Min	Max	Observations
gdp	0.210	0.054	0.090	0.337	280
gini	0.227	0.046	0.134	0.389	280

invest	0.555	0.295	0.167	1.501	280
hyrav	7.488	1.594	2.124	9.862	280
Panel D: Subsample of bottom 10 provinces					
Variables	Mean	Std. Dev.	Min	Max	Observations
gdp	0.166	0.049	0.064	0.271	280
gini	0.253	0.048	0.108	0.364	280
invest	0.536	0.286	0.153	1.399	280
hyrav	7.277	1.144	4.608	9.513	280

The descriptive statistics of the whole sample and three subsamples is shown in Table 5-3. Noticeably, the average Gini coefficient in the top subsample is the lowest among all the subsamples, while the Gini coefficient in the bottom subsample has the highest Gini coefficient. Moreover, the top group has the highest average human capital (*hyrav*), while the bottom group has the lowest average human capital. Meanwhile, the physical capital (*invest*) in the middle group is the highest among the groups.

5.5. Empirical results

5.5.1. Empirical results for the whole sample

The results of panel unit root tests (PURT) are presented in table 5-3.

Table 5-4. Unit root test

	CIPS		IPS		LLC	
Variable	Intercept	Intercept & trend	Intercept	Intercept & trend	Intercept	Intercept & trend
Variables in their level forms						
lngdp	0.320	2.051	1.235	-2.040	0.764	-3.090***
gini	-0.072	-2.285**	-2.554***	-0.451	-2.355***	-0.987
lninvest	1.395	2.921	0.346	-2.311**	2.253	0.986
lnhyrav	-7.957 ***	-7.583 ***	-5.594***	-7.026***	-5.659***	-8.108***
ginilninvest	0.255	0.905	-0.681	-1.643*	-0.542	-0.446
ginilnhyrav	-2.086**	-2.799***	-2.575***	-0.687	-2.336***	-0.424
First-differenced variables						
Δlngdp	-13.173***	-11.190***	-14.35***	-12.714***	-13.517***	-11.757***

Δgini	-19.951***	-18.741***	-21.568***	-19.631***	-18.495***	-14.402***
Δlninvest	-10.222***	-7.539***	-13.582***	-10.182***	-6.833***	-4.602***
Δginilninvest	-12.470***	-10.057***	-16.030***	-12.718***	-12.418***	-9.048***
Δginilnhyrav	-19.985***	-18.783***	-23.016***	-20.986***	-21.452***	-17.954***

Note: H_0: Panel contains unit roots. ***, ** and * represent the significance level of 1%, 5% and 10% respectively. Δ is the first difference operator. Lag selection is based on Akaike information criterion (AIC).

According to Table 5-4 above, the variables are either stationary at levels, or stationary in first differences, namely a mixture of I(1) and I(0). In this sense, panel ARDL model can be used.

Table 5-5. Cointegration test

Panel cointegration test	Intercept	Intercept & trend
Pedroni		
Modified Phillips-Perron t	5.133***	5.120***
Phillips-Perron t	4.492***	2.429***
Augmented Dickey-Fuller t	4.569***	2.951***
Westerlund		
	3.077***	3.250***
Kao		
ADF	2.184**	

Note: H_0: No cointegration between *lngdp, gini, lninvest* and *lnhyrav*. ***, ** and * represent the significance level of 1%, 5% and 10% respectively. Lag selection is based on Akaike information criterion (AIC).

The panel cointegration tests presented by table 5-5 indicates a long term relationship between the variables, as the null hypothesis of no cointegration is rejected at 1% or 5% significance level. With the presence of long run relationship, the error correction model (ARDL-ECM) can be constructed.

Table 5-6. Inequality-growth nexus estimated by panel ARDL-ECM

ARDL-ECM	FE	MG
p=q=1	(1)	(2)
Long run coefficients		
gini	2.260***	4.863***
	(0.500)	(1.407)
lninvest	0.149***	0.536***
	(0.047)	(0.141)
lnhyrav	-0.112	1.325*
	(0.218)	(0.713)
ect	-0.118***	-0.243***
	(0.011)	(0.023)
Short run coefficients		
$\Delta gini_{i,t}$	-0.900***	-1.262***
	(0.123)	(0.133)
$\Delta lninvest_{i,t}$	-0.101***	-0.213***
	(0.013)	(0.022)
$\Delta lnhyrav_{i,t}$	0.074*	0.102
	(0.044)	(0.082)

Note: ***, ** and * represent the significance level of 1%, 5% and 10% respectively.

Table 5-6 presents the long run and short run results estimated by panel ARDL using both FE and MG estimators. According to the BIC, the optimal lag is 1.

In both columns (1) and (2), it can be seen that the coefficients of the error correction terms are negative at the significance of 1%, suggesting the presence of a long-term equilibrium between the dependent and explanatory variables, and the disequilibrium caused by a shock will be corrected. The results from the FE estimator in column (1) show that higher inequality fosters growth in the long term, when the lag is 1. Physical capital also has a significant and positive effect on economic growth, as expected. Meanwhile, human capital exhibits a significant and positive effect on growth according to the MG estimator, and does not affect growth, according to the FE estimator.

In the short term, inequality and physical capital both have a significantly negative effect on growth, while a higher level of human capital can promote growth. Meanwhile, the MG estimator in column (2) generates similar results as column (1), showing that inequality can improve economic growth. As for physical capital, both the FE and MG estimators show that it positively affects growth in the long term, at the significance level of 1%. Regarding human capital, the MG estimator implies a positive effect of human capital on growth as expected, while the FE estimator generates an insignificant coefficient. In the short term, inequality and physical capital both reduce economic growth, while human capital does not have a significant effect on growth. Regarding the magnitude of each coefficient, the absolute value of each coefficient estimated by the MG estimator is larger than that estimated by the FE estimator.

In short, the results generated by both estimators are generally consistent. From the results presented in Table 5-6, it is clear that income inequality enhances economic growth in China in the long term, as both FE and MG estimators yield significantly positive coefficients of inequality. The table also reveals the positive and significant long-term effect of physical capital on growth as expected, and the long-term effect of human capital on growth is significantly positive as suggested by the MG estimation.

Table 5-7. Inequality's effects on growth through different channels estimated by panel ARDL-ECM

panel ARDL-ECM	FE	MG
p=q=1	(1)	(2)
Long run coefficients		
gini	4.639*	70.520***
	(2.740)	(24.670)
lninvest	-0.328***	0.319
	(0.125)	(0.818)
lnhyrav	-0.017	4.358*
	(0.348)	(2.570)
ginilninvest	2.204***	-0.012
	(0.605)	(3.770)
ginilnhyrav	-0.105	-30.74***
	(1.249)	(11.20)

ect	-0.125***	-0.257***
	(0.012)	(0.024)
Short run coefficients		
$\Delta gini_{i,t}$	0.843	-0.320
	(0.755)	(4.718)
$\Delta lninvest_{i,t}$	-0.011	-0.066
	(0.040)	(0.134)
$\Delta lnhyrav_{i,t}$	0.397***	0.482
	(0.111)	(0.465)
$\Delta ginilninvest_{i,t}$	-0.449**	-0.179
	(0.180)	(0.702)
$\Delta ginilnhyrav_{i,t}$	-1.169***	-0.888
	(0.378)	(2.203)

Note: ***, ** and * represent the significance level of 1%, 5% and 10% respectively.

In order to evaluate the impact of inequality on growth through both physical capital and human capital, the long- and short-term coefficients of inequality, and of physical and human capital, are estimated, along with the coefficients of the interaction terms, *ginilninvest* and *ginilnhyrav*. The coefficients are shown in Table 5-7.

In Table 5-7, columns (1) and column (2) exhibit the results estimated by panel ARDL, using both FE and MG estimators. Both of the two estimators present significant and negative coefficients of the error correction terms, which implies the existence of a long-term relationship between economic growth and the explanatory variables.

In column (1), the direct long-term effect of inequality on growth is positive at the significance level of 10%. The long-term effect of physical capital on growth is negative, while human capital does not have a significant long-term effect on growth. Focusing on the interaction terms, the coefficient of $ginilninvest$ is significant at 1% with a positive sign, suggesting that inequality can promote economic growth through physical capital. This result is in line with the classical channel, which argues that due to rich people's higher marginal propensity to save, a higher level of inequality can improve capital accumulation, hence boost economic growth (Kaldor, 1956). As for the interaction term *ginilnhyrav*, the coefficient is negative but statistically insignificant, implying that inequality does not significantly affect growth through human capital in the long term. In the short term, inequality and physical capital show no significant impact on economic growth, while inequality negatively affects growth through physical capital.

Similar to the FE estimator in column (1), the MG estimator in column (2) obtains a significantly positive long-term coefficient of inequality, with a much larger magnitude. This means the direct effect of inequality on growth is positive. Although physical capital does not have a significant long-term effect on growth, human capital does have a positive effect on growth at 10% significance, which is as expected. The coefficient of *ginilnhyrav* is negative at 1% significance, meaning that inequality harms economic growth through human capital.

This finding is consistent with the credit market imperfections channel, which suggests that income inequality harms growth by limiting poor people's access to human capital, a factor that plays an important role in economic growth. In the short term, the explanatory variables do not exhibit a significant impact on growth.

Overall, Table 5-7 presents two different mechanisms through which inequality affects growth. To be specific, panel ARDL model is applied to estimate China's inequality-growth nexus based on the classical channel and the credit market imperfections channel. Previous theories are supported by the empirical results. In the long term, the direct effect of inequality on growth is positive and significant, under both FE and MG estimations. As for the indirect impact of inequality on growth, two estimators provide different results. The FE estimator suggests that inequality positively affects growth by encouraging the accumulation of physical capital, which supports the classical channel, while the impact of inequality on growth through human capital is insignificant; the MG estimator suggests that inequality harms growth by impeding the accumulation of human capital and supporting the credit market imperfections channel, while the impact of inequality's on growth through physical capital is insignificant. In short, despite some insignificant coefficients, the results are generally in line with the arguments of the classical channel and the credit market imperfections channel, especially considering the positive and significant coefficients of *ginilninvest* and the negative and significant coefficients of *ginilnhyrav*.

5.5.2. Empirical results for the subsamples

Table 5-8 presents the long run and short run inequality-growth nexus of the three subsamples of Chinese provinces, including the top 10 provinces which have the highest per capita GDP, as well as the middle 10 and bottom 10 provinces.

Table 5-8. Inequality-growth nexus estimated by panel ARDL-ECM in three subsamples

ARDL-ECM	Top 10		Middle 10		Bottom 10	
p=q=1	FE	MG	FE	MG	FE	MG
	(1)	(2)	(3)	(4)	(5)	(6)
Long run coefficients						
gini	1.839	3.444**	1.650**	6.752*	2.308***	4.394***
	(1.268)	(1.662)	(0.679)	(3.650)	(0.592)	(1.554)
lninvest	-0.053	0.384**	0.159***	0.426***	0.348***	0.796**
	(0.107)	(0.159)	(0.060)	(0.107)	(0.074)	(0.380)
lnhyrav	-0.008	-0.568	0.093	-1.275	-0.390	-2.131
	(0.543)	(1.395)	(0.232)	(0.977)	(0.365)	(1.370)
ect	-0.097***	-0.236***	-0.142***	-0.231***	-0.166***	-0.263***
	(0.020)	(0.0428)	(0.019)	(0.037)	(0.025)	(0.041)
Short run coefficients						
$\Delta gini_{i,t}$	-0.452*	-0.968***	-0.939***	-1.178***	-1.184***	-1.640***
	(0.250)	(0.217)	(0.203)	(0.258)	(0.191)	(0.178)
$\Delta lninvest_{i,t}$	-0.088***	-0.198***	-0.098***	-0.192***	-0.140***	-0.249***
	(0.025)	(0.030)	(0.020)	(0.052)	(0.025)	(0.029)
$\Delta lnhyrav_{i,t}$	0.061	0.052	0.026	-0.009	0.178**	0.263***
	(0.101)	(0.213)	(0.061)	(0.105)	(0.074)	(0.064)

Note: ***, ** and * represent the significance level of 1%, 5% and 10% respectively.

In table 5-8, the coefficient of the error correction term is significant in each column, showing a long run relationship between the dependent and independent variables. When looking at the long-term connection between inequality and growth across the three subsamples, the FE and MG estimators gain, by and large, consistent results. In the top 10 provinces, while the coefficients of inequality is insignificant under the FE estimation, it is positive at 5% significance level under the MG estimation. In the middle and bottom subsamples, both estimators yield positive and significant inequality coefficients. Thus it can be concluded that inequality can promote economic growth in the provinces in the long term, which is in line with the findings of Frank (2009) for the United States. In the short term, the coefficients of income inequality in each subsample are negative and significant, both under the FE and MG estimations, implying a harmful short-term effect of inequality on growth in each of the subsamples.

As for physical capital, according to column (1) and (2), while FE estimator yields an insignificant coefficient of *lninvest,* the MG estimator generates a significantly positive long-term coefficient for *lninvest*, suggesting that physical capital has a stimulating effect on growth, which is in line with previous research. In the short term, physical capital has a negative impact on growth in the top provinces. Regarding the middle and bottom provinces, physical capital has a positive and significant long-term impact on growth as expected, and a negative impact in the short-term. It is worth noting that the magnitudes of the long-term coefficients of *lninvest* are the largest in the bottom group, at 0.348 and 0.796 under FE and MG estimations. Compared to the bottom group, the middle groups shows the smaller magnitudes of 0.158 and 0.426, and the top group (the most developed one) displays the smallest magnitudes of coefficients. Such findings imply that in the later stage of economic development, the encouraging effect of physical capital on growth decreases. As for human capital, it is surprising that the coefficient of *lnhyrav* is insignificant in each column, meaning that human capital does not have a long-term influence on growth in the subsamples.

In short, the table suggests that income inequality hinders growth in the short term but promotes economic growth in the long term, in all three subsamples. To explain the positive long-term connection, Galor and Tsiddon (1997b) states that income inequality generates incentives for the labour force to work harder or move to high-return sectors, hence leading to higher economic growth. Another explanation is that due to the higher marginal propensity of wealthy people to save, a larger income gap can result in more savings and investments, hence boosting the economic growth (Kaldor, 1956). In this sense, the poverty reduction policies may achieve a more equal distribution at the cost of growth. Besides, the results in the table also suggest that the bottom group, compared with the results for the other two groups, physical capital has a stronger positive effect on growth in the long term, meaning that the positive effect of physical capital on growth is more obvious in the less developed provinces. Generally, the results are in line with the argument of unified growth theory that in the earlier stage of economic growth, physical capital generates higher rate of return, and therefore plays a more important role in growth, but during further economic development, the influence of physical capital on growth becomes less important (Galor and Moav, 2004).

Table 5-9. Inequality's effects on growth through different channels in three subsamples

Panel	Top 10		Middle 10		Bottom 10	
ARDL-ECM	FE	MG	FE	MG	FE	MG
(p=q=1)	(1)	(2)	(3)	(4)	(5)	(6)
Long run coefficients						
gini	23.25***	137.0**	-4.265	75.567**	-8.988	-0.979
	(8.638)	(55.28)	(2.932)	(29.711)	(11.82)	(29.75)
lninvest	-1.028***	-0.039	0.228	-0.632	0.330	1.627
	(0.290)	(1.558)	(0.217)	(0.479)	(0.355)	(1.873)
lnhyrav	1.150	11.00**	-0.317	6.696***	-2.515	-4.625
	(0.729)	(5.033)	(0.444)	(2.338)	(1.707)	(4.309)
ginilninvest	5.859***	-0.479	-0.525	4.492**	0.490	-4.049
	(1.761)	(8.867)	(1.043)	(2.088)	(1.362)	(7.095)
ginilnhyrav	-7.480**	-61.96**	3.046**	-33.022**	6.461	2.766
	(3.600)	(24.97)	(1.435)	(13.672)	(5.623)	(13.03)
ect	-0.102***	-0.271***	-0.155***	-0.281***	-0.144***	-0.22***
	(0.021)	(0.056)	(0.021)	(0.023)	(0.026)	(0.042)
Short run coefficients						
$\Delta gini_{i,t}$	4.008*	3.824	1.610	-11.04***	-0.535	6.251
	(2.123)	(12.39)	(1.026)	(3.495)	(2.183)	(5.474)
$\Delta lninvest_{i,t}$	0.137**	-0.197	-0.110	0.213	-0.0361	-0.215
	(0.068)	(0.236)	(0.080)	(0.163)	(0.096)	(0.281)
$\Delta lnhyrav_{i,t}$	0.721***	0.877	0.410***	-0.910***	0.359	1.480**
	(0.262)	(1.112)	(0.156)	(0.313)	(0.301)	(0.642)
$\Delta ginilninvest_{i,t}$	-1.344***	1.182	0.055	-1.601**	-0.477	-0.117
	(0.365)	(1.685)	(0.361)	(0.747)	(0.357)	(0.970)
$\Delta ginilnhyrav_{i,t}$	-2.981***	-2.448	-1.372***	3.966***	-0.591	-4.182*

	(1.080)	(5.938)	(0.508)	(1.435)	(1.034)	(2.342)

Note: ***, ** and * represent the significance level of 1%, 5% and 10% respectively.

The model with interaction terms is estimated for the three subsamples, as presented in Table 5-9. The coefficients of the error correction terms in all the 6 columns are significant and negative, revealing a long-term relationship between the independent and dependent variables.

Focusing on the top group, the first 2 columns show the results of the top 10 provinces. In column (1), the estimation of the FE approach shows that inequality has a stimulating direct effect on growth in the long term. This finding is confirmed by the MG approach. Physical capital negatively impacts growth in the long term, as shown in column (1). However, such results are not supported by the MG estimator in column (2), which gains no significant coefficients, implying that physical capital does not have a long-term impact on economic growth in the top 10 provinces. This is reflected by the results that the top 10 provinces may have over-invested in physical capital, so that the investments can no longer enhance economic growth. As for human capital, the estimators gain different results. In column (1), the FE estimator suggests that there is no long term impact of human capital on growth in, however, in column (2), it can be seen that human capital has a positive effect on growth, at the significance level of 5%. The magnitude of the coefficient is 11.00, which is significantly different from zero, indicating that human capital is an important stimulator of economic growth. When comparing the effects of human capital and physical capital on growth in the top 10 provinces, it can be seen that compared to physical capital, human capital has a more positive effect on growth, hence human capital is the prime engine of economic growth in the top-income, more developed provinces, which supports the argument of Galor and Moav (2004) that the marginal product of human capital rises during the course of development, and in the latter stage of economic growth, the marginal return on human capital outweighs that of physical capital.

When looking at the coefficients of the two interaction terms, *ginilninvest* and *ginihrav*, it can be found that inequality exerts a significant and positive effect on growth through physical capital, whereas it exerts a significant and negative effect on growth by affecting human capital. Specifically, in column (1), the coefficient of *ginilninvest* is 5.859 at 1%

significance level. Meanwhile, in column (1) and (2), the coefficients of *ginilnhyrav* are -4.780 and -61.96 respectively, at 5% significance level. The magnitude of the coefficients varies across different estimators, and is significantly different from zero. The findings that inequality stimulates growth through physical capital and hinders growth through human capital support both the classical mechanism and the credit market imperfection mechanism.

In terms of the short-term relationship, the direct impact of inequality on growth is positive as suggested by the FE estimator and insignificant according to the MG estimator. Similarly, column (1) shows that physical capital and human capital both have positive effects on growth, as expected. Meanwhile, inequality exerts a negative impact on growth through both physical and human capital in the short term.

Generally speaking, the findings of the top 10 provinces confirm both classical and credit market imperfection mechanisms, when growth is dominated by human capital instead of physical capital. There are several implications for policy based on the empirical findings. First, more education should be introduced to increase human capital, which is the key to boosting economic growth. Second, the negative coefficients of *ginilnhyrav* suggest that inequality negatively affects growth by constraining people's investment in human capital. In order to make the credit constraints less binding and reduce inequality's negative impact on growth through human capital, more support for students, such as scholarships and student loans, should therefore be provided. Third, as physical capital does not have a significant encouraging effect on growth, there is a possibility that the top 10 provinces may have overinvested in physical capital, thus in the future, fewer investments in physical capital may be needed. At the same time, efforts should be made to raise the efficiency of physical capital, such as adjusting the industrial structures in those provinces.

When concentrating on columns (3) and (4), which show the empirical results of the middle 10 provinces, it can be seen that the FE estimator generates an insignificant coefficient for *gini*, while the MG estimator yields a positive and significant coefficient at 5% significance level. Whereas physical capital and growth are not related in the long term, human capital has a significant and positive effect on growth at a 1% significance level, according to the MG estimator in column (4). Regarding the coefficients of the interaction terms that capture the channels through which inequality affects growth, the MG estimator in column (4) presents a significant and positive coefficient of *ginilninvest*, meaning that inequality enhances growth by encouraging physical capital, supporting the classic channel, while the FE estimator in column (3) gains an insignificant coefficient. As the FE and MG estimators in columns (3) and (4) present significant coefficients of *ginilnhyrav* of opposite signs, it is therefore unclear how inequality affects growth through human capital. In general, in the middle 10 provinces, human capital exerts a more encouraging effect on growth than physical capital does, but it is unclear how inequality affects growth through human capital and physical capital. In order to stimulate the economic growth in the middle 10 provinces, more education should be introduced.

To compare the results of the top 10 and the middle 10 provinces, the coefficient of human capital of the middle group has a smaller magnitude than those of the top group. In the top group, the positive and significant coefficient of human capital is 11.00, while in the middle group, the coefficient is 6.696. Such a difference reveals the fact that in the more developed provinces, human capital plays a more important role in economic growth, thereby supporting the assumption of unified growth theory that the driving effect of human capital on growth becomes more obvious at a later stage of economic development (Galor and Moav, 2004). Moreover, compared to the significant and negative coefficients of *ginilnhyrav* in the top group, the coefficients of *ginilnhyrav* in the middle group are either insignificant or smaller in the absolute value, indicating that inequality's negative impact on growth through human capital becomes more obvious in the more developed top 10 provinces. This conclusion also confirms the assumption of unified growth theory that during the development towards a later stage, the negative effect of inequality on growth through human capital is amplified.

When it comes to the bottom 10 provinces, the inequality-growth nexus as presented in the last two columns becomes statistically insignificant. Although the coefficients of the error correction terms are negative and significant, it can be concluded that no long-term relationship exists between economic growth and the explanatory variables in these provinces. The results are surprising, and one possible explanation of the results could be that the economic reform in these areas is not sufficient. To be specific, among the bottom provinces, only one province belongs to the eastern region, while six are from the western region and three are from the central region. Over recent decades (from 1990 to 2017 in this study), China experienced an economic reform that took the country from a centrally planned economy to a market economy, but the transition towards the market economy in the western and central provinces, especially the western provinces, is slower than that in the eastern provinces. As a result, the bottom group suffers from insufficient development of the market economy, which can probably explain why the bottom group does not exhibit a strong connection between growth and the explanatory variables, because the channels through which inequality affects growth are less applicable to the insufficiently marketized provinces. Thus, to boost economic growth, these provinces may need further economic reform and should accelerate their transition to a market economy. In the future, to shed more light on the possible explanation that the bottom group suffers from insufficient marketisation, the empirical model can be improved by adding more control variables, such as openness and international trades, which can measure the level of marketisation, when high-quality data are available. The research in this chapter, however, concentrates only on the mechanisms through which inequality and growth are connected. Moreover, in order to keep a parsimonious model and avoid losing degrees of freedom, no more variables are included in the model of this study.

From the empirical analysis of the three subsamples, it can be seen that the subsamples are in different stages of development. This reflects the problem of an uneven regional economic development in China since the economic reform started. To narrow down the gap between the eastern and the western regions, and promote the development of the bottom provinces, more efforts should be made to enhance the opening up and economic reform in the bottom provinces, hence accelerating the transition to a market economy.

5.6. Conclusion

The relationship between inequality and growth has attracted the interest of many researchers, but how these factors are connected is still unclear. While many empirical studies focus on the inequality-growth nexus, fewer studies are carried out to examine the mechanisms behind their connection, and the studies in the context of China are even fewer. Moreover, most of the previous empirical studies test the inequality-growth relationship only through a single mechanism, but in the contest of the real world, inequality can affect growth through different channels at the same time, and its effect on growth through one channel can be offset by its effect through another channel (Galor and Moav, 2004). For the above reasons, this chapter constructed a four-variable model to examine the long- and short- term relationship between income inequality and economic growth in China. In addition, a six-variable model was constructed to test the mechanisms through which inequality affects growth. In particular, the model considered both classical and credit market imperfection channels, which are adopted by the unified growth theory. The data are collected from 30 provinces of China between 1990 and 2017, and panel ARDL-ECM approach is adopted in the study, with both FE and MG estimators for robustness check. As discussed earlier, FE estimator assumes slope homogeneity across the provinces, while MG estimator relaxes this assumption and allows slope heterogeneity across the provinces. Although the issue of heterogeneous slopes is mitigated by using provincial data and panel ARDL-ECM model, the issue can still exist across the provinces. Thus the MG estimator is preferred when interpreting the empirical results. The study also splits the whole sample into three subsamples based on the development levels of the provinces, in order to test how the inequality-growth nexus varies in different development stages, and to provide policy implications targeting each subsample.

The study first carried out unit root tests and found a mixture of I(1) and I(0) variables, thus the panel ARDL-ECM technique was adopted to deal with the non-stationarity of the variables. A four-variable model was first constructed to explore the effects of inequality on growth, then a six-variable model was constructed to investigate two mechanisms through which inequality affects growth.

Regarding the main findings of this chapter, first, the four-variable model based on the whole sample suggests that income inequality enhances economic growth in the long term, as seen in the period between 1990 and 2017. When it comes to the subsamples, the results show that inequality stimulates growth in each of the three subgroups. Meanwhile, physical capital has a positive influence on growth, while human capital shows no significant impact on growth.

Second, regarding the findings based on the six-variable model, the results are in line with the credit market imperfection channel, the savings channel and the unified growth theory. The results of the whole sample indicate that human capital is the prime driver for economic growth, as the coefficient of *lnhyrav* is significant and positive, while the coefficient of *lninvest* is insignificant. Moreover, according to the coefficients of the interaction terms, which capture the mechanisms, it is found that the coefficient of *ginilnhyrav* is significant and negative, indicating that inequality has a negative impact on growth through human capital. The finding supports the credit market imperfection theory of Galor and Zeira (1993). Specifically, this theory argues that due to borrowing constraints, the borrowing interest rates are high, making it hard for the poor to obtain loans for investment in human capital. As a result, in a society with high inequality, the poor invest less in human capital, which is a key driver of economic growth, so inequality harms growth by via human capital.

When comparing the subsamples, it was found that human capital played a more important role in economic growth in the more developed top group and a less important role in the middle and bottom groups. The coefficient of *lnhyrav* in the top group is 11 at the significance level of 1%, the coefficient is 6.696 in the middle group and is insignificant in the bottom group. The results are in line with the assumption of the unified growth theory that the driving effect of human capital on growth becomes more apparent at a later stage of economic development. In this stage, the rate of return on physical capital decreases because of a higher capital-labour ratio, while the return on human capital increases as a result of capital-skill complementarity (Galor and Moav, 2004).

Regarding the interaction terms, compared to the significant and negative coefficient of *ginilnhyrav* in the top group, the negative coefficient of *ginilnhyrav* in the middle group is smaller in absolute value, indicating that the negative impact of inequality on growth through human capital becomes more obvious in the more developed top 10 provinces. This finding also confirms the assumption of the unified growth theory that during the development towards a later stage, the negative effect of inequality on growth through human capital is amplified. As aforementioned, in the top provinces that are in the later stage of economic development, human capital is more important for growth. Meanwhile, according to the credit market imperfections channel, thwarts the accumulation of human capital, and therefore harms growth. The more that human capital is needed for growth, the more harm inequality will cause to the growth through human capital. Thus, for the top provinces where human capital is more important for growth, inequality harms growth more through human capital.

When looking at the coefficients of *ginilninvest*, it can be found that the coefficient in the middle group is positive and significant, meaning that inequality enhances growth through physical capital. This finding is in line with the savings channel developed from the research of Kaldor (1956), which states that the wealthy have a high marginal propensity to save, and therefore make more investment from the savings, leading to economic growth. Thus, in a more unequal society, the total savings—and the growth rate—are higher. The coefficient of *ginilninvest* in the top 10 provinces is insignificant, which can be explained by the unified growth theory, which states that at a later stage of development, physical capital is replaced by human capital as the main stimulator of growth, and so the savings channel becomes less important for growth. As for the bottom group, there is no evidence to show that inequality and growth are connected. It can be potentially caused by the insufficient marketisation of the bottom provinces.

Third, it can be seen that China faces unbalanced regional development. When comparing the results of each subsample, the top, middle and bottom groups exhibit different inequality-growth relationships, and the dominating channels through which inequality affects growth also vary across groups. Considering this, there is no universal policy to maximise the economic growth in all the provinces. Thus, to best enhance economic growth in each group of provinces, policies should be customised according to the development stage of each group.

Fourth, the robustness check section shows that the results are generally robust when two alternative income inequality measurements are adopted. Besides, although the coefficients are mostly consistent across different estimation approaches, lag orders and estimators, they still vary more or less under different model specifications, proving the comments made by Frank (2009) and Deininger and Squire (1996) that the lack of consensus among empirical studies can be explained by sample choice and different model specifications.

In spite of the contributions made by this chapter, there is room for further improvements in the future. In this chapter, the empirical study has focused on the inequality-growth nexus and the channels through which inequality affects growth, and in order to retain a parsimonious model and preserve a sufficient degree of freedom, no more variables are included in the empirical models. Further control variables can be added in future work to improve the models.

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Appendix 5-A. Empirical results with different lag lengths

In addition to the results estimated with the optimal lag (p=q=1), the results estimated with lag lengths of 2 and 3 are reported in this section in order to make comparisons.

Table 5-A1. Inequality-growth nexus with different lag lengths

ARDL-ECM	p=q=2		p=q=3	
	FE	MG	FE	MG
	(1)	(2)	(3)	(4)
Long run coefficients				
gini	0.242	-3.414	-0.601	-1.171
	(0.420)	(6.293)	(0.424)	(2.727)
lninvest	0.021	0.284	-0.062	0.174
	(0.043)	(0.233)	(0.044)	(0.200)
lnhyrav	1.121***	0.998	1.270***	1.027
	(0.152)	(1.553)	(0.154)	(0.873)
ect	-0.112***	-0.310***	-0.116***	-0.404***
	(0.011)	(0.030)	(0.012)	(0.057)
Short run coefficients				
$\Delta gini_{i,t}$	-0.423***	-1.068***	-0.528***	-1.235***
	(0.114)	(0.160)	(0.121)	(0.265)
$\Delta lninvest_{i,t}$	-0.116***	-0.231***	-0.095***	-0.270***
	(0.011)	(0.021)	(0.011)	(0.030)
$\Delta lnhyrav_{i,t}$	-0.012	0.110	-0.080**	0.032
	(0.037)	(0.100)	(0.038)	(0.114)
$\Delta lngdp_{i,t-1}$	0.522***	0.193***	0.467***	0.095*
	(0.029)	(0.045)	(0.034)	(0.051)
$\Delta gini_{i,t-1}$	0.611***	-0.280*	0.558***	-0.533***
	(0.108)	(0.159)	(0.113)	(0.198)
$\Delta lninvest_{i,t-1}$	0.114***	-0.031	0.091***	-0.096***
	(0.013)	(0.021)	(0.014)	(0.029)
$\Delta lnhyrav_{i,t-1}$	-0.042	0.035	-0.105***	0.070
	(0.037)	(0.051)	(0.037)	(0.096)
$\Delta lngdp_{i,t-2}$			0.007	-0.083
			(0.035)	(0.058)

$\Delta gini_{i,t-2}$	0.374***	-0.220
	(0.109)	(0.166)
$\Delta lninvest_{i,t-2}$	0.065***	-0.010
	(0.015)	(0.018)
$\Delta lnhyrav_{i,t-2}$	-0.138***	-0.120*
	(0.036)	(0.067)

Note: ***, ** and * represent the significance level of 1%, 5% and 10% respectively.

Column (1) and (2) present the long run and short run coefficients when the lag length is 2. The coefficients of the error correction terms are significantly negative. Both FE and MG estimators suggest that inequality does not have a significant long term influence on economic growth, as the coefficients are insignificant with opposite signs. According to the FE estimator, physical capital does not significantly affect growth, while human capital has an encouraging effect on growth in the long term, which is as expected. However in the short term, human capital does not significantly affect growth. Meanwhile, MG estimator presents an insignificantly positive long run coefficient of human capital.

The results provided by columns (1) and (2) are generally in line with the results in columns (3) and (4), when the lag length is 3. Inequality and physical capital are not significantly connected with growth in the long run, while human capital has a positive influence on growth at the significance level of 1%, according to FE estimator. The long run coefficient of *lnhyrav* is 1.270, which means that when average years of schooling increases by 1%, GDP per capita increases by 1.27%.

In general, unlike the positive inequality-growth nexus when lag is 1, from the results presented by table 5-10 when lag is 2 and 3, it is hard to decide whether inequality and growth are positively or negatively connected in China. While the coefficients of inequality is significantly positive with 1 year's lag, when different lag lengths are adopted, the coefficients are no longer significant. With 2 and 3 years' lag, it is implied that inequality and growth are not significantly connected in the long run in China. The table also reveals an insignificant long run effect of physical capital on growth, while the long run effect of human capital on growth is significantly positive as expected, as suggested by FE estimator. Compared with the results with the lag length of 1, it can be seen that the results vary according to different lag lengths and estimators. As mentioned by Frank (2009) and Deininger and Squire (1996), different model specifications can lead to the variation of empirical results.

Table 5-A2. Inequality's effects on growth through different channels with different lag lengths

ARDL-ECM	p=q=2		p=q=3	
	FE	MG	FE	MG
	(1)	(2)	(3)	(4)
Long run coefficients				
gini	5.115**	203.370**	5.979***	-254.095
	(2.420)	(98.107)	(2.293)	(463.066)
lninvest	-0.459***	-7.895	-0.671***	13.250
	(0.112)	(5.716)	(0.109)	(13.905)
lnhyrav	1.384***	20.032*	1.523***	-18.405
	(0.266)	(10.711)	(0.255)	(44.710)
ginilninvest	2.230***	30.220	2.978***	-53.666
	(0.539)	(20.882)	(0.515)	(61.190)
ginilnhyrav	-1.289	-88.219**	-1.845*	113.377
	(1.087)	(41.579)	(1.025)	(204.685)
ect	-0.125***	-0.367***	-0.137***	-0.074
	(0.012)	(0.053)	(0.013)	(0.338)
Short run coefficients				
$\Delta gini_{i,t}$	0.443	-5.628	0.360	30.48
	(0.681)	(8.948)	(0.672)	(43.33)
$\Delta lninvest_{i,t}$	0.022	0.189	0.093**	0.198
	(0.037)	(0.213)	(0.037)	(1.100)
$\Delta lnhyrav_{i,t}$	0.201**	0.121	0.176*	1.713
	(0.098)	(0.894)	(0.097)	(4.513)
$\Delta ginilninvest_{i,t}$	-0.650***	-1.241	-0.875***	-0.515
	(0.162)	(1.190)	(0.163)	(4.819)
$\Delta ginilnhyrav_{i,t}$	-0.806**	1.329	-0.905***	-14.485
	(0.342)	(4.106)	(0.334)	(19.67)
$\Delta lngdp_{i,t-1}$	0.513***	0.052	0.443***	-0.750**
	(0.029)	(0.072)	(0.034)	(0.338)

$\Delta gini_{i,t-1}$	1.360**	-4.508	1.342**	41.133
	(0.630)	(6.357)	(0.665)	(37.147)
$\Delta lninvest_{i,t-1}$	0.104***	-0.049	0.074*	-0.281
	(0.038)	(0.149)	(0.040)	(0.931)
$\Delta lnhyrav_{i,t-1}$	0.054	-0.089	0.011	1.728
	(0.093)	(0.640)	(0.096)	(3.031)
$\Delta ginilninvest_{i,t-1}$	-0.014	-0.003	-0.018	3.124
	(0.166)	(0.754)	(0.175)	(4.147)
$\Delta ginilnhyrav_{i,t-1}$	-0.411	1.759	-0.449	-17.364
	(0.315)	(2.897)	(0.331)	(16.441)
$\Delta lngdp_{i,t-2}$			0.008	-0.58***
			(0.035)	(0.199)
$\Delta gini_{i,t-2}$			-1.054*	26.698
			(0.620)	(19.088)
$\Delta lninvest_{i,t-2}$			0.129***	-0.370
			(0.040)	(0.623)
$\Delta lnhyrav_{i,t-2}$			-0.302***	2.538
			(0.090)	(1.668)
$\Delta ginilninvest_{i,t-2}$			-0.313*	2.479
			(0.168)	(3.673)
$\Delta ginilnhyrav_{i,t-2}$			0.615**	-12.194
			(0.309)	(8.235)

Note: ***, ** and * represent the significance level of 1%, 5% and 10% respectively.

In table 5-A2, columns (1) and (2) provide the estimated results when lag length is 2, and the results are more or less consistent with those with the lag length of 1. In the long term, inequality has a positive direct impact on growth; physical capital negatively affects growth as estimated by FE estimator, while insignificantly impacts growth as estimated by MG estimator; human capital has an expected positive effect on growth in both columns, with the magnitude ranging from 1.384 to 20.032. The difference between the magnitudes is due to the different assumptions of FE and MG estimator. The former assumes homogeneous slopes while the latter assumes heterogeneous slopes. With regards to the coefficients of the interaction terms, while FE estimator yields an insignificant coefficient, MG estimator in column (2) implies that inequality negatively impacts growth thorough human capital, at 5% significant level, which is consistent with the findings of previous research such as the theoretical study of Galor and Zeira (1993). Thus, when focusing on the significant coefficients, the results are in line with both the classical theory and the credit market imperfection theory.

When it comes to the short run effects, in column (1), the sums of the coefficients on lagged physical capital and human capital are both significantly positive, meaning that physical capital and human capital can boost economic growth in the short term. The coefficients of the interaction terms show that inequality negatively affects growth through physical and human capital in the short term. Different from column (1), the short run coefficients in column (2) are no longer significant.

When p=3, FE estimator in column (3) shows that the direct effect of inequality on growth in the long run is positive. While physical capital has a negative impact on growth, human capital can enhance economic growth at 1% significant level. The coefficients of the interaction terms are also as expected. The coefficient of *ginilninvest* is 2.978, and that of *ginilnhyrav* is -1.845. Both coefficients are significant at the significance level of 1% and 10% respectively, supporting the classical and the credit market imperfection theories. In the short term, when adding up the coefficients of the lagged variables, it can be found that inequality and physical capital are positively connected with growth, while human capital is negatively related to growth. Meanwhile, inequality can harm growth through physical and human capital in the short term. In contrast to the results in column (3), column (4) does not obtain significant coefficients.

In summary, table 5-A2 examines the classical channel and the credit market imperfection channel, with lag lengths of 2 and 3. Similar to the empirical results when the lag length is 1, the results with lag lengths of 2 and 3 are also in line with the arguments of both theoretical channels.

Table 5-A3. Inequality-growth nexus in three subsamples with lag of 2

ARDL-ECM	Top 10		Middle 10		Bottom 10	
p=q=2	FE	MG	FE	MG	FE	MG
	(1)	(2)	(3)	(4)	(5)	(6)
Long run coefficients						
gini	-0.550	2.520	-0.031	-16.644	0.705	3.882**
	(0.961)	(1.783)	(0.560)	(18.640)	(0.528)	(1.694)
lninvest	-0.233***	0.142	0.063	-0.182	0.277***	0.891*
	(0.080)	(0.100)	(0.053)	(0.482)	(0.081)	(0.466)
lnhyrav	1.457***	0.592	1.053***	4.474	0.537*	-2.073
	(0.282)	(0.788)	(0.180)	(4.188)	(0.309)	(1.653)
ect	-0.117***	-0.310***	-0.135***	-0.304***	-0.147***	-0.329***
	(0.019)	(0.030)	(0.0178)	(0.047)	(0.025)	(0.056)
Short run coefficients						
$\Delta gini_{i,t}$	-0.126	-0.298***	-0.406**	-0.951***	-0.532***	-1.226***
	(0.226)	(0.057)	(0.178)	(0.346)	(0.191)	(0.209)
$\Delta lninvest_{i,t}$	-0.109***	-0.219***	-0.104***	-0.206***	-0.154***	-0.268***
	(0.022)	(0.034)	(0.016)	(0.047)	(0.022)	(0.030)
$\Delta lnhyrav_{i,t}$	-0.054	-0.0131	-0.038	0.042	0.088	0.302***
	(0.089)	(0.269)	(0.049)	(0.114)	(0.067)	(0.073)
$\Delta lngdp_{i,t-1}$	0.479***	0.228***	0.479***	0.130	0.518***	0.223***
	(0.052)	(0.060)	(0.052)	(0.107)	(0.051)	(0.063)
$\Delta gini_{i,t-1}$	0.453**	-0.242	0.680***	-0.121	0.577***	-0.478**
	(0.218)	(0.408)	(0.168)	(0.168)	(0.180)	(0.208)
$\Delta lninvest_{i,t-1}$	0.124***	-0.014	0.097***	-0.042	0.117***	-0.039
	(0.024)	(0.026)	(0.020)	(0.051)	(0.026)	(0.030)
$\Delta lnhyrav_{i,t-1}$	-0.027	-0.074	-0.048	0.077	0.007	0.101
	(0.087)	(0.080)	(0.049)	(0.100)	(0.066)	(0.082)

Note: ***, ** and * represent the significance level of 1%, 5% and 10% respectively.

According to table 5-A3, when adopting two years' lag, the long run coefficients of inequality are insignificant in the top and middle groups, while as for the bottom group, the coefficient is insignificant as estimated by FE and positive and significant as estimated by MG. In the top group, FE estimator yields a significantly negative coefficient of physical capital, while in the top group, both estimators get significantly positive coefficients of physical capital. Regarding human capital, the FE estimator shows a positive and significant coefficient in each group, but the coefficients are insignificant with MG estimator. Such results are different from the results estimated when lag is 1, as the latter implies a positive effect of inequality on growth.

Table 5-A4. Inequality-growth nexus in three subsamples with lag of 3

ARDL-ECM	Top 10		Middle 10		Bottom 10	
p=q=3	FE	MG	FE	MG	FE	MG
	(1)	(2)	(3)	(4)	(5)	(6)
Long run coefficients						
gini	-1.769**	1.339	-0.785	-4.522	-0.068	-0.330
	(0.852)	(3.439)	(0.589)	(7.375)	(0.489)	(1.901)
lninvest	-0.312***	0.267	0.0003	0.335	0.146*	-0.079
	(0.068)	(0.353)	(0.056)	(0.250)	(0.076)	(0.436)
lnhyrav	1.524***	0.250	1.118***	1.260	1.032***	1.570
	(0.235)	(0.999)	(0.194)	(1.857)	(0.277)	(1.678)
ect	-0.144***	-0.389***	-0.136***	-0.349***	-0.163***	-0.474***
	(0.021)	(0.120)	(0.020)	(0.086)	(0.029)	(0.093)
Short run coefficients						
$\Delta gini_{i,t}$	-0.337	-0.714*	-0.462**	-1.716***	-0.483**	-1.276***
	(0.242)	(0.423)	(0.193)	(0.584)	(0.203)	(0.320)
$\Delta lninvest_{i,t}$	-0.064***	-0.238***	-0.096***	-0.207***	-0.135***	-0.363***
	(0.023)	(0.0505)	(0.016)	(0.048)	(0.024)	(0.050)
$\Delta lnhyrav_{i,t}$	-0.142	-0.136	-0.101**	0.120	-0.016	0.111
	(0.090)	(0.295)	(0.051)	(0.131)	(0.071)	(0.128)
$\Delta lngdp_{i,t-1}$	0.400***	0.0730	0.518***	-0.010	0.460***	0.221***
	(0.061)	(0.0623)	(0.058)	(0.107)	(0.061)	(0.085)
$\Delta gini_{i,t-1}$	0.408*	-0.613	0.717***	-0.583**	0.439**	-0.405**
	(0.220)	(0.500)	(0.178)	(0.290)	(0.195)	(0.202)
$\Delta lninvest_{i,t-1}$	0.088***	-0.087**	0.087***	-0.111	0.099***	-0.090**
	(0.025)	(0.035)	(0.021)	(0.070)	(0.027)	(0.043)
$\Delta lnhyrav_{i,t-1}$	-0.114	0.008	-0.092*	0.197*	-0.087	0.005
	(0.087)	(0.239)	(0.050)	(0.116)	(0.068)	(0.127)

$\Delta lngdp_{i,t-2}$	0.015	-0.0494	-0.015	-0.069	0.092	-0.336
	(0.061)	(0.0944)	(0.060)	(0.229)	(0.062)	(0.224)
$\Delta gini_{i,t-2}$	0.513**	-0.256	0.314*	-0.256	0.285	-0.256
	(0.215)	(0.399)	(0.174)	(0.399)	(0.181)	(0.399)
$\Delta lninvest_{i,t-2}$	0.090***	0.019	0.055***	-0.008	0.063**	-0.041
	(0.030)	(0.031)	(0.021)	(0.033)	(0.027)	(0.032)
$\Delta lnhyrav_{i,t-2}$	-0.163*	-0.184	-0.050	0.008	-0.226***	-0.183**
	(0.086)	(0.148)	(0.049)	(0.102)	(0.066)	(0.090)

Note: ***, ** and * represent the significance level of 1%, 5% and 10% respectively.

Table 5-A4 shows the inequality-growth relationship in three subsamples when lag is 3. While inequality promotes growth in the long term with 1 year's lag, when lag is 3, the results of FE and MG estimators suggest that inequality has a negative and insignificant impact on growth respectively, in the top group. In the middle and bottom groups, inequality does not have a long run effect on growth.

Table 5-A5. Inequality's effects on growth through different channels in three subsamples with lag of 2

ARDL-ECM	Top 10		Middle 10		Bottom 10	
p=q=2	FE	MG	FE	MG	FE	MG
	(1)	(2)	(3)	(4)	(5)	(6)
Long run coefficients						
gini	7.464	490.440*	0.983	50.246	-6.150	69.42
	(6.904)	(262.172)	(2.705)	(31.103)	(13.21)	(97.90)
lninvest	-0.814***	-20.65	-0.135	-0.035	0.357	-3.003
	(0.225)	(16.596)	(0.211)	(0.634)	(0.407)	(3.521)
lnhyrav	1.508***	49.646*	1.188***	4.171	-0.810	6.295
	(0.558)	(27.970)	(0.364)	(3.184)	(1.736)	(13.05)
ginilninvest	3.464***	76.010	0.734	2.322	-0.09	12.33
	(1.338)	(60.904)	(1.002)	(2.568)	(1.570)	(12.01)
ginilnhyrav	-1.961	-214.0**	0.059	-21.67	3.938	-29.02
	(2.916)	(109.0)	(1.258)	(14.18)	(6.160)	(44.69)
ect	-0.117***	-0.387***	-0.142***	-0.457***	-0.129***	-0.257***
	(0.020)	(0.115)	(0.020)	(0.061)	(0.026)	(0.087)

Short run coefficients						
$\Delta gini_{i,t}$	3.122*	-11.18	1.496	-8.032	-0.258	2.332
	(1.892)	(24.56)	(0.912)	(6.621)	(2.028)	(10.77)
$\Delta lninvest_{i,t}$	0.140**	0.062	-0.057	0.106	0.012	0.400
	(0.062)	(0.440)	(0.069)	(0.254)	(0.093)	(0.417)
$\Delta lnhyrav_{i,t}$	0.483**	-0.314	0.285**	-0.641	0.255	1.319
	(0.232)	(2.184)	(0.138)	(0.748)	(0.282)	(1.464)
$\Delta ginilninvest_{i,t}$	-1.423***	0.155	-0.191	-1.610	-0.683**	-2.269
	(0.329)	(3.151)	(0.308)	(1.092)	(0.344)	(1.493)
$\Delta ginilnhyrav_{i,t}$	-2.360**	4.239	-1.149**	2.511	-0.541	-2.763
	(0.958)	(11.26)	(0.461)	(2.829)	(0.961)	(5.024)
$\Delta lngdp_{i,t-1}$	0.443***	0.021	0.554***	0.075	0.500***	0.059
	(0.053)	(0.123)	(0.048)	(0.132)	(0.055)	(0.133)
$\Delta gini_{i,t-1}$	3.535*	-6.035	0.749	-5.134	-1.096	-2.353
	(1.830)	(16.89)	(0.819)	(6.061)	(2.033)	(8.243)
$\Delta lninvest_{i,t-1}$	0.103	0.034	0.146**	-0.128	0.149	-0.053
	(0.064)	(0.310)	(0.074)	(0.154)	(0.097)	(0.305)
$\Delta lnhyrav_{i,t-1}$	0.387*	0.085	-0.027	-0.547	-0.219	0.194
	(0.228)	(1.568)	(0.126)	(0.645)	(0.279)	(1.023)
$\Delta ginilninvest_{i,t-1}$	-0.024	-0.101	-0.262	0.232	-0.183	-0.138
	(0.341)	(1.941)	(0.317)	(0.676)	(0.361)	(1.125)
$\Delta ginilnhyrav_{i,t-1}$	-1.624*	2.175	-0.180	2.471	0.777	0.631
	(0.931)	(7.713)	(0.410)	(2.755)	(0.959)	(3.720)

Note: ***, ** and * represent the significance level of 1%, 5% and 10% respectively.

Table 5-A6. Inequality's effects on growth through different channels in three subsamples with lag of 3

ARDL-ECM	Top 10		Middle 10		Bottom 10	
p=q=3	FE	MG	FE	MG	FE	MG
	(1)	(2)	(3)	(4)	(5)	(6)
Long run coefficients						
gini	3.945	-112.1	2.725	-736.7	-7.892	86.53
	(5.539)	(127.0)	(3.162)	(1.407)	(12.90)	(193.2)
lninvest	-0.859***	-2.883	-0.304	45.52	0.189	-2.887

	(0.176)	(4.473)	(0.250)	(40.34)	(0.385)	(6.940)
lnhyrav	1.370***	-7.388	1.378***	-55.47	-0.481	7.642
	(0.437)	(8.194)	(0.438)	(136.0)	(1.654)	(22.71)
ginilninvest	3.300***	22.23	1.256	-195.2	0.090	12.01
	(1.044)	(25.44)	(1.170)	(177.1)	(1.503)	(28.65)
ginilnhyrav	-1.040	56.27	-0.910	322.9	4.306	-39.01
	(2.300)	(53.07)	(1.453)	(621.7)	(5.989)	(88.90)
ect	-0.154***	-0.574	-0.132***	0.828	-0.150***	-0.475
	(0.021)	(0.422)	(0.024)	(0.813)	(0.029)	(0.362)
Short run coefficients						
$\Delta gini_{i,t}$	4.163**	84.16	1.027	-6.356	-0.777	13.64
	(1.975)	(77.88)	(0.956)	(76.64)	(2.211)	(75.53)
$\Delta lninvest_{i,t}$	0.197***	-0.854	0.015	0.642	0.143	0.808
	(0.064)	(1.584)	(0.069)	(1.646)	(0.105)	(2.508)
$\Delta lnhyrav_{i,t}$	0.531**	4.844	0.249*	-0.365	0.116	0.660
	(0.232)	(6.259)	(0.145)	(8.102)	(0.303)	(9.506)
$\Delta ginilninvest_{i,t}$	-1.491***	4.477	-0.489	-2.770	-1.114***	-3.251
	(0.338)	(9.429)	(0.308)	(7.076)	(0.385)	(9.020)
$\Delta ginilnhyrav_{i,t}$	-2.979***	-40.09	-1.077**	2.801	-0.428	-6.171
	(0.979)	(34.80)	(0.471)	(33.96)	(1.043)	(35.54)
$\Delta lngdp_{i,t-1}$	0.351***	-0.739**	0.488***	-0.966	0.456***	-0.546
	(0.062)	(0.333)	(0.059)	(0.918)	(0.065)	(0.376)
$\Delta gini_{i,t-1}$	2.603	142.7*	1.002	-22.40	-2.222	3.057
	(1.790)	(81.82)	(0.921)	(51.49)	(2.085)	(47.29)
$\Delta lninvest_{i,t-1}$	0.075	-2.335**	0.152**	1.324	0.155	0.167
	(0.067)	(0.984)	(0.077)	(1.279)	(0.010)	(2.234)
$\Delta lnhyrav_{i,t-1}$	0.193	7.026	0.020	-1.793	-0.461	-0.050
	(0.222)	(4.803)	(0.141)	(5.132)	(0.291)	(5.877)
$\Delta ginilninvest_{i,t-1}$	-0.110	15.37**	-0.335	-4.996	-0.290	-1.002
	(0.351)	(7.041)	(0.333)	(4.987)	(0.375)	(8.122)
$\Delta ginilnhyrav_{i,t-1}$	-1.202	-61.80*	-0.350	10.22	1.213	-0.520
	(0.910)	(35.87)	(0.464)	(22.91)	(0.993)	(21.59)
$\Delta lngdp_{i,t-2}$	0.019	-0.365*	0.007	-0.750*	0.081	-0.636*
	(0.061)	(0.204)	(0.062)	(0.438)	(0.064)	(0.376)

$\Delta gini_{i,t-2}$	-0.361	53.00	-1.414*	-3.793	-1.167	30.88*
	(1.784)	(44.58)	(0.813)	(32.03)	(1.987)	(18.07)
$\Delta lninvest_{i,t-2}$	0.162**	-1.003	0.132*	0.898	0.054	-1.006
	(0.069)	(1.227)	(0.076)	(1.266)	(0.097)	(0.617)
$\Delta lnhyrav_{i,t-2}$	-0.188	2.714	-0.256**	0.485	-0.468*	4.414*
	(0.221)	(2.780)	(0.128)	(3.621)	(0.275)	(2.281)
$\Delta ginilninvest_{i,t-2}$	-0.392	7.726	-0.371	-3.063	-0.011	2.773
	(0.333)	(9.290)	(0.325)	(5.707)	(0.357)	(2.240)
$\Delta ginilnhyrav_{i,t-2}$	0.200	-23.56	0.752*	1.170	0.792	-14.19*
	(0.900)	(18.86)	(0.417)	(14.02)	(0.942)	(8.280)

Note: ***, ** and * represent the significance level of 1%, 5% and 10% respectively.

Table 5-A5 and 5-A6 show inequality's effects on growth in each subsample, through different channels, when lag is 2 and 3 respectively. Compared to the results when the lag length is 1, the results in table 5-A5 and 5-A6 are slightly different. Specifically, when 1 year's lag is adopted, inequality's direct effect on growth is positive in the top group, while when lag is 2, only the MG estimator generates a significant and positive coefficient of *gini,* and when lag is 3, the coefficients of *gini* are insignificant. The positive and significant coefficients of *ginilninvest* and negative and significant coefficients of *ginilnhyrav* when lag is 2 and 3 are in line with the classical and credit market imperfection theories.

Appendix 5-B. Robustness check with different inequality measurements

Table 5-B1 presents the results estimated with Theil index as the inequality measurement.

Table 5-B1. Inequality-growth nexus estimated by panel ARDL-ECM (inequality measurement: *theil*)

panel	p=1		p=2		p=3	
ARDL-ECM	FE	MG	FE	MG	FE	MG
	(1)	(2)	(3)	(4)	(5)	(6)
Long run coefficients						
theil	2.163***	7.245***	-0.032	-0.221	-0.831**	0.469
	(0.555)	(1.877)	(0.417)	(4.508)	(0.414)	(2.748)
lninvest	0.179***	0.637***	0.012	0.508*	-0.068*	0.243*
	(0.051)	(0.221)	(0.041)	(0.266)	(0.041)	(0.131)
lnhyrav	-0.206	-1.835*	1.121***	-0.102	1.240***	0.744
	(0.240)	(1.026)	(0.148)	(1.194)	(0.148)	(0.648)
ect	-0.110***	-0.233***	-0.117***	-0.306***	-0.123***	-0.399***
	(0.011)	(0.020)	(0.010)	(0.028)	(0.012)	(0.058)
Short run coefficients						
$\Delta theil_{i,t}$	-0.870***	-1.366***	-0.401***	-1.189***	-0.482***	-1.473***
	(0.118)	(0.146)	(0.109)	(0.194)	(0.113)	(0.291)
$\Delta lninvest_{i,t}$	-0.101***	-0.207***	-0.112***	-0.225***	-0.094***	-0.252***
	(0.013)	(0.021)	(0.011)	(0.020)	(0.011)	(0.027)
$\Delta lnhyrav_{i,t}$	0.083*	0.102	-0.012	0.095	-0.084**	-0.033
	(0.044)	(0.079)	(0.037)	(0.104)	(0.038)	(0.103)
$\Delta lngdp_{i,t-1}$			0.526***	0.185***	0.482***	0.100*
			(0.029)	(0.049)	(0.034)	(0.053)
$\Delta theil_{i,t-1}$			0.513***	-0.466**	0.469***	-0.850***
			(0.104)	(0.186)	(0.108)	(0.254)
$\Delta lninvest_{i,t-1}$			0.118***	-0.024	0.098***	-0.084***
			(0.013)	(0.020)	(0.013)	(0.027)
$\Delta lnhyrav_{i,t-1}$			-0.045	0.044	-0.112***	0.020
			(0.037)	(0.051)	(0.037)	(0.096)
$\Delta lngdp_{i,t-2}$					-0.004	-0.082
					(0.035)	(0.059)
$\Delta theil_{i,t-2}$					0.343***	-0.420**
					(0.103)	(0.183)
$\Delta lninvest_{i,t-2}$					0.065***	0.013

					(0.015)	(0.022)
$\Delta lnhyrav_{i,t-2}$					-0.139***	-0.149**
					(0.036)	(0.062)

Note: ***, ** and * represent the significance level of 1%, 5% and 10% respectively.

According to table 5-B1, the results are highly consistent with that provided in table 5-5, where Gini coefficient is used. The coefficients of the error terms are significant and negative. The coefficients of *gini* in the first two columns are significant and positive, but negative in column (5), thus inequality's effects on growth are unclear. The coefficients of *lninvest* are mostly significant and positive, with one coefficient being negative, and the coefficients of *lnhyrav* in column (3) and (5) are positive. Such results are generally in line with the results estimated with *gini*.

Table 5-B2. Inequality-growth nexus estimated by panel ARDL-ECM (inequality measurement: *ineq*)

panel	p=1		p=2		p=3	
ARDL-ECM	FE	MG	FE	MG	FE	MG
	(1)	(2)	(3)	(4)	(5)	(6)
Long run coefficients						
ineq	0.200***	0.657***	0.028	-1.164	-0.026	-0.324
	(0.043)	(0.174)	(0.034)	(4.176)	(0.035)	(0.449)
lninvest	0.172***	0.664**	0.011	1.882	-0.062	0.268*
	(0.045)	(0.317)	(0.038)	(1.687)	(0.038)	(0.144)
lnhyrav	-0.183	-2.251*	1.125***	-5.788	1.238***	1.144
	(0.221)	(1.340)	(0.140)	(3.796)	(0.142)	(0.933)
ect	-0.117***	-0.205***	-0.120***	-0.279***	-0.125***	-0.376***
	(0.011)	(0.019)	(0.010)	(0.027)	(0.011)	(0.056)
Short run coefficients						
$\Delta ineq_{i,t}$	-0.070***	-0.096***	-0.030***	-0.080***	-0.035***	-0.093***
	(0.010)	(0.015)	(0.009)	(0.017)	(0.009)	(0.022)
$\Delta lninvest_{i,t}$	-0.091***	-0.194***	-0.111***	-0.213***	-0.093***	-0.235***
	(0.013)	(0.024)	(0.011)	(0.019)	(0.011)	(0.027)
$\Delta lnhyrav_{i,t}$	0.086**	0.107	-0.0164	0.111	-0.086**	-0.006
	(0.043)	(0.078)	(0.037)	(0.102)	(0.038)	(0.098)

$\Delta lngdp_{i,t-1}$	0.526***	0.174***	0.489***	0.081
	(0.028)	(0.046)	(0.033)	(0.051)
$\Delta ineq_{i,t-1}$	0.040***	-0.017	0.035***	-0.041**
	(0.009)	(0.014)	(0.009)	(0.019)
$\Delta lninvest_{i,t-1}$	0.116***	-0.013	0.094***	-0.065***
	(0.013)	(0.022)	(0.013)	(0.025)
$\Delta lnhyrav_{i,t-1}$	-0.042	0.052	-0.108***	0.058
	(0.036)	(0.051)	(0.037)	(0.092)
$\Delta lngdp_{i,t-2}$			-0.012	-0.082
			(0.035)	(0.055)
$\Delta ineq_{i,t-2}$			0.022**	-0.024
			(0.009)	(0.015)
$\Delta lninvest_{i,t-2}$			0.063***	0.009
			(0.015)	(0.016)
$\Delta lnhyrav_{i,t-2}$			-0.146***	-0.113*
			(0.036)	(0.060)

Note: ***, ** and * represent the significance level of 1%, 5% and 10% respectively.

Table 5-B2 presents the ARDL-ECM results when income inequality is proxied by *ineq*. The tables generate similar results to previous ones, implying robustness when different inequality measures are adopted.

Besides, it can be seen that inequality's direct impact on growth is positive, its long run impact through physical capital is positive in general and its long run impact through human capital is negative, supporting the findings of table 5-7 using Gini coefficient.

Table 5-B3. Inequality's effects on growth through different channels (inequality measurement: *theil*)

panel	p=1		p=2		p=3	
ARDL-ECM	FE	MG	FE	MG	FE	MG
	(1)	(2)	(3)	(4)	(5)	(6)
Long run coefficients						
theil	-2.909	99.92***	2.625	108.7**	5.229***	424.4**
	(2.825)	(32.44)	(2.144)	(47.04)	(1.991)	(196.8)
lninvest	0.073	0.341	-0.172**	-0.093	-0.324***	-7.176*
	(0.086)	(0.313)	(0.068)	(0.535)	(0.065)	(4.104)
lnhyrav	-0.702*	4.239**	1.109***	4.141*	1.347***	21.43**
	(0.376)	(2.051)	(0.211)	(2.128)	(0.198)	(10.46)
theillninvest	1.061	0.313	1.732***	1.870	2.608***	62.34**
	(0.723)	(4.129)	(0.582)	(6.540)	(0.551)	(31.21)
theillnhyrav	3.562**	-47.38***	-0.337	-49.56**	-1.836*	-192.5**
	(1.445)	(14.98)	(1.034)	(20.93)	(0.951)	(89.56)
ect	-0.108***	-0.248***	-0.121***	-0.350***	-0.133***	-0.348
	(0.012)	(0.027)	(0.012)	(0.043)	(0.013)	(0.317)
Short run coefficients						
$\Delta theil_{i,t}$	0.766	0.654	0.496	-0.103	0.155	-102.7*
	(0.612)	(5.989)	(0.540)	(13.12)	(0.530)	(61.83)
$\Delta lninvest_{i,t}$	-0.060**	-0.121	-0.059***	-0.081	-0.013	1.253**
	(0.024)	(0.073)	(0.021)	(0.134)	(0.022)	(0.630)
$\Delta lnhyrav_{i,t}$	0.280***	0.213	0.123**	-0.126	0.062	-4.750*
	(0.068)	(0.265)	(0.060)	(0.592)	(0.059)	(2.642)
$\Delta theillninvest_{i,t}$	-0.434**	0.243	-0.507***	0.460	-0.744***	-10.52*
	(0.183)	(0.855)	(0.162)	(1.975)	(0.163)	(6.331)
$\Delta theillnhyrav_{i,t}$	-1.108***	-1.164	-0.755***	-0.504	-0.702***	45.79
	(0.311)	(2.761)	(0.276)	(5.791)	(0.266)	(27.95)
$\Delta lngdp_{i,t-1}$			0.514***	0.030	0.453***	-0.106
			(0.030)	(0.079)	(0.034)	(0.345)
$\Delta theil_{i,t-1}$			0.458	-4.886	0.491	-52.69
			(0.517)	(8.056)	(0.534)	(42.76)
$\Delta lninvest_{i,t-1}$			0.132***	-0.054	0.102***	1.162**

			(0.022)	(0.088)	(0.023)	(0.500)
$\Delta lnhyrav_{i,t-1}$			-0.043	-0.251	-0.090	-2.701
			(0.058)	(0.352)	(0.059)	(1.651)
$\Delta theillninvest_{i,t-1}$			-0.251	0.979	-0.224	-7.724
			(0.166)	(1.599)	(0.173)	(5.250)
$\Delta theillnhyrav_{i,t-1}$			-0.100	2.373	-0.130	23.35
			(0.261)	(3.703)	(0.270)	(19.09)
$\Delta lngdp_{i,t-2}$					0.014	0.120
					(0.035)	(0.478)
$\Delta theil_{i,t-2}$					-1.034**	-31.12*
					(0.503)	(17.31)
$\Delta lninvest_{i,t-2}$					0.095***	0.135
					(0.024)	(0.293)
$\Delta lnhyrav_{i,t-2}$					-0.245***	-1.618*
					(0.056)	(0.895)
$\Delta theillninvest_{i,t-2}$					-0.290*	0.530
					(0.167)	(3.333)
$\Delta theillnhyrav_{i,t-2}$					0.642**	15.35*
					(0.255)	(8.217)

Note: ***, ** and * represent the significance level of 1%, 5% and 10% respectively.

Table 5-B4. Inequality's effects on growth through different channels (inequality measurement: *ineq*)

panel	p=1		p=2		p=3	
ARDL-ECM	FE	MG	FE	MG	FE	MG
	(1)	(2)	(3)	(4)	(5)	(6)
Long run coefficients						
ineq	-0.749***	6.980	-0.062	9.080	0.256	8.674
	(0.258)	(4.262)	(0.204)	(8.264)	(0.194)	(11.27)
lninvest	0.122	-0.130	-0.272*	9.035	-0.591***	-1.624
	(0.168)	(1.449)	(0.146)	(7.594)	(0.146)	(3.277)
lnhyrav	-2.211***	6.338	0.492	-6.048	1.090***	9.011
	(0.621)	(4.565)	(0.399)	(14.05)	(0.382)	(11.33)
ineqlninvest	0.037	0.169	0.111**	-2.629	0.203***	0.514

	(0.062)	(0.557)	(0.054)	(2.265)	(0.053)	(1.194)
ineqlnhyrav	0.578***	-2.882	0.150	-3.877	-0.019	-3.713
	(0.140)	(1.795)	(0.104)	(3.732)	(0.099)	(4.869)
ect	-0.107***	-0.247***	-0.111***	-0.310***	-0.120***	0.658
	(0.012)	(0.036)	(0.011)	(0.062)	(0.012)	(0.651)
Short run coefficients						
$\Delta ineq_{i,t}$	0.062	0.706*	0.044	1.477**	0.012	6.973
	(0.050)	(0.395)	(0.043)	(0.679)	(0.044)	(5.373)
$\Delta lninvest_{i,t}$	0.005	-0.242*	0.030	-0.501**	0.094**	-1.455
	(0.044)	(0.139)	(0.040)	(0.231)	(0.041)	(1.746)
$\Delta lnhyrav_{i,t}$	0.413***	1.052**	0.235***	2.043**	0.152*	8.475
	(0.091)	(0.448)	(0.084)	(0.843)	(0.083)	(6.154)
$\Delta ineqlninvest_{i,t}$	-0.039**	0.027	-0.054***	0.123	-0.070***	0.661
	(0.016)	(0.049)	(0.014)	(0.083)	(0.014)	(0.638)
$\Delta ineqlnhyrav_{i,t}$	-0.091***	-0.386**	-0.068***	-0.726**	-0.059***	-3.065
	(0.025)	(0.175)	(0.022)	(0.306)	(0.022)	(2.404)
$\Delta lngdp_{i,t-1}$			0.507***	0.018	0.452***	-0.844
			(0.029)	(0.068)	(0.034)	(0.557)
$\Delta ineq_{i,t-1}$			0.028	0.798*	0.033	4.480
			(0.042)	(0.409)	(0.044)	(4.239)
$\Delta lninvest_{i,t-1}$			0.201***	-0.349***	0.157***	-1.439
			(0.040)	(0.104)	(0.042)	(1.214)
$\Delta lnhyrav_{i,t-1}$			0.003	1.134**	-0.046	5.212
			(0.080)	(0.525)	(0.084)	(4.878)
$\Delta ineqlninvest_{i,t-1}$			-0.04***	0.106***	-0.032**	0.640
			(0.014)	(0.038)	(0.015)	(0.453)
$\Delta ineqlnhyrav_{i,t-1}$			-0.014	-0.371*	-0.016	-1.889
			(0.021)	(0.193)	(0.022)	(1.929)
$\Delta lngdp_{i,t-2}$					0.006	-0.646*
					(0.035)	(0.348)
$\Delta ineq_{i,t-2}$					-0.086**	1.862
					(0.041)	(1.755)
$\Delta lninvest_{i,t-2}$					0.144***	-0.907
					(0.040)	(0.584)

$\Delta lnhyrav_{i,t-2}$	-0.286***	2.156
	(0.079)	(2.152)
$\Delta ineqlninvest_{i,t-2}$	-0.030**	0.367
	(0.014)	(0.228)
$\Delta ineqlnhyrav_{i,t-2}$	0.045**	-0.747
	(0.021)	(0.818)

Note: ***, ** and * represent the significance level of 1%, 5% and 10% respectively.

In table 5-B4, the coefficients of *ginilninvest* are significant and positive in column (3) and (5), supporting the findings estimated when Gini coefficients are used.

Chapter 6. Concluding remarks

Since China's economic reform in 1978, the country has gone through a transition from a planned economy to a market economy. During this transition, the country experienced rapid economic growth, but the high rate of growth was accompanied by an increase in the level of income inequality, giving rise to concerns among researchers regarding its potential impacts on future economic growth. In this sense, it is important to deepen the understanding of China's income inequality and economic growth, and to establish how inequality and growth affect each other, in order to offer some useful insights for policy makers. While researchers have conducted both theoretical and empirical studies to examine the relationship between inequality and growth, no consensus has been reached, thus whether inequality and growth are negatively or positively connected remains a controversial topic. In addition, considering the unique economic environment of China, the findings of previous studies based on other countries may not be applicable. In addition, the conclusion may vary with the different various research methods and model specifications. Thus, this thesis conducts studies based on the context of China, intending to provide new empirical evidences on this topic. Specifically, this thesis investigates three fundamental research questions: i) What are the patterns and evolution of China's regional inequality and growth? ii) What is the relationship between income inequality and economic growth in China? iii) Through which mechanisms does inequality affects growth?

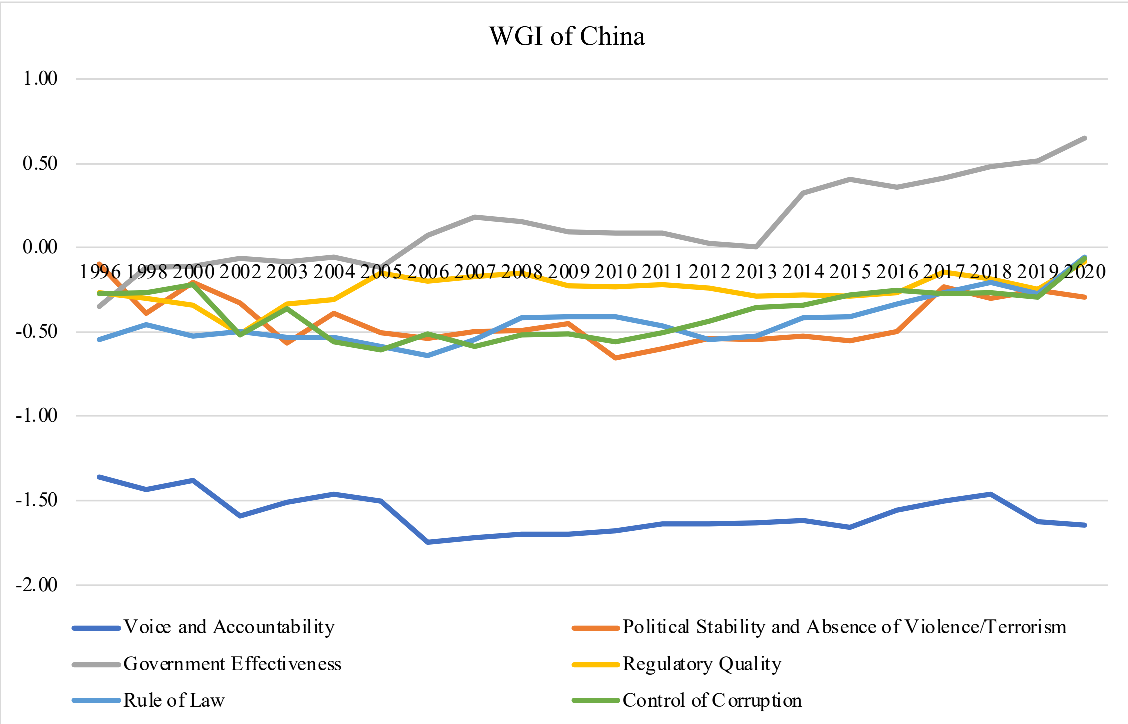
Chapter 3 has provided a comprehensive overview of the spatial dynamics of China's income inequality, economic growth, human capital and physical capital. According to Theil-T and Theil-L decompositions, the country's overall inequality has been lessened in recent decades, and in recent years, the intra-regional inequality has surpassed the inter-regional inequality as the main contributor of the overall inequality.

As for the inequality and growth on the provincial level, the economy has been growing steadily over the years, while inequality starts from a low level in 1990, peaks in 2003, and declines afterwards. Human capital has increased in the past decades, and although basic human capital accounts for the largest proportion of the total human capital, medium and advanced human capital have been growing fast and are taking larger proportions than before. Investment also increases during the years, but is unevenly distributed among the provinces. This chapter could facilitate a better understanding of the country's inequality and growth background by exploring the spatial dynamics of China's inequality and growth. The pattern that the income inequality starts from a low point in 1990, peaks in 2003 and declines afterwards shows that the inverted U-curve is relevant in the context of China.

The decrease in the overall income inequality, including the inequality within and between the regions, is possibly due to the government policies to alleviate inequality. As mentioned in Chapter 3, policies have been conducted to enhance the growth of the underdeveloped areas. Specific policies have been introduced to reduce inequality among the regions. 'China's Western Development Strategy', for example, aims to boost economic growth in the western provinces by helping them to build new infrastructures, improve their education and protect the environment, etc., and the 'Northeast Area Revitalization Plan' helps to improve the economy in the north-eastern region by rebuilding their traditional industries. In addition, as mentioned before, the government has implemented policies to reduce urban-rural inequality, including 'the Outline for Poverty Reduction and Development of China's Rural Areas (2001–2010)', 'the Outline for Development-oriented Poverty Reduction for China's Rural Areas (2011–2020)', the project of agricultural tax exemption and the subsidies provided for farmers.

Regarding the possible reasons underlying the evolvement pattern of inequality, except for the policy interventions mentioned in Chapter 3, institutional factors, such as voice and accountability, political stability and the absence of violence or terrorism, government effectiveness, regulatory quality, the rule of law and control of corruption, may have also affected the evolvement of inequality. The factors include voice and accountability, political stability and absence of violence/terrorism, government effectiveness, regulatory quality, rule of law and control of corruption. Figure 6-1 presents China's WGI indicators. The higher the values, the stronger the governance performance. The indices are collected from the Worldwide Governance Indicators (WGI) project database. As can be seen from the figure, the values of regulatory quality and government effectiveness during the period from 2004 and 2017 are generally higher than those in 2003, and control of corruption has an overall upward trend from 2005. Considering that income inequality lessened after 2003, it is possible that the higher regulatory quality, government effectiveness and control of corruption helped to reduce the country's income inequality. The picture is ambiguous as to how political stability and rule of law can affect inequality. Voice and accountability declines over time, so it may not be the key factor to influence inequality. The main driver of inequality reduction might be government effectiveness, because higher government effectiveness means the government can better implement inequality alleviation policies to help the poor regions, and if the government wants a more equal society, it is easier to achieve the goal.

Figure 6-1. WGI of China



Chapter 4 investigated both the long- and short-term relationships between income inequality and economic growth in both directions, using panel VECM. Apart from the impact of inequality on growth, the influence of growth on inequality, which was largely overlooked by previous studies, was also evaluated by the empirical model. The study also took advantage of provincial level data to address the issues that exist in cross-country studies, such as cross-country heterogeneity, data comparability and sample selection issues. Further, the presence of cross-sectional dependence (CSD) in panel data are neglected in most of the previous studies. Neglecting CSD can lead to estimations that are potentially biased, thus the study in chapter 4 adopted the Driscoll-Kraay estimator to deal with the CSD issue. The empirical results of the chapter indicated that income inequality and economic growth were positively related in the long run during 1990–2003 and negative related during 2003–2017, supporting the inverted-U hypothesis proposed by Kuznets (Kuznets, 1955). In the future, when more data are available and more years are included, the research may get a better idea of how well the inverted-U hypothesis fits in the context of China.

Inequality enhanced growth in the short term after 2003, thereby supporting the findings of Forbes (2000) for a panel of countries. Regarding the impact of growth on inequality, the study found that growth reduces the income gap before 2003, also in the short term, but increased the gap thereafter. The results also suggested that rather than human capital, physical capital was the main contributor of economic growth. While human capital did not have an effect on inequality, physical capital enlarged the income disparity over the period from 1990 to 2003, which is in line with the conclusion of Chen (2007). As for the impacts of human capital in its three different levels, the results suggested that prior to 2003, growth was enhanced by medium-level human capital, but was harmed by basic and advanced human capital. The income disparity was reduced by basic and medium human capital, but is widened by advanced human capital. After 2003, while basic human capital enhanced growth, medium human capital harmed growth, whereas advanced human capital did not affect growth.

The chapter also offered two potential explanations for the insignificant or negative influence of human capital on growth. First, the insignificant short-term impact of advanced human capital on growth might be due to the nature of tertiary education- it takes longer for tertiary education to influence growth, as the knowledge taught are not as practical as vocational education. Thus, human capital's effect on growth is not reflected by the short-run coefficients. Second, human capital's negative impact on growth is probably due to the quality of education. If the knowledge taught in schools cannot meet the standards and requirements of the market, human capital may fail to enhance growth. Meanwhile, the reason that physical capital enlarged income disparity between1990 and 2003 can be explained by the higher marginal propensity to save of the rich. Specifically, in the early stage of development in China (1990–2003), the rate of return on physical capital was high. For a province with more physical capital, this was largely concentrated in the wealthy urban area, which means the rich saved and invested more, with the high returns adding to their high income. On the other hand, the poor saved and invested less, and got fewer returns. In this manner, physical capital can enlarge the urban-rural income gap.

Chapter 5 constructed two empirical models. The first model revisited the relationship between income inequality and economic growth. Using panel ARDL-ECM allowed the study to estimate the long-term impacts of inequality, and of human and physical capital on growth. The model can also address slope heterogeneity and data non-stationarity issues. The second model examined the mechanisms underlying the inequality-growth relationship by adding two interaction terms. As most of the existing empirical studies merely focus on the inequality-growth connection without exploring the underlying theoretical mechanisms, the study in this chapter fills this gap by testing two mechanisms, the classical mechanism and the credit market imperfection mechanism.

Apart from the estimation for the whole sample, the chapter also presented the estimations performed for three subsamples, namely those at the top, middle and bottom income levels. The empirical evidences of the first model suggested that between 1990 and 2017, income inequality has a stimulating long-term effect on economic growth, both in the whole sample and in all the subsamples. Meanwhile, the growth was enhanced by physical capital, but was not affected by human capital. As for the results of the second model, it was found that human capital was found to be the prime driver of China's economy in the long term. The coefficients of the interaction terms implied that inequality enhances growth through physical capital, which is in line with the classical mechanism. Meanwhile, inequality was found to harm growth by affecting human capital, thereby supporting the credit market imperfection mechanism.

Regarding the subsamples, the results indicated that human capital played a more important role in economic growth in the top provinces, and a less important role in the middle provinces. Furthermore, it was found that the negative impact of inequality on growth through human capital became more apparent in the top 10 provinces. The inequality-growth relationship was unclear in the bottom group because of the insignificant coefficients. Overall, the results of the first model found that inequality and physical capital enhanced growth in the long term, while human capital did not have a significant influence on growth. The results of the second model supported both the classical and credit market imperfection mechanisms. Additionally, the empirical evidences implied a possibility that the bottom 10 provinces in China suffered from insufficient marketisation.

The present study has investigated the relationship between inequality and growth and the mechanisms behind their relationship. It has focused on the roles of human capital and physical capital in the inequality-growth relationship. The research can be deepened by adding more control variables in the models, when more high-quality data are available. For example, factors that may promote economic growth, such as trade openness, infrastructure and foreign direct investment, can be added to the model. Meanwhile, as discussed before, governance indicators like government effectiveness, regulatory quality, control of corruption, etc. can also be considered, as they also have potential influence on economic growth. Besides, future avenues of research could consider Human Development Index (HDI) as an alternative to GDP. HDI is an indicator to reflect the social and economic development of a country. Different from GDP that focuses on production, HDI emphasizes the importance of human development and well-being, although it does not directly reflect a nation's income as GDP does.

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