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The Rise and Fall of Income Inequality in Post-Reform China

An empirical analysis of the development and determinants of income inequality in China in the period 1985-2015

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Abstract

Over the last couple of decades, there has been progressive commitment and remarkable achievements by the international community in lifting people out of poverty across the world. At the same time, elevated levels of inequality in income persists as a global phenomenon – threatening long-term social and economic development, but also undermining individuals' self-worth and sense of fulfillment by putting certain people at a persistent disadvantage.

In this, China is no exception. Following the economic reforms in the late 70s and early 80s, the country embarked upon one of the greatest economic expansions in modern history. An unprecedented development that has brought the nation to the verge of eradicating poverty. In spite of these achievements, the economic gains from the growth miracle has been far from equally distributed. Before integrated into the world market, the income distribution in China was considered egalitarian in all aspects, with inequality comparable to the Nordic countries. This changed dramatically over the following decades with the level of inequality rising at one of the fastest rates ever recorded, rendering China among the world's most unequal nations.

In the interest of understanding this development, the purpose of this dissertation is to explain how the aggregate disparity in income distribution has evolved in China in the period between 1985 and 2015, but also to shed light on some of the most significant drivers of this evolution. From the descriptive analysis pertaining to the former, there is clear consensus among previous empirical work in that income inequality increased markedly in the years following the economic reforms up until the late 00s. From 1978 to 2010, the top 10% income earners increased its share of national income by 16%, while the share assumed by the bottom 40% of the distribution decreased by 13% in the period. Around 2010, there is a reversal in the trend, as the relative disparity between top and bottom earners declined by 7% up until 2015.

The findings from the empirical analysis suggest that trade liberalization has had a significant positive impact on the level of disparity between the top 10% and bottom 40% income earners in post-reform China. At the same time, the regression results find that increased efficiency of redistributive policies has significantly contributed to reduce aggregate income inequality in the period. The analysis is unable to find evidence to support the hypotheses of Kuznets and Milanovic related to determinants of the development. However, given the limitations of the study, more data and dynamic models is needed to conclusively validate these findings.

Acknowledgements

Less than two and a half years ago, I embarked upon one of the most exciting and enriching journeys of my life thus far. This thesis marks the end of what has been two incredible years at Norwegian School of Economics and National University of Singapore, from where I have experienced and learned more than I could have ever wished for - more than anything about myself. I will be forever grateful for the opportunity the educational system and these institutional platforms has given me to pursue my dreams and realize my academic potential.

The process of writing this thesis has been protracted and challenging, but all the more rewarding. Through this research, I have been able to delve into a subject matter that lies close to my heart and achieve a greater understanding of the dynamics of income inequality in China and other developing countries. A process that has further inspired me to strive towards economic inclusion and empowerment of lower income earners in my future profession. I aspire to make use of the knowledge acquired from this research to make a positive impact, and I hope that the work that has been done for this thesis can be of meaningful value to others.

I would also like to express my sincerest gratitude and appreciation to my supervisor Prof. Kjetil Bjorvatn. Throughout this long-lasting process, he has continually offered his availability for valuable guidance, practical support and good conversations. This thesis, nor the process itself, would have been the same without him. Lastly, and most importantly, I would like to thank my family and friends for their continuous support and encouragement throughout my scholastic undertakings. Without your moral support and backing, I would not be where I am today. You inspire and motivate me to be the best I can be.

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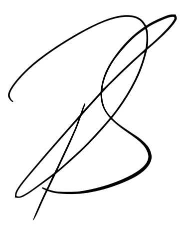

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1. Introduction

1.1 Background

From the outset of the market-oriented economic reforms in 1978 when China started its process of 'opening-up', it was a poor nation with GDP per capita less than half of the average in Asia (Eckart, 2016). Despite the poor economic conditions of the country, it was a relatively equal nation in terms of wage distribution. In the time leading up to the economic liberalization, China's wage equality was comparable to the most egalitarian Scandinavian countries today and significantly more equal than for example France or United States at the time (Piketty et al., 2017). At this time, the share of national income assumed by the top decile income earners at around 27% was equivalent to the share assumed by the bottom 50% of the distribution. The Asian Development Bank Institute (Shixue, 2003) described the pre-reform conditions as follows: *"before China implemented reform and open-door policies in 1978, its income distribution patterns was characterized as egalitarianism in all aspects"*.

Following the first wave of economic reforms in 1978, the country embarked upon one of fastest and largest economic expansions in modern history. From 1980 to 2012, per capita income rose from 320$ to around 5,500$ (Cevik & Correa-Caro, 2015). Even though the transition from a centrally planned economy to a more market-oriented economy raised more than 660 million people out of poverty, the economic gains has been far from equally distributed. In the same period of time, China experienced one of the most rapid rises in levels of income inequality ever recorded (Li, 2016). From 1978 to 2015, the share of national income assumed by the 50% lowest income earners fell to around 15%, whereas the top decile profoundly increased its share to around 41% (Piketty et al., 2017). Gini coefficient estimates based on the same dataset suggests an increase of around 20 Gini points over the whole period, from 35 in 1978 to 55 by 2015. A substantial increase equivalent to nearly three times the rise in income inequality in United States for the same period, at 6.9 Gini points (World Bank, 2019). Consequently, China had gone from being a relatively egalitarian nation to being ranked one of the most unequal societies in the world in 2015 (Cevik & Correa-Caro, 2015). Howbeit, as advocated by Deng Xiaoping in his famous dictum, the paradoxical policy of the Communist Party was to *"let some people get rich first"* to gradually achieve common prosperity (Shawki, 1997). A political intention that may come into fruition as recent estimates indicates a reversal of the trend towards a more equal income distribution from the late 00s.

1.2 Motivation and contribution

The motivation for this thesis can be seen from two fundamental perspectives. First, from a personal perspective, my experiences of living in China motivated me to get a better understanding of the development and drivers of income inequality in the country. The second perspective pertains to gaps in relevant literature and empirical research related to the aggregate development and determinants of change over time.

In 2016, I got the opportunity to live in China as a part of an exchange program during my bachelor's degree. This was a mind-altering experience along a myriad of dimensions, but one impression manifested itself; the dramatic contrast between rich and poor. The collectivistic nation ruled by a communist party paradoxically felt more like a polarized plutocracy. Seeing how university staff cramped up in pocket-sized bunkbeds in the basement ventilation room around the corner from the luxury fashion mall occupied by extravagant sportscars inspired me to better understand this disparity. These experiences and a prolonged aspiration of towards contributing to sustainable development had me reflect on how I could make a difference. I realized that by pursuing a greater understanding myself, I could contribute to an enhanced understanding for others, which led me to devote my master thesis to the subject. After consolidating with my supervisor and reviewing existing empirical work in the case of China, I identified gaps in the literature which I could contribute to narrow by shedding more light on both development and dynamics of income inequality in the modern post-reform era.

The rapid increase in income inequality in China following the economic reforms in 1978 is a well-documented phenomenon (e.g. Shi et al., 2013; Khan & Riskin, 2001; Ravallion & Chen, 2007; Li et al., 2014). However, existing literature is largely fragmented and limited to certain conceptual facets because of data limitations (e.g. regional disparity or impact of policy; Gustafson and Li, 2002; Kanbur and Zhang, 1999; Fan et al., 2002; Heerink et al., 2006). Through this thesis, I hope to contribute to existing research by providing a more holistic and comprehensive account of the long-term evolution and dynamics of within-country income inequality in post-reform China. Wan and Zhang (2006) argues that current empirical work has primarily been descriptive and underlines the need for more analytical work that attends to the causes of the rise in inequality. The limited empirical work that is attending to the determinants of change in the income distribution also often focus on endogenous transmission channels rather than the exogenous structural drivers. Through this dissertation, I hope to contribute to a better understanding of the structural determinants in a long-term perspective.

1.3 Research question and purpose

Following the motivation of the research described above, the purpose of this research paper is to provide a better understanding and close existing knowledge gaps about the development and determinants of aggregate income inequality in the post-reform era in China. I hope to shed more light on economic disparity in China by comparing existing empirical research, but also adopt an alternative measurement approach that could help mitigate some of the existing bias. Additionally, to hopefully provide new insights into the dynamics of income inequality in China after the economic reforms by analyzing determinants in light of renowned theories and empirical work in a global, regional and country-specific perspective. In accordance with this purpose, the research question of this thesis is formulated accordingly:

"How has disparity in the distribution of income evolved in China in the period 1985-2015, and what are the most significant determinants of the development?"

1.4 Scope and limitation

The scope of this thesis will be limited to the development and determinants of aggregate inequality in the income distribution for the period between 1985 to 2015. Accordingly, this thesis will not attend to consequences, implications nor solutions to an elevated level of inequality beyond a brief discussion related to the importance of such disparity in chapter 2. The research paper will further not attempt to make any estimations in terms of forecasting or projection of future development. Despite the importance of these conceptual facets, such estimations and predictions entail too much complexity and ambiguity for this study to make a meaningful contribution to existing empirical work. Marked limitations in terms of data availability, quality and measurement alignment have also prevented the empirical analysis from address determinants of inequality in the immediate years following the economic reforms between 1978 and 1985. Data limitations that has further restricted the study of this paper from attending to the most recent development in the period after 2015.

1.5 Structure of thesis

In accordance with the purpose and research question of this study, the dissertation will be structured into two main bodies. The first of which will attend to the first part of the research question, which will embody a descriptive and explanatory analysis of the development of disparity in the income distribution from 1985 to 2015. This part of the thesis will first account for fundamental analytical elements in studying income inequality by defining the concept of income inequality, discussing the related importance and elaborating on different measurement techniques. Thereafter follows a comprehensive review of existing empirical research with a descriptive analysis of the related estimates of the development in levels of inequality for the period. This will further include new estimates of the changes to the income distribution by introducing an alternative measurement technique based on existing secondary data. Subsequently, the estimated degree of disparity will be decomposed along critical dimensions to shed light on the composition and dynamics of the aggregate income dispersion. More specifically, attending to the relative contribution and disparity of groupings based on spatial distribution, educational attainment, sectorial employment and income sources.

The second main body of the thesis consist of the exploratory analysis in determining drivers of the established development in inequality. In this, I will first present a review of relevant theoretical predictions and empirical evidence which will function as the basis for variable selections and regression modelling. Chapter 6 will then account for the research design, methodological approach and necessary stastical assumptions for the empirical analysis. Followingly, chapter 7 presents the employed dataset for the analysis with a description of the included predictors, the variable construction technique adopted and relevant historical development in each of the processes. This will also include a discussion related to the limitations of the employed measurement techniques. In chapter 8, I will present the regression analysis and results related to the second part of the research question. This chapter will first account for the regression modelling procedure and rationale, before relevant diagnostics and adaptations of the data and model specifications is described in accordance with necessary assumptions. Thereafter, the final regression results are presented with a related description of the hypothesis tests for each of the given model specifications and predictor variables. These results will subsequently be summarized, discussed and interpreted in light of the theoretical predictions in the following subsection. At last, I will give an account for potential limitations and weaknesses of the analysis and methodological approach before the paper is concluded.

2. Fundamentals of Income Inequality Analysis

In this section, I will present an overview of the fundamental theoretical and conceptual background for studying income inequality. This include, defining the concept of income inequality, discussing why the income dispersion matters and how to measure such disparity in a meaningful way. This will also include a discussion related to implications of applying different measurement techniques. A background intended to provide a basic conceptual understanding of the coming analysis of evolution and configuration of inequality.

2.1 Defining income inequality

The Oxford advanced learners dictionary (2019) defines inequality as *"the unfair difference between groups of people in society, when some have more wealth, status or opportunities than others"*. A broad definition that has been prone to debate, as the wording leaves much room for subjective interpretation and perceptional differences of the concept. A common way to distinguish the phenomenon is to differentiate between inequality of rights and obligations and inequality based on living conditions, also known as economic inequality (United Nations, 2015a). Such economic inequality refers to the distribution of economic variables including income, consumption and wealth across populations, between subgroups or countries.

Along the dimension of economic inequality, two conceptual perspectives prevail; inequality of outcomes or opportunity. The outcome-oriented view focuses on income as proxy for well-being, while the latter perspective understands the concept of well-being differently, as it emphasizes the freedom to choose rather than ensuring equality in outcomes. The relative importance of these perspectives is not straightforward and has been subject to strongly diverging standpoints in both political and academic spheres. At the same time, Rawls (1971) argues that distribution of outcomes and opportunities is of equal importance, but also that they equally informative in understanding the extent and nature of inequality.

Income inequality is an aspect of economic inequality that describes a condition in which cumulative income is unequally distributed across a population. In other words, income inequality exists if certain individuals or a subgroup assumes a disproportionate share of national income relative to its size (Dinca-Panauitescu and Walks, 2015). An increase in the level of income inequality must consequently be a result of low-income earners becoming relatively poorer, high income earners become relatively richer, a relatively smaller share of national income assumed by the middle-class or a combination of any of these processes.

2.2 Why income inequality matters

The concept of fairness and equality is a fundamental social value in societies across the world. In this, the economic dimension of inequality, specifically in the form of disparity in the distribution of income can be considered to be an elemental factor. Even though the phenomenon of income inequality directly relates to inequality in outcomes, such disparity undoubtedly affects equality and fairness in opportunities through social mobility as well. High levels of disparity in the income distribution reflects an economic condition whereas certain segments of the population are put at a persistent disadvantage. A condition that could entail a myriad of negative implications for long-term economic and social development. In line with these consequences, I will account for some of the reasons why income inequality matters. In doing so, I hope to share some of my devotedness for the topic with the reader.

In a free-market economy, a certain level of inequality is inevitable. Some degree of inequality can even be deemed a desirable economic condition in certain aspects, as there is an *"important role of income differences in in providing incentives to invest in education, physical capital, to work hard, and to take risks"* (World Bank, 2006). Correspondingly, Lazear and Rosen (1981) argues that inequality incentivizes entrepreneurship and innovation which can have a positive effect on growth. Barro (2000) further suggests that inequality can be especially positive for growth in developing countries, in that it facilitates conditions for some individuals to obtain means for educational or entrepreneurial purposes. At the same time, it is important to underline the ambiguity related to these proposed causal mechanisms.

In terms of economic growth stimulus, which seems to be prevalent argument for some degree of inequality, recent literature finds that income inequality can impair both the rate and sustainability of economic growth (Ostry, Berg, and Tsangarides 2014; Berg and Ostry 2011; Dabla-Norris et al., 2015). Galor and Moav (2004) finds that increased inequality leads to reduced growth by preventing poor individuals from accumulating either human- or physical capital, thus restraining social mobility. A mechanism that again would induce negative consequences on labor productivity (Stiglitz, 2012). Widening inequality is further found to have a detrimental effect on political, financial and economic stability, which again hampers investments and have constraining effects on economic growth (Dabla-Norris et al., 2015).

This on-going academic and political debate reflects the ambiguity related to economic consequences, but also what can be deemed as a beneficial level of income inequality. At the same time, there is far less dispute to the notion that an elevated and sustained level of inequality over time will have harmful consequences, both socially and economically. In terms of inequality in opportunity, high and persistent levels of inequality is found to inflict significant social cost and have adverse effects on sustainable development and poverty reduction (Dabla-Norris et al., 2015; World Bank, 2006). In this, inducing a risk of reduced provision of public goods and diminish support for growth-enhancing policies (Claessens and Perotti, 2007; Putnam, 2000; Bourguignon and Dessus, 2009). In the perspective of outcomes, elevated levels of inequality can undermine both occupational- and educational choices, at an individual level. Such conditions can further generate incentives for corruption, nepotism, resources misallocation and behavior linked to securing and conserving beneficial treatment if these incentives are based on rents (Stiglitz, 2012). Consequences which again could lead to undermined institutions, amplification of polarization and stimulation of social unrest.

Finally, returning to the notion of fairness and equality as a boundaryless social value. There is a widely accepted ethical premise throughout most societies, cultures, religions and ideologies that there ought to be a reasonable degree of equality between individuals (Mckay, 2002). Accordingly, even though it may be unclear what can be deemed a fair extent of equality, high and sustained level of disparity over time should be addressed. Not only because of the detrimental economic consequences such a condition may induce, but also because an unreasonable level of inequality between individuals matters in its own right.

2.3 Measuring income inequality

According to Cowell (1998), we can see the objective of estimating the level of disparity as an intention to give meaning to inequality based on selected criterions such as ethical principles, basic intuition or mathematical constructs. Following this conceptual multifariousness related to the perception of the phenomenon, there is a great variety of advocated methods and measurement techniques on how to operationalize income inequality. This spectrum of methodologies offers a great assortment of alternative techniques to achieve a more nuanced understanding of earnings disparity, but it also implies that different measures can be meaningful for certain purposes or facets to inequality. Consequently, finding an appropriate estimator that fits the purpose of the analysis is fundamental, but also one of the key challenges for appropriate and justifiable research.

Sen and Foster (1973) suggested a two-fold categorization of income inequality metrics. The first category can be described as normative measures pertaining to social welfare and attending to the losses deriving from income dispersion. The second group of measures can be described as more objective and does not consider the effect on social welfare. Since the methodical approach of this thesis is predominantly descriptive and does not consider potential losses in social welfare deriving from income inequality, this section will only attend to measures from the latter category, and metrics related to the former will thus not be addressed.

Beyond the second metric categorization by Sen and Foster (1973), the preferred measure should embody properties that makes it an objective, unbiased and accurate estimator. According the World Bank Institute (2005), there are four criterions that needs to be fulfilled for the measurement or index of income inequality to hold the above-mentioned qualities and thus represent a satisfactory measure. If we assume that $I(x)$ represent the inequality metric with $x = x_1, x_2, x_3 \ldots x_n$, and x_i reflects the income level of x individuals or households, the formal denotation of the property is given below the description of each of the criterions.

- **Mean independence or homogeneity**

  The mean independence criteria mean that the scale of the economy is irrelevant for the income inequality metrics. In other words, that the estimate remains the same despite changes in the mean of income, as long as the distribution of income remains unchanged.

$$I(ax) = I(x) \tag{2.1}$$

- **Population size independence**

  The size of the populations is irrelevant for the level of disparity in cumulative income. If the population would change dramatically, the metric would not change given that the original distribution remains unchanged.

$$I(x \cup x) = I(x) \tag{2.2}$$

- **Symmetry or anonymity**

  Which individuals or households that represents high- and low-income earners in a population is irrelevant. Accordingly, if two individuals would swap their income, it would not impact the level of income inequality.

$$I\{P(x)\} = I(x) \tag{2.3}$$

- **Pigou-Dalton Transfer sensitivity**
  Disparity in distribution of cumulative income would be reduced if high-earning individual would transfer his or her earnings to a low-earning individual.

In addition to these criterions, there is non-mandatory properties described in economic literature which are deemed desirable, but not necessary for an estimate to be denoted as satisfactory. These properties include *decomposability*, which means that the measure can be divided up into different subgroups within the population, be broken down by income sources or segregated based on other dimensions. In other words, the measure should be additive, in that the level of disparity within different populations groups equals the aggregate level of inequality. Another condition is that of *non-negativity*, which suggest that the metric of inequality should not have a negative value, thus greater or equal to 0.

Based on the above-mentioned criterions, the purpose of this dissertation and relevant data limitations, a set of systematic methods in operationalizing income inequality have been selected for the descriptive and empirical analysis. These mathematical constructs of measuring disparity in income distribution are described in further detail in the sections below.

2.3.1 Share and ratio of income

One of the most basic and intuitive ways to conduct descriptive analyses of income inequality is to analyze the share and ratio of income across different groupings of people. For this thesis, the share of income would simply describe how much of the cumulative national income that is being assumed or acquired by a given segment of the population. The second of these conventional measures is a basic ration, which simply represents a comparison of assumed income between two subgroups. The common base comparisons in measuring income inequality through such ratios consist of percentiles, deciles and quintiles which again describes the relevant percent, 10_{th} percent or 20_{th} percent of a distribution spectrum. A limitation of these elementary measures of disparity in distribution of income is that they only capture parts of the distribution. For this reason, more formal measure of income inequality has been developed, which I will now attend to in further detail.

2.3.2 Lorenz curve

In 1905, Max O. Lorenz suggested a graphical representation of disparity in the cumulative income or wealth distribution as an improved method to interpret levels and variation in inequality. The graphical plot, which is known as the Lorenz curve, illustrates the share of total income assumed by individuals or households below a given percentile. The model is given by the cumulated proportion of the population from poorest to richest on the horizontal axis, and the percent of cumulated income or wealth accruing to these percentiles on the vertical axis as illustrated in Figure 1. If there would perfect income equality in a population, the Lorenz curve would align with the 45-degree ray from origin, which is denoted as the perfect equality line. In the alternative scenario of ultimate inequality, the Lorenz curve would align with the horizontal axis known as the line of perfect inequality. By means of this, the curvature of the Lorenz curve and its proximity to the perfect inequality line indicates the formation and level of disparity in the cumulative income distribution (Clarke, 1992).

Figure 1: The Lorenz Curve

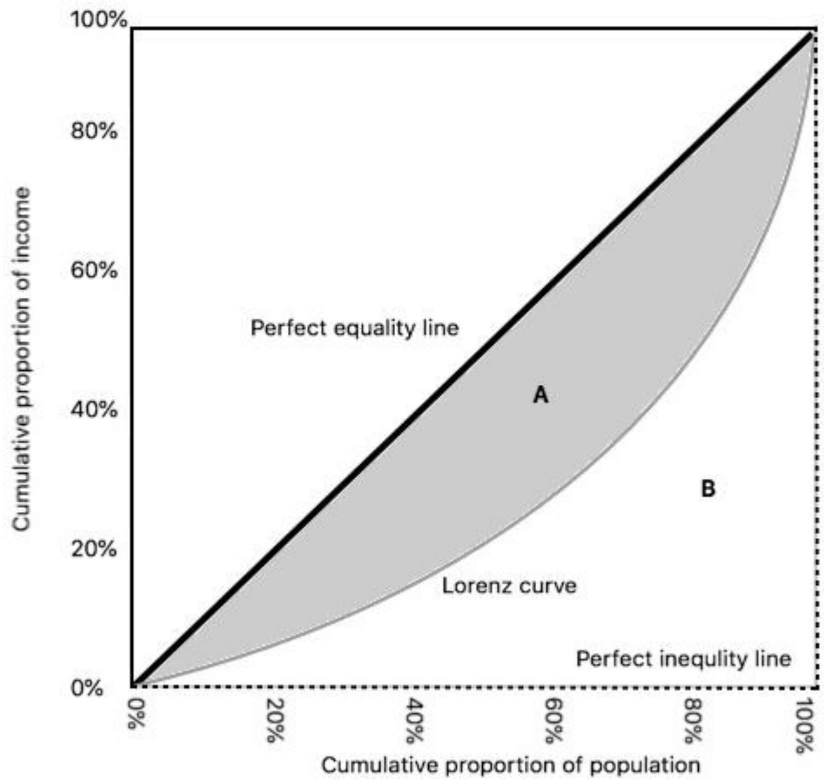


Illustration by author based on theory proposed by Lorenz (1905)

2.3.3 Gini coefficient

Building on the work of Max Lorenz (1905) and the hypothetical plot of a Lorenz curve, Corrado Gini (1913) derived a mathematical index that measures inequality in the distribution of income, wealth and expenditures known as the Gini coefficient. Today, this coefficient is applied in several other fields of science, but primarily in economics. Since it was introduced in the early 20th century, the metric has become the most conventional measures of inequality among economist because of its simplicity. Stuart and Ord (1994) defines the measure as the mean of absolute differences between all pairs of individuals, whereby reflecting the expected gap in income between two randomly selected individuals in a sample (Sen and Foster, 1973). The Gini coefficient ranges from a value of 0 to 1, whereas 0 represents complete equality in distribution, while a value of 1 reflects ultimate inequality. Accordingly, a comparatively high coefficient estimate would indicate a relatively more unequal distribution. In this thesis, the Gini coefficient is given as an index, which represents the coefficient value multiplied by 100.

The Gini coefficient is calculated as a ratio of the area between the Lorenz curve and the perfect equality line (a) over the total area below the perfect equality line $(a+b)$. Accordingly, Gini denoted as G is a result of $\frac{a}{a+b}$. Given that area $a+b$ has the geometrical property of an isosceles triangle, it necessarily equals a value of ½. As such, the Gini coefficient could be written as given by equation 2.4:

$$G = 2a = 1 - 2b \tag{2.4}$$

More formally, G can be expressed as equation 2.5, if we assume x_i to be a point on the X-axis and let y_i be a point on the Y-axis. If we assume N to equal intervals on the X-axis, the equation can be simplified as given in equation 2.6. Further technical properties of Gini coefficients are beyond the scope of this paper and will thus not be described in further detail.

$$G = 1 - \sum_{i=1}^{N} (x_i - x_{i-1})\left(y_i + y_{(i-1)}\right) \tag{2.5}$$

$$G = 1 - \frac{1}{N} \sum_{i=1}^{N} (y_i + y_{i-1}) \tag{2.6}$$

As mentioned previously, one of the primary benefits of employing Gini coefficient as a measure of income inequality is the comprehensibility of estimation and interpretation, but there are also several other advantages to the conventional technique. The properties of Gini coefficients satisfy the four necessary criterions portrayed by the World Bank Institute (2005) for an estimator to be denoted a satisfactory measure of income inequality. Beyond these four parameters, a great advantage of employing a Gini coefficient is the enablement of direct comparisons in the cumulative distribution of income between countries and subgroups, but also the ability to compare results within and between nations over time.

Despite these technical benefits, the Gini coefficient has also been subject criticism for some of its conceptual problems and limitations. First, a Gini coefficient is not easily decomposable or additive between subgroups, which means that the desired criteria of decomposability is not satisfied. More importantly, Atkinson (1969) claimed that this conventional measure of inequality could be directly misleading because of its over-sensitivity to changes in the middle of the distribution, and thus insensitivity to changes in the top and the bottom. These properties could be problematic in that it could potentially lead to underestimations of inequality, but also give misleading indications of change in distribution among to the top and bottom deciles.

2.3.4 Palma ratio

Following Atkinson's argument, José G. Palma (2011; 2016) questioned the effectiveness of the Gini as an indicator of income inequality. In his paper from 2011, he investigated 135 nations with elevated levels of within-nation inequality. From this research, he found that the middle and upper-middle income deciles share of distribution, from decile 5 to 9, was homogenous and relatively stable over time. The share assumed by this group approximated half of gross national income, an observation that was consistent across datasets, countries and time periods. A phenomenon which can be identified in China between 1985 and 2015 as well (see Appendix A). In the tails of the distribution, Palma observed a completely different dynamic. For the very top and bottom of the distribution, he found a high degree of heterogeneity and inconsistency over time. According to Palma, the phenomenon of these centrifugal and centripetal movements derives from the top income earners 'catching up' with rich nations in absolute terms, while the bottom 40 percent is falling behind and the middle classes normally being able to *defend* their share of national income.

Based on these findings, Palma suggested a new index of the income distribution that would be more appropriate for understanding high levels of within-nation inequality. An index that Cobham and Sumner (2013) later denoted as the “Palma ratio”. The so-called ‘Palma ratio’ indicates the ratio of gross national income shares of the top 10 percent earners divided by the share of the bottom 40 percent of the distribution. An indicator that according to José Palma (2016) measures inequality in a transparent and intuitive way where disparity in distribution is prevailing. This can be written as follows:

$$P = \frac{p0p10}{p60p100} \tag{2.7}$$

In addition to mitigating the problem of oversensitivity for the middle-income groups that arises when employing a Gini coefficient, the Palma ratio satisfies all the necessary criterions described earlier by the World Bank Institute (2005) for an estimator to be a satisfactory measure of income inequality. Based on findings from Palma and the development in the tails of distribution in China, which will be discussed further in Chapter 3 - the Palma ration will function as the preferred measure of aggregate income dispersion in the empirical analysis

Even though the Palma ration can be segregated along the dimension of the given percentiles, it is not a measure that can be decomposed based on alternative subgroups of the population. As such, to analyze the composition of income inequality along other dimensions and groupings of the population, we need a supplementary measure which is fully decomposable. Technical properties which is offered by general entropy measures, specifically Theil indices.

2.3.5 General Entropy (GE) measures and Theil index

In accordance with the limitations of the Gini coefficient and Palma ratio, measures of the Generalized Entropy (GE) class offers full decomposability, in addition to satisfying all the criterions suggested by the United Nations. Accordingly, GE class measures which originally stems from information theory, facilitates analyses of income inequality both within and between groupings of the population. Whereas such decomposition offers more detailed observations of income composition and changes in the national income distribution over time. In this, the value or outcome of GE measures can vary between zero and infinity, whereas a value of zero indicates perfect equality (United Nations, 2015b). The general formula for generalized entropy measures can be described formally as:

$$GE(\alpha) = \frac{1}{n\alpha(\alpha - 1)} \sum_{i=1}^{n} \left[\left(\frac{y_i}{\bar{y}} \right)^{\alpha} - 1 \right] \tag{2.8}$$

The income of i is given by Y_i and the mean income of group n is indicated by $\bar{y}$. The parameter α reflects the weight given to the distance in income in various parts of the income distribution. In this, a key feature of GE measures of inequality is the opportunity to choose this parameter, whereas lower values are more sensitive to changes in the bottom tail of the distribution and higher values are more sensitive to change in the upper tail (Atkinson & Bourguignon, 2015). The most common value for parameter α is 0, 1 and 2, whereas a value of zero is most commonly denoted as a 'Theil's L' index or mean logarithmic deviation. For this parameter, the contribution to aggregate income disparity by an individual or grouping of the population that obtains exactly mean income will be zero. Whilst the contribution to overall income inequality will be relatively larger compared to a higher parameter if the sub-population earns less than mean income. This dynamic and the 'Theil's L' can be described formally as such:

$$E(0) = \frac{1}{n} \sum_{i=1}^{n} \log \frac{\bar{y}}{y_i} \tag{2.9}$$

A parameter value of 1 is often called a 'Theil's T' index. In accordance with Theil's L, the contribution to overall inequality by a population segment with income corresponding to the mean income will be zero. This dynamic follows the same logic, as the logarithmic value of 1 will give a value of 0. In a Theil's T index, the contribution to aggregate income disparity of a grouping that earns less than the mean income will be relatively smaller than for Theil's L. The formal notion of the Theil's T index and the described dynamics can be given as:

$$E(1) = \frac{1}{n} \sum_{i=1}^{n} \frac{\mathrm{y_i}}{\bar{y}} \log \frac{\bar{y}}{y_i} \tag{2.9}$$

For a parameter value of 2, the produced index is known as 'coefficient of variation', but the technical properties of this parameter will not be addressed in any further detail for this paper. The reason for this is that the index is relatively more sensitive to changes in the top of the income distribution than that of Theil's T indices, which is deemed undesirable for the analysis. To ensure consistency in the forthcoming decomposition analyses, I will exclusively apply Theil's T as a standard GE class measure following a pragmatic middle way principle.

3. Analysis of evolution and composition of inequality

In this chapter, I will attend to the first facet of the research question by analyzing the evolution and composition of overall income inequality in China from 1978 to 2015. The analysis will embody two encompassing subsections in accordance with the purpose of the dissertation. The first part of this chapter will provide a descriptive analysis of estimates and findings from previous empirical work, in addition to giving an account for relevant official estimates. This section will also introduce a new perspective of the development by describing the changes to aggregate income dispersion in China by means of a Palma ratio estimate of inequality. Thereby, addressing some of the methodological criticism described in the previous chapter, but also shed more light on the greatly significant development in the tails of the distribution.

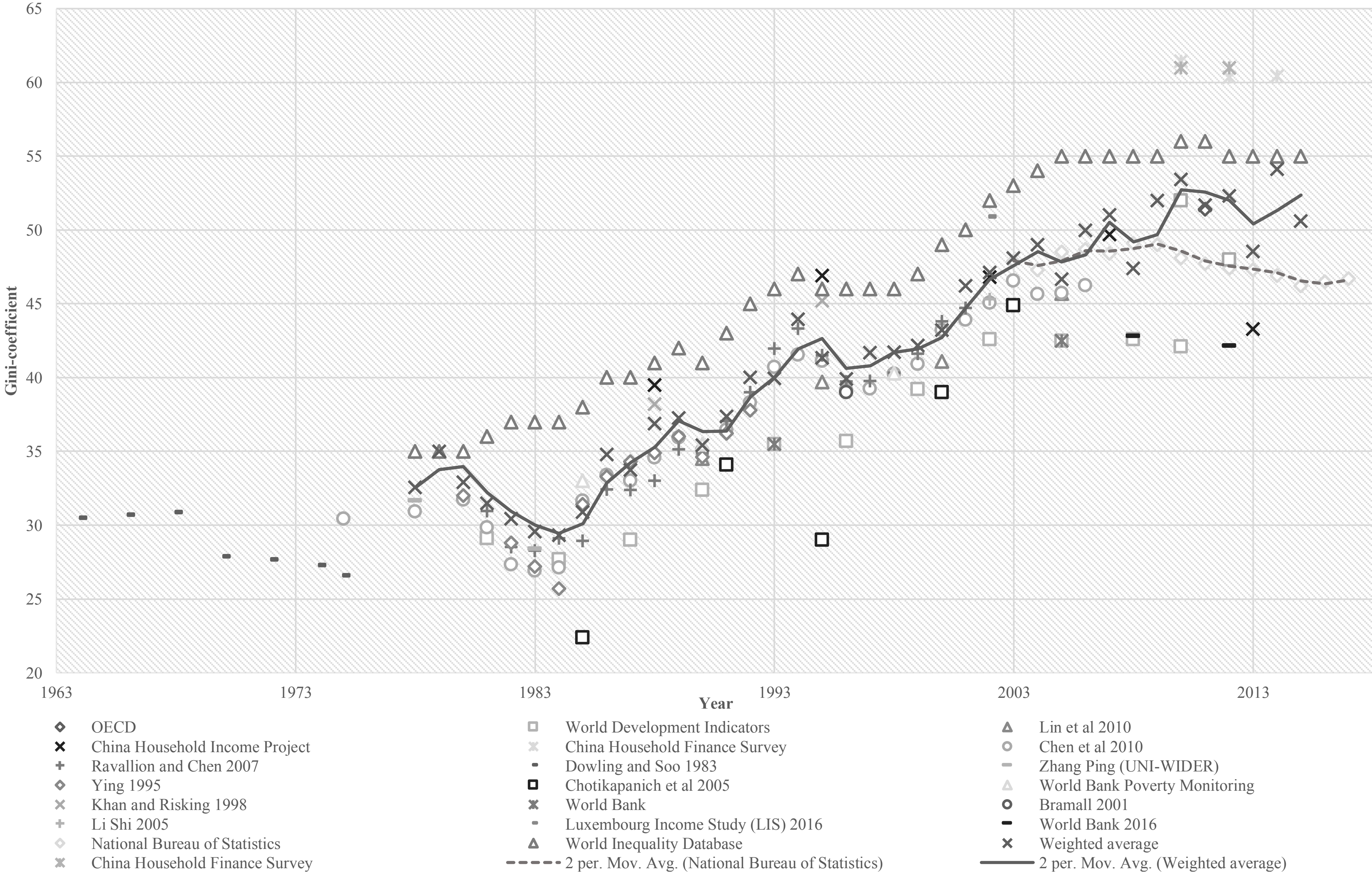
The second body of the analysis will attend to the composition of cumulative income inequality along dimensions of substance to understanding dynamics of inequality in China. This will include a deep dive into the evolution and contribution of spatial disparity. Specifically looking at the prevalent earnings gap between residents in urban and rural areas, but also the relevant divide between and among the different regions and provinces. Beyond the spatial dimension, the analysis will also give an account for the development, composition and contribution of income dispersal based on differences in educational attainment, employment structure and income source. In decomposing aggregate income disparity to address these facets of cumulative inequality discretely, I hope to contribute to existing research by providing the reader with a greater understanding of the nature, dynamics and manifestation of national inequality in post-reform China.

3.1 Development of aggregate income inequality

3.1.1 Development by estimates from existing empirical research

As mentioned previously, the considerable rise in income inequality that followed the economic reforms and market liberalization in China is a well-documented phenomenon. Accordingly, to ensure a holistic and comprehensive understanding of the historical development, this section will attempt to give an account of some of these estimations and most relevant findings from existing research. An overview of 21 estimates for the level of inequality in the period is illustrated graphically in Figure 2 on the next page, with a non-weighted average of the grouping given by the solid line. These findings will then be discussed in further detail below, distinguished by time intervals based on the related observations.

Figure 2: Gini coefficient estimates from existing literature and previous empirical work



1978 – 1984

In the two years following the first round of economic reforms (*gaige kaifang*) there is limited earnings data available, and therefore also few estimates on overall income disparity. From the few estimations that are given for these two years, Chen et al., (2010) and Piketty et al., (2017) through the World Inequality Database suggests changes to overall levels of inequality were inconsequential. A stagnant offset that change dramatically in the early 1980s. In the start of the new decade, there is consensus in that levels of inequality dropped markedly and continued to decline up until the mid 80s ((Chen et al. (2010); Ying (1995); Ping (1997); Ravallion and Chen (2007); World Development Indicators (WDI) by World Bank (2019)). In this period, Chen et al. (2010) estimates a drop in the Gini coefficient from 31,74 to 26,93, while Ying (1995) finds a change from 32 to 25,7 Gini. Ravallion and Chen (2007) argues that this shift towards greater equality can be explained by rising income among rural households following the economic reforms and the introduction of a household responsibility system.

In contrast to the broad consensus of a decline in overall income inequality in the period between 1980 to 1985, estimates from Piketty et al. (2017) suggest that national income dispersion has actually widened in the same period. In accordance with these estimates, the Gini coefficient has increased from 35 points in 1980 to 38 in 1985, with a minor stagnation from 1982 to 1984. This is an interesting observation given the distinction in the dataset and methodological approach adopted by Piketty et al. (2017). Although the primary source of data for all the above-mentioned empirical estimates is given by the National Bureau of Statistics (2019), the datasets and methodologies are still widely contrasting. While the estimates from Ying's (1995) is based on income and expenditure surveys, Ravallion and Chen (2007) makes use of broader household surveys distinguished by urban and rural areas. Piketty et al. (2017) on the other hand, makes use of several different types and sources of data for their estimations, including national income, household income surveys and income tax data. Another noteworthy distinction in the methodological approach by Piketty at al. (2017) is the systematic downward correction of official income growth that follows Young's (2003) careful treatment of overstated growth.

1984 – 1994

In the period between 1984 and 1994, there is a far greater consensus in the empirical estimates related to change in the cumulative income distribution. From 1984 to 1989, there seems to be a marked increase in accumulated disparity of 5 Gini points from 37 to 42 according to Piketty et al. (2017). Chen et al. (2010) on the other hand, estimated a rise of 8,83 Gini points in the period, while Ying (1995) found an increased Gini coefficient from 25,7 in 1984 to 36 by 1989. This steep rise was subsequently followed by a minor break in the trend around 1990, given by a dip of 0,86 points according to Chen et al. (2010) or by 0,30 Gini points from Ravallion and Chen (2007). In the following period from 1990 to 1994, the rise in disparity looks to exceed the growth identified between 1984 and 1989. Piketty et al. (2017) estimates the increase in this four-year period to approximate a rise of 6 Gini points.

This staggering rise in aggregate inequality around the late 80s can be seen in light of the process of opening-up Hainan island and fourteen other coastal port cities to overseas investment by creating so-called "Special Economic Zones". A process that started in 1984 and realized 3.49 billion dollars of inward FDI by 1990 (Chang, 2018). Following these regional reforms, the relative growth in income for coastal areas exceeded that of the inland areas. This contributed to an increase in spatial disparity, and thus overall inequality in the late 80s and early 90s (Luo and Zhu, 2008). As a response to this growing regional dispersion, the 'open-door policies' were adjusted in the early 90s, which spurred more inclusive nation-wide reforms in 1992. A policy adjustment that saw increasing decentralization of state control and increased privatization. At the same time, labor mobility was liberalized, and local city governments were authorized to accept migrants from rural areas as a share of their non-agricultural population (Chang, 2018). The sharp increase in income dispersion that followed in urban areas is suggested to have accounted for a majority of the increase in overall inequality in this period according to Luo and Zhu (2008).

Another aspect that was subject to considerable change from the economic reforms in the mid- to late 80s was employment structure. The 'iron rice bowl' policy (*tie fan wan*) was aborted, restructuring of state-owned enterprises became the priority and enterprise flexibility was significantly liberalized in terms of wage-control and freedom to hire or fire workers. This liberalization lead to a tendency of increasing the salary of skilled workers, while reducing the number of unskilled workers at the same time. A trend that lead to a marked increase in the absolute number of workers being laid-off, particularly unskilled workers (Luo & Zhu, 2008).

1994 – 1998

As illustrated in Figure 2, overall income inequality remained relatively stable in the period between 1994 and 1998, with a moderate decrease across all relevant estimations. Specifically, Piketty et al. (2017) estimated a minor decrease of around 1 Gini point from a coefficient of 47 in 1994 to a stable level around 46 in the three subsequent years. Ravallion and Chen (2007) estimates a more distinct decrease in the period from 43,31 Gini in 1994 to 40,33 in 1998. Correspondingly, Chen et al. (2010) estimates a drop of 1,26 Gini points in the same period. A noteworthy observation in this period, similar to that of the early 1980s, is that relative income growth in rural areas exceeded that of urban income in the mid 90s. While the relatively stronger growth for rural income in the early 80s was driven primarily by the introduction of a household responsibility system, the growth in the mid 90s is suggested to be a result of an increase in the purchasing prices of grain (Luo and Zhu, 2008). A process that further aligns with the one of the primary objectives stipulated in the 5th plenary session of the 14th CPC Central Committee in 1995, whereas the objective of eliminating poverty was integrated in the 9th five-year plan on national economic and social development (Peng, 1996).

1998 – 2010

In the following period from the late 90s to the early 00s, there is a steep rise in overall inequality up until 2005. After that, the levels of disparity stagnate, with a moderate increase up until 2010. Based on estimations from Piketty et al. (2017), national income inequality rose considerably from 1998 to 2005, with an increase in the Gini coefficient from 46 to 55. From 2005 to 2010, the same dataset suggests a minor increase from 55 to 56 Gini. Chen et al. (2010) similarly finds an increase of 5,47 Gini points in the period between 1998 and 2005. The World Development Indicators (World Bank, 2019) suggest a far less significant development from 39,2 in 1999 to 42,5 in 2005m followed by a decrease of 0,4 points up until 2010.

Zhang and Wan (2006) finds that rural poverty increased in the late 90s following adverse distributional changes which led to an increase in rural inequality, and thus overall disparity. The period between 1995 and 2007 was further subject to significant technological changes and rapid accumulation of capital that spurred a marked increase in demand for skilled workers and consequently the skill premium (Dollar, 2007; Zhang & Kanbur, 2005; Liu, 2009). Chuliang et al. (2018) suggests that changes in household income structure was an important factor for the widening income gap from 2000 onwards. Particularly, a considerable and unequal growth in property income that could be regarded as negligible in the 80s and 90s.

From 2007 onwards, estimates from the National Bureau of Statistics (2019) suggests that spatial disparity in the form of urban-rural inequality narrowed. In this, Huang and Luo (2008) and Zhuang and Shi (2016) suggests that the accelerated process of urbanization in the period induced a negative effect on inequality by reducing the rural surplus labor. Jain-Chandra et al. (2018) further emphasizes the importance of several government policies in the turnaround of regional disparity since 2000. Specifically, a series of pro-farmers policies, which included direct subsidies, general-purpose grants, abolishment of agricultural tax and the 'Western Development Strategy'. Another important observation from Jain-Chandra et al. (2018) is a decline in the skill premium from 2008 onwards, which is suggested to be driven by an increase in the supply of highly skilled and educated workers (Chan, 2015; Knight et al., 2016).

2010 – 2015

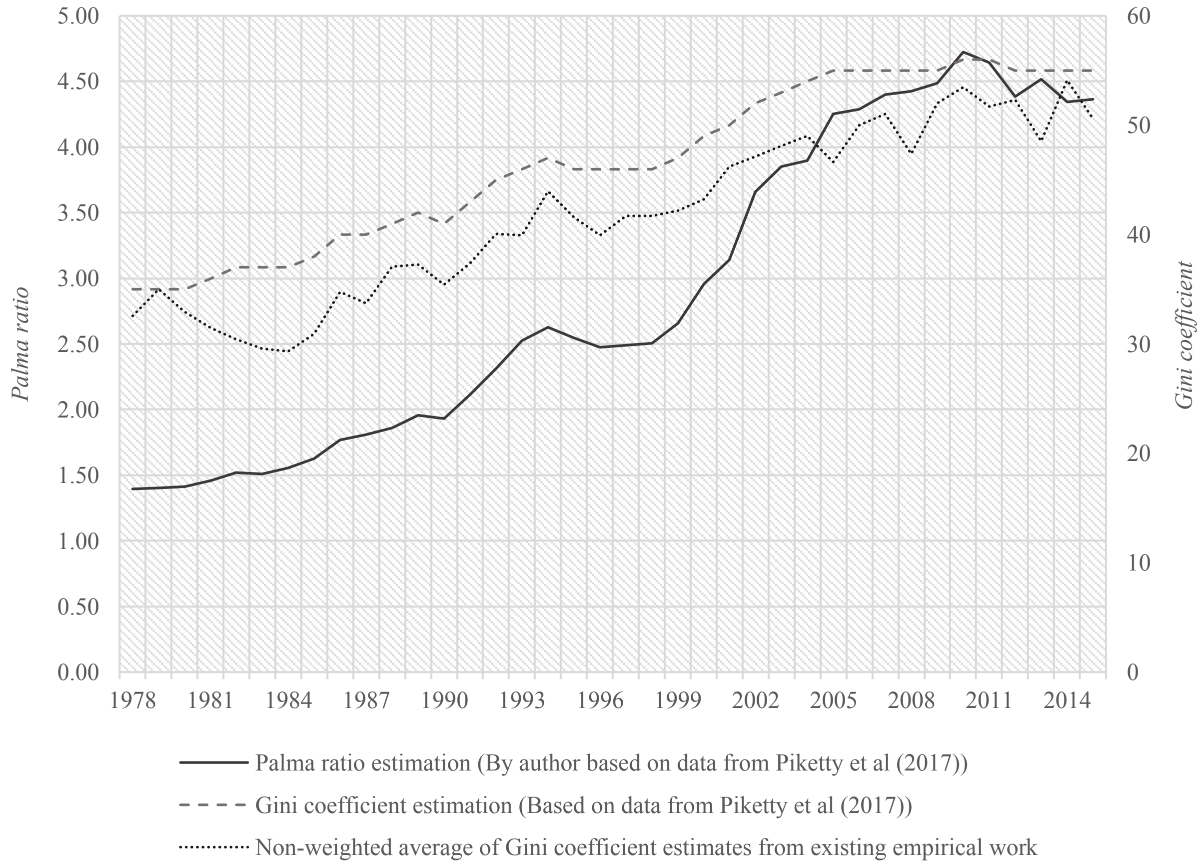
For the period 2010 to 2015, there seems to be an empirical consensus for a stagnant and even progressively more equal income distribution. Official estimates by the National Bureau of Statistics (2019) suggests a continuous decline from a Gini coefficient of 48,1 in 2010 to 46,2 in 2015. Piketty et al. (2017) on the other hand, finds a relatively more moderate decline over the period with a drop of 1 Gini point from 56 in 2011 to 55 in 2012. In light of this discrepancy, Shi (2016) argues that official estimates of income inequality tend to be underestimated due to omittance of top income earners in the household surveys of the National Bureau of Statistics. At the same time, we have already established that most of the above-mentioned empirical works employs data from the National Bureau of Statistics. In addition to that, it would be unreasonable to assume that other macrodata or microdata from various independent surveys is excepted from such an omittance bias. The relevant discrepancy is also fairly modest and indicates the same trend over the five-year period.

The estimated shift towards a more equal income distribution in the period between 2010 and 2015 is lent further support from the findings of Zhuang and Shi (2016). Since the late 00s, they found that regional income disparity had declined, the skill premium had been reduced and the share of labor income relative to that of capital income had increased. Observations that all support to the premise of a reduced level of income dispersion as identified by the above-mentioned estimates. This is a highly interesting finding and estimation alignment considering the development over the previous decades and political agenda of the Twelfth Five Year Plan in 2011. In this, the State Council of the PRC (2011) expressed a commitment to: "*speeding up the formation of a reasonable pattern of income distribution… and reversing the widening income gap as soon as possible*".

3.1.2 Development by the tails of distribution

As discussed in section 2.3, the Gini coefficient has received criticism in the academic sphere since the late 1960s for some of its technical properties and appropriateness as the predominant measure of income inequality (Atkinson, 1969; Alison, 1978; De Maio, 2007; Cobham & Sumner, 2013; Schmid & Stein, 2013; Thewissen et al., 2015). In this, Palma (2011; 2016) argues that the Gini coefficient is too sensitive to changes in distribution for middle and upper-middle deciles. Consequently, underemphasizing changes in the tail of the distribution. In fact, changes to the income distribution between rich and poor is also arguably what ought to be the focal point, both normatively and instrumentally. As a response to this criticism and absence of empirical attention to this perspective in China, I have estimated an aggregate Palma ratio based on data from Piketty et al. (2017) in the period 1978 to 2015 (See Figure 3). The purpose of this estimation and related analysis is to shed more light on the development in the tails of the distribution, and hopefully provide a greater understanding of the divide between rich and poor in post-reform China. Further, to control for potential dissonance with existing estimates, which is almost exclusively measured by the conventional Gini coefficient.

Figure 3: Estimated Palma ratio and comparison to Gini coefficient estimates



In Figure 4 presented above, the estimated Palma ratio is indicated by the solid line and measured along the left-hand axis. The dashed line gives an estimated Gini coefficient based on the same data measured along the right-hand axis. Whilst the dotted lines represent the non-weighted average of available Gini coefficient estimates from empirical work and official channels as given in Figure 3. From this graphical illustration of the comparative income inequality trend and development estimated by different measurement techniques and data, there is several highly interesting observations that needs to be addressed and discussed.

Similar pattern in progressive rise until 1994 and subsequent drop up until 1998

From the introduction of the 'open-door' policies in 1978 until to first significant peak in income inequality in 1994, the development, trend and fluctuations in levels of disparity is rather similar between the measures. The only significant misalignment stems from the marked decline in the non-weighted average from 1979 to 1985. Given the coinciding pattern between the estimated Palma ratio and Gini coefficient based on data from Piketty et al. (2017) this dissonance could be explained by conflicting data.

Steeper rise from 1998 to 2010 amounting to relatively higher levels of inequality

After the stagnation and modest reduction in aggregate disparity between 1994 to 1998, the development resumes an upward trajectory among all three specifications of measurement. In this, a significant rise in overall inequality that seems to peak simultaneously around 2010. However, the growth rate and apex of the estimated Palma ration, Gini coefficient and the average of empirical estimates between 1998 to 2010 is widely diverging. The estimated Palma ratio had an average growth rate of approximately 7,4% annually in this period and the related level of inequality in 2010 represented an 89% increase from the 1998-levels. The Gini coefficient estimates based on the same dataset indicates an average annual growth rate of 1,8%, amounting to a rise of 22%, equivalent to 10 Gini points from the level in 1998. The non-weighted average of estimates from empirical work and official estimates grew by 2,3% yearly up until 2010, whereas the peak amounted to an increase of 28% from the 1998-level.

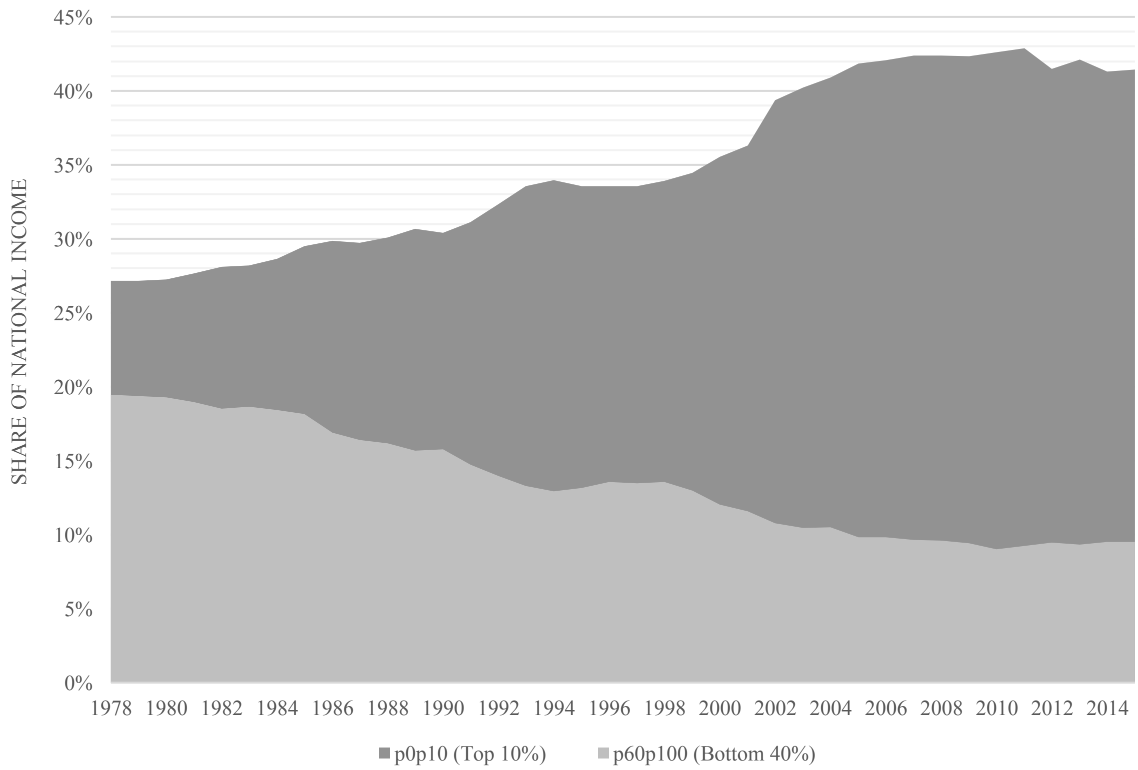
This is a greatly interesting finding, which suggests that the estimates of inequality based on Gini underestimates the level of inequality relative to that of the Palma ratio. A discrepancy that merely derives from the omittance of changes in dispersion among middle income earners. An observation that lends support to Palma's notion, reflecting the Gini sensitivity to changes in middle income groups and inadequacy in reporting changes to the tails of the distributions.

Distinct descent in level of disparity from 2010 to 2015

In accordance with the discussion related to the most recent development in section 3.1.1, existing empirical- and official estimates indicates a stagnation or a moderate decrease in national income inequality from 2010 to 2015. In view of this, the Palma ratio estimation indicates a more distinct reduction in the gap between rich and poor since 2010, thereby lending further support to the official notion of reduced national income inequality in recent years. From 2010 to 2015, the Palma ratio indicates a reduction from 4,72 to 4,37, with minor variations in 2013 and 2015. A reduction in the aggregate disparity of income that amounts to a 7% decrease between the top decile income earners and the bottom to 4th decile in the period.

The technical properties of the Palma ratio offer another benefit in that it can easily be decomposed to study the contribution from each end of the tails in the development. As given in Figure 4 below, we can observe the widening gap from the economic reforms and more recent decline in income inequality is driven by the development in both tails of distribution. In this, the share of national income assumed by the top 10% and bottom 40% income earners naturally covaries markedly with synchronized interruptions to the long-term trend. Still, the growth in the share acquired by the top decile exceeds the rate of decline in the share assumed by the bottom to 4th decile. In this, the former increased its share by 16% from 1978 to 2010, whereas the latter experienced a 13% loss in its share for the same period.

Figure 4: Decomposed Palma ratio

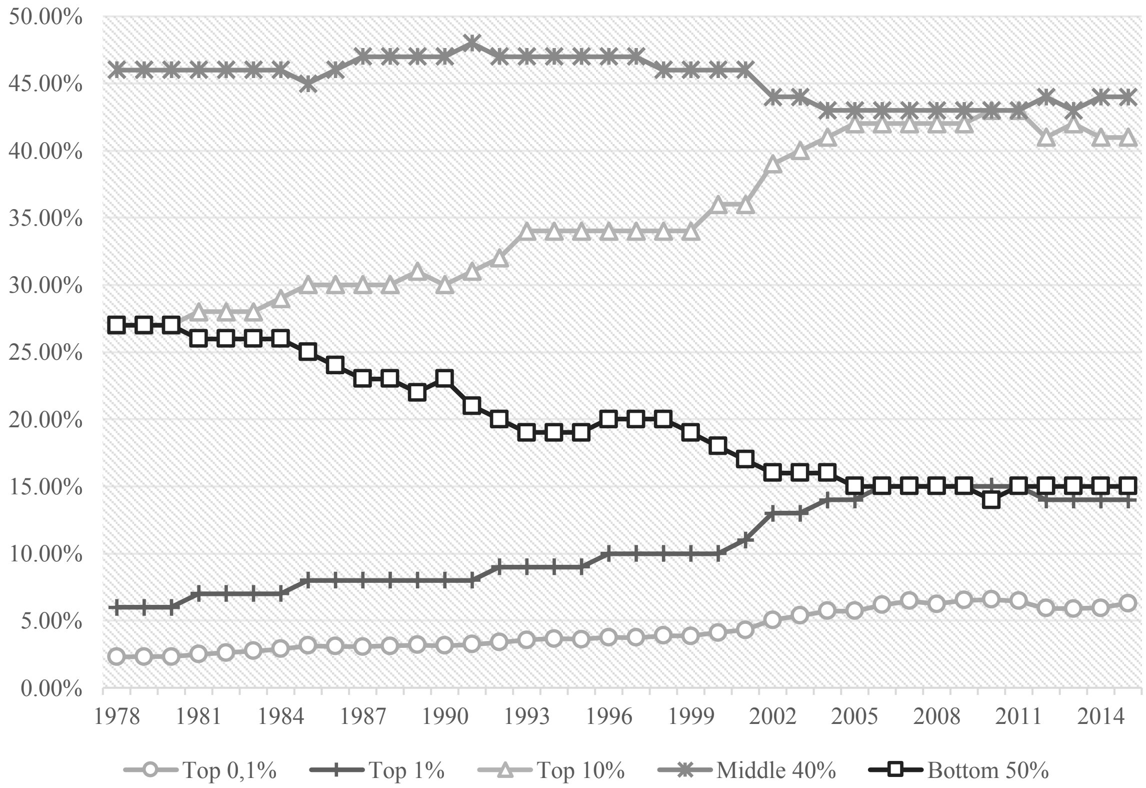


3.1.3 Development by ratio and shares of distribution

Building on the insights drawn from the decomposition of the Palma ratio and the tails of distribution, I will now broaden the scope to include the relative share of the complete income distribution. The evolution and related changes to the assumed share of national income for various percentiles provide critical information in term of achieving a comprehensive understanding of the composition and development of aggregate inequality.

In Figure 6 below, a graphical illustration of the evolution in distribution among specified percentiles is presented based on data from by Piketty et al. (2017). To account for the entire distribution of income earners in a pragmatic manner, I will classify the lowest income earners as the bottom 50% of the distribution, the middle and upper-middle income earners as percentiles 10 to 50 and finally the highest income earners by the top 10%. In addition to this, I will further account for the top income earners of the population by looking at the development among the top 1% and top 0,1% of the distribution.

Figure 5: Distribution of pre-tax national disposable income by share (%)



Bottom 50% (p50p100)
As illustrated in Figure 6, the share of national income assumed by the lowest 50% of income earners in China has followed a negative trend almost continuously from 1978 up until 2005. Herein, the bottom half of the distribution including more than 530 million individuals in 2015, has experienced a 12% decline in the share of national income from 27% in 1978 to 15% in 2005 (Piketty et al., 2017). A trend that has only been disrupted by a slight increase in 1990 and a modest growth in the period 1994 to 1998. Minor interruptions to the trend that corresponds to the development in aggregate inequality measured by both Gini and Palma.

In the same period, the bottom half of the distribution experienced a significant increase in average annual income, which by 2005 amounted to 15 times the average measured in 1978. A substantial increase from 344RMB (local currency) in 1978 to 5.212RMB by 2005 (Piketty et al., 2017). Accordingly, the lowest income earners increased their average earnings significantly in the first three decades of following economic liberalization. Still, their relative earnings growth lagged far behind the top half of the distribution. From 2005 up until 2015, the negative trend stabilizes, and the share assumed by the bottom half of the distribution remain stable at around 15% of national income. In this period, the average annual growth rate in income for this earnings group was around 32,9%, increasing from 5.212RMB in 2005 to 17.150RMB in 2015 (Piketty et al., 2017). Even though the growth rate of average earnings for this period was relatively lower than between 1978 to 2005, the absolute income in 1978 was so low that such a comparison is not of much meaningful value. In accordance with these findings, the bottom 50% of income earners assume a far lower share of national income then previously. Concurrently, the average income of this group has increased dramatically over the period with a relative inequality that has stabilized over the past decade.

Middle 40% (p10p50)
In line with Palma's (2011; 2016) postulation, Figure 6 indicates that the middle to upper-middle earnings group given by p10p50 holds a relatively stable share of national income over time. Increasing from an average annual income of 6.853RMB in 1978 to 62.444RMB in 2015 (Piketty et al., 2017). Given by p10p60, the middle 50% income earners assumed a stable share around 50% of national income. A finding which again supports Palma's notion and emphasizes the importance of the tails of the distribution. However, in conjunction with the development in the aggregate level of inequality described previously, the income share assumed by the middle 40% earners declined moderately in the period from 1998 to 2010.

This finding suggests that the steep rise in overall inequality for the above-mentioned period was a result of reduced relative income growth in the middle and upper-middle earnings group. However, given the relatively diminutive negative shift by around 3% of national pre-tax income, the effect on the aggregate level of disparity is comparatively negligible.

Top 10% (p0p90)

In contrast to the stable development in average income among the middle-income earners, the relative earnings growth among the top 10% of the distribution has changed dramatically from 1978 to 2015. This group, including more than 106 million individuals by 2015, increased its relative share of national income from 27% in 1978 to 43% in 2010, with a modest decline of around 2% by 2015. In terms of average annual income, the top income earners (p0p90) progressed from 16.214RMB in 1978 to 236.572RMB in 2015 (Piketty et al., 2017). A relative income growth that is 4 times higher than the national average in the relevant period. Accordingly, from this finding we can conclude that the major share of the substantial rise in overall inequality can be reflected by the relative income growth among top income earners.

Top 1% (p0p99) and 0,1% (p0p99.9)

As given by Figure 6, the top 1% of income earners in China assumed around one third of the share acquired by top 10%, a ratio that remains relatively stable over the whole period. The relative income growth for this group covaries closely with that of p0p10, despite less significant fluctuations over time. The top 0,1% on the other hand, assumes around one tenth of p0p10's income share with a stable increase in relative income up until 2005. From 2005 to 2010, the relative growth seems to stagnate, with a modest decline in a short period after 2010. This is an interesting finding which indicates that the progressive development towards a more equal income distribution in the period between 2010 and 2015 included that of the very top income earners in China. That being said, the relevant earnings data for this top income group is likely to be both underestimated from underreporting, but also biased following omittance of the richest individuals. At the same time, these findings give solid indications that the relevant distributional effect also took place in the top earnings group.

3.2 Decomposition of aggregate income inequality

In this subsection, I will investigate the composition of aggregate inequality by earnings dispersion among and between relevant population segments, but also the related contribution of these dimensions to overall income disparity. This decomposition analysis will specifically attend to disparity between groupings distinguished by spatial distribution, educational attainment, sectorial employment and the configuration of income sources. In much of the existing empirical work, earnings dispersion along spatial, educational and skill dimensions are often interpreted as factorial drivers to the development (Ping, 1997; Knight & Song; 1999, Sicular et al., 2007; Whyte, 2010). In this paper, I will attend these variations as compositional facets and transmission channels rather than as determinants to change in inequality over time.

3.2.1 By spatial disparity

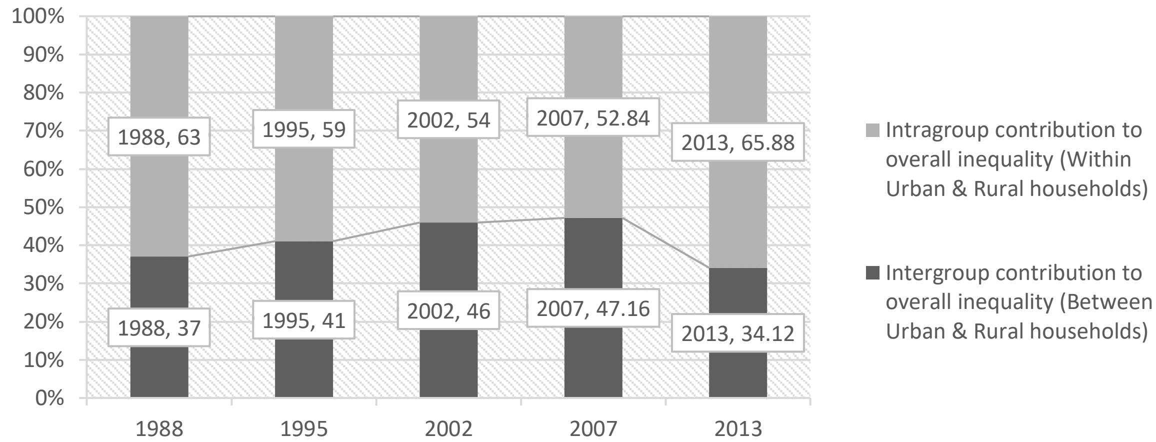
Income inequality based on spatial distribution can be reflected along several dimensions, depending on what can be deemed a meaningful geographic scope. According to Wan (2008) spatial disparity in China should be analyzed along two dimensions; urban-rural dispersion and regional disparity through eastern, central and western regions. Jain-Chandra et al. (2018) on the other hand, suggest that the focus should be on provincial disparity instead of regional. To give a comprehensive account of the relevant dynamics, I will examine the composition and contribution of all three dimensions, but primarily focus on the marked urban-rural divide.

Urban – Rural disparity

In terms of spatial disparity between the residents in urban and rural areas, there is great consensus among existing research that levels of earnings dispersion have been elevated for most of the period attended to in this paper (Sicular et al., 2007). Correspondingly, the so-called 'urban-rural divide' is found to have contributed significantly to the overall rise and level of disparity. Based on household surveys from the Chinese Academy of Social Science, Sicular et al. (2007) estimates the relevant contribution through a decomposition of Theil's T for aggregate inequality. As given by Figure 6 below, they find that the relevant contribution to overall dispersion amounted to 37% in 1988, 41% in 1995 and 46% in 2002. Findings which suggest that aggregate inequality primarily derives from income dispersion within rural and urban areas. At the same time, indicating that the urban-rural divide contributed to nearly half the accumulated inequality and that the relevant contribution has increased up until the 00s. Estimations which clearly demonstrates that intragroup inequality between the urban and rural households has been a significant component to accumulated income dispersion in the period.

In more recent years, estimations from Jain-Chandra et al. (2018) based on data from the China Household Income Project suggest that the contribution amounted to approximately 47% in 2007, dropping to 34% in 2013. Findings that indicates a turn in the trend around the late 00s, whereas the urban-rural divide started to become a less significant factor of overall inequality.

Figure 6: Contribution of Urban-Rural disparity to overall inequality (%)

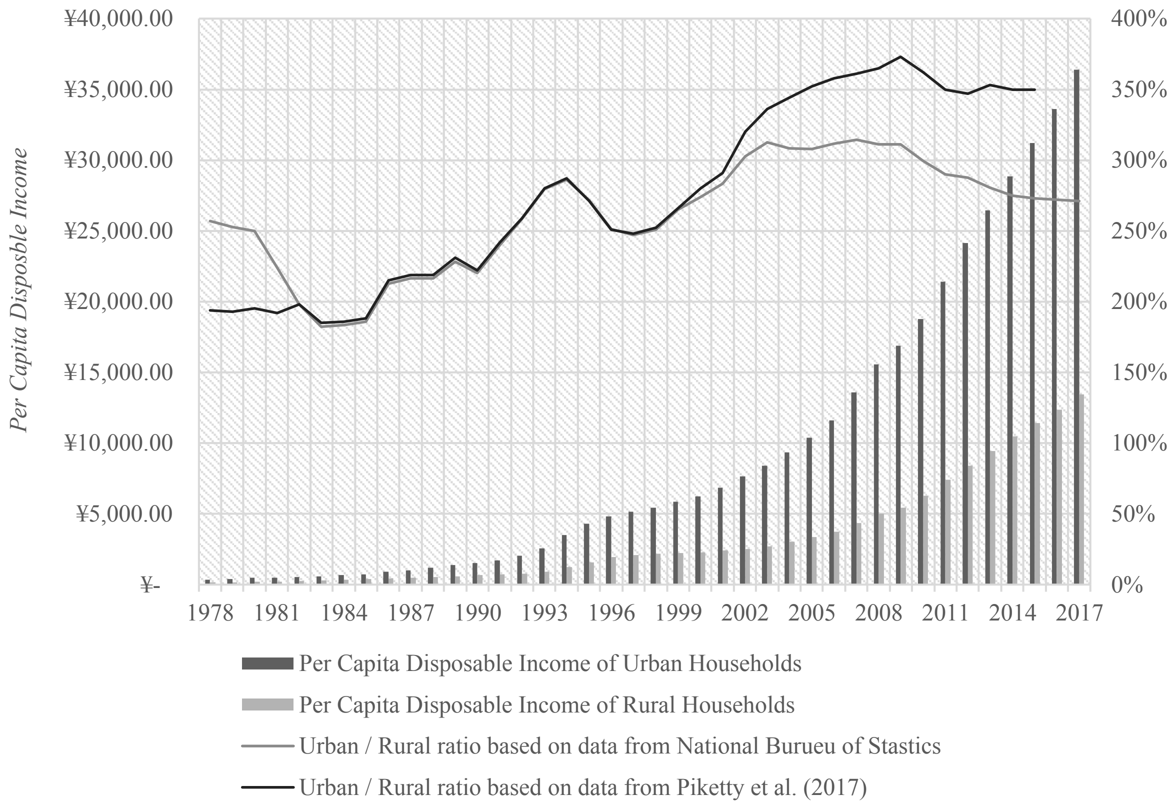


As illustrated in Figure 7 on the next page, urban – rural inequality has increased since the mid-1980s, with a considerable uprise from 1997 to 2008 followed by a modest decline in the years after the global financial crisis (Li, 2016). In this, the average income ratio between urban and rural households increased from 200% to 350% between 1978 and 2015 (Piketty et al., 2017). Accordingly, at the offset of the economic reforms in 1978, urban households earned on average twice as much as rural households at the time, whilst in 2015 they earned 3.5 times more on average. At this ration of urban – rural income dispersion, China holds one of the largest spatial inequalities in the world along this dimension (Sicular et al., 2007).

Following the reforms in 1978, China has experienced extensive internal migration from rural to urban areas. From 1978 to 2015, the urban adult population increased from around 100 million people to approximately 600 million in 2015 (Piketty et al., 2017). At the same time, the rural population increased in the first two post-reform decades to 600 million, before it dropped below 500 million in 2015. Still, the significant income dispersion between urban and rural households has often been linked to restrictions on labor mobility deriving from policies that inhibit spatial mobility, primarily through the hukou system[1] (Sicular et al., 2007). Despite recent reforms of the hukou system to dampen restrictions on internal migration, and thus labor mobility through spatial mobility, significant barriers still prevail (Wang, 2004).

[1] A household registrations system restraining migrants from seeking employment and public services in foreign regions to protect employment and welfare of urban households.

Figure 7: Average income and disparity ratio between Urban and Rural household



In line with the dissonance related to the recent development in aggregate income inequality, the latest development in the urban-rural dispersion is also found to deviate considerably from official estimates. As given in Figure 7, estimates by the National Bureau of Statistics correlates nearly perfectly with data from Piketty et al. (2017) up until 1999. From the millennium onwards, estimates are widely diverging, which can suggest that the official urban-rural ration also is underestimated given the survey biases. An observation that could help shed light on the official underestimation of overall income inequality from 2007 to 2015.

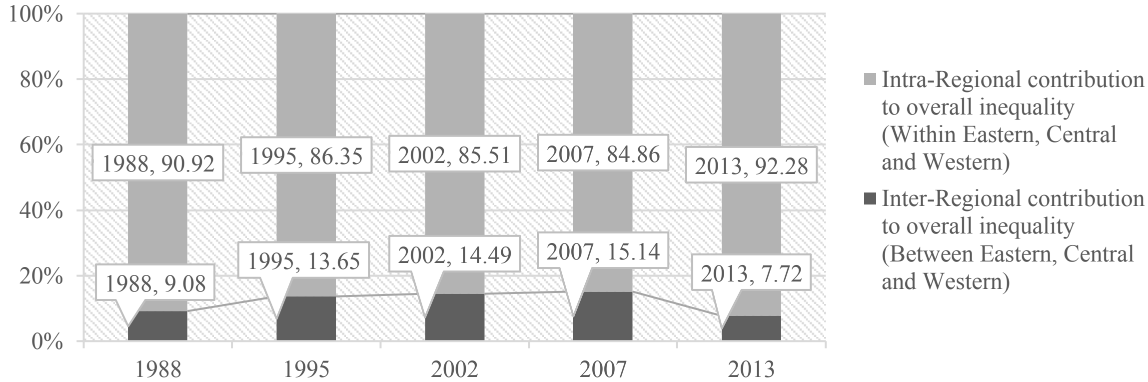
Despite discussions related to the extent of urban-rural income dispersion, there is consensus within both academic and political spheres that the urban-rural divide has been elevated and needs to be addressed. In attending to this, several policy reforms and initiatives has been implemented in recent years to increase and improve public spending in rural areas, for example by the campaign to *'build a socialist new countryside'* [2](Sicular et al., 2007). A political intention that has manifested itself through various pro-rural policies and reforms, which again could be reflected in the empirical consensus of a decline in the urban-rural income gap from the late 00s onwards.

[2] A Central Government campaign to promote village modernization through increasing rural investment, agricultural subsidies and improving social services for rural households

Regional disparity (Eastern, Central & Western)

The second spatial dimensions of interest according to Wan (2008) relates to regional inequality between eastern, central and western regions (See Appendix B). As for the urban-rural dimension, the economic development within these different regions has been strikingly contrasting. However, as given in Figure 8 below, the contribution of inter-regional inequality to overall level of income disparity is significantly lower than intergroup contribution for urban and rural areas. From the same process of decomposing the Theil index of survey data from the China Household Income Project (CHIP), Chuliang et al. (2018) finds that the contribution of regional disparity to the overall level of inequality has increase from around 9% in 1988 to ~15% in 2007. In line with the contributional variation for the urban-rural dimension, inter-regional dispersion contribution was found to reverse around the late 00s, dropping by more than 7% in the five years following the global financial crisis in 2007.

Figure 8: Contribution of regional disparity to overall inequality (%)



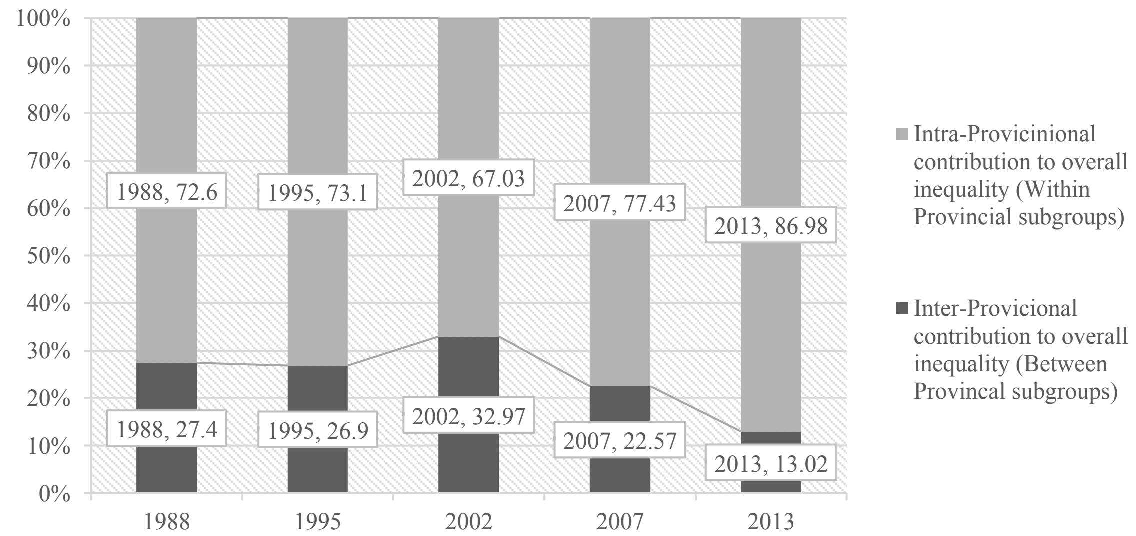
In accordance with the development in the share of intra-regional contribution to aggregate levels of inequality, the Theil's T for within-group regional disparity rose from 0.2140 to 0.3467 in the period 1988 to 2007 (Chuliang et al. 2018). In line with the trend identified previously, intra-regional income dispersion also experienced a modest decline from 2007 to 2013, below estimates for within-group regional inequality in both 1995 and 2002. In this, estimates of inequality within each of the regions shows that west prevails with the highest income dispersion for all observation years, followed by the central region. Interestingly, within-group income disparity in both the eastern and western region rose significantly from 1988 to 1995, from where the estimates peaked. Thereafter the Theil indices dropped and remained relatively stable up until the late 00s, before declining again after 2007. Fan, Kanbur and Zhang (2011) suggests that this can be partly explained by the 'Great Western Development Strategy' implemented by the Central Government in 1999.[3]

[3] A development program to invest in infrastructure and ensure exploitation of natural resources in the Western region

Provincial disparity

The last spatial dimension relates to income dispersion within and between China's 31 provinces (See Appendix B), which also represents the most intricate perspective. From the estimated contribution given in Figure 9, we can see that inter-provincial income inequality has been significantly more influential for aggregate income disparity than regional dispersion. However, still less significant than the inter-group contribution between urban and rural areas. Based on the same data from the CHIP[4] study, a Theil index decomposition from Chuliang et al. (2018) shows a diverging contribution pattern than for the previous two dimensions. Between-group inequality among the 31 provinces show that the contribution to aggregate income disparity peaked at almost 33% already in the early 00s, before the contribution of both provincial and urban-rural dispersion. From 2002, steadily decreasing to around 13% by 2013. An interesting observation that indicates that inter-provincial inequality was more a significant factor in the composition of overall inequality in the early phase of the transition.

Figure 9: Contribution of provincial disparity to overall inequality (%)



The development in within-group provincial income dispersion follows a diverging trend. In the period 1988 to 1995, the Theil index estimations for this composition increases substantially from 0.1709 to 0.2906. Thereafter, the level of intra-provincial remains relatively stable with less significant fluctuations until 2013. However, the share of within-group inequality to the estimated overall provincial Theil index increases by less than 1% and followed a marked upward trajectory from 2002 onwards, which contradicts to the absolute change. Consequently, we find that the development of inter-provincial has affected the spatial dispersion along the provincial dimension to a greater extent than within-group inequality.

[4] China Household Income Project (Household survey)

3.2.2 By educational attainment

As for the urban-rural divide, there is wide empirical consensus in that income dispersion deriving from differences in educational attainment has been a significant component in cumulated income inequality in post-reform China (Jain-Chandra et al. 2018; Chuliang et al. 2018; Cevik & Correa-Caro, 2015). An intuitive tendency in the composition of earnings dispersion that generally tend to represent a key component in the aggregate level of disparity. The importance of educational disparity in China has been particularly significant following transformative reforms of the education system, which again has had a marked impact on the supply of high-skilled labor, in parallel to socio-economic forces that has shifted demand.

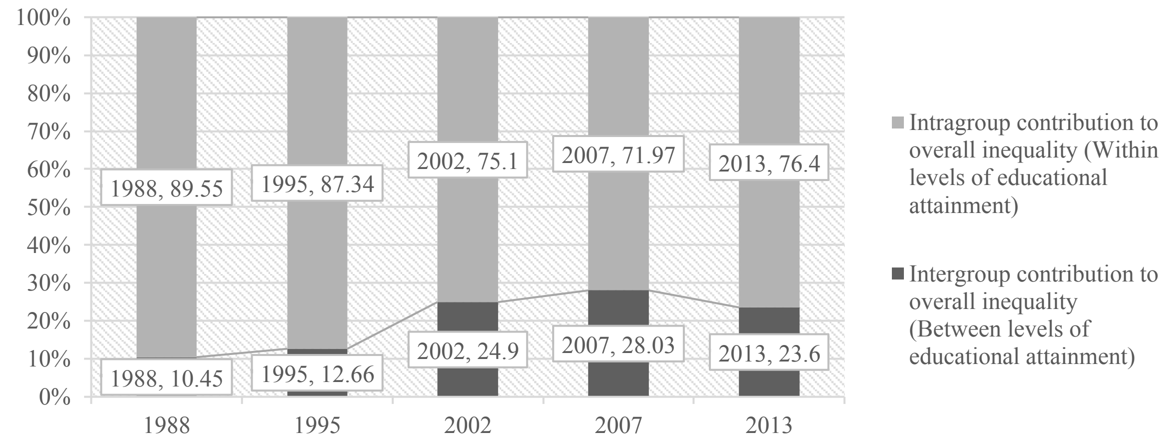
At the offset of China's economic liberalization process, enrolment in primary- and middle schools was remarkably high, while gross enrolment in tertiary education was relatively low (Heckman & Yi, 2012). A condition that entailed limited supply of domestic high-skilled labor in the early phases of the market-oriented transition. At the same time, the demand for skilled workers increased profoundly following accelerated technological progress and national capital accumulation. This again led to a considerable rise in the skill premium, which bolstered returns to education, and thus earnings dispersion based on educational attainment (Zhang & Kanbur, 2005; Dollar, 2007; Liu, 2009). These dynamics changed significantly with the educational reforms of the 90s, which lead to an upsurge in the supply of high-skilled labor.

Over the last two decades, there has been an unprecedented educational expansion in terms of opportunity and enrolment in higher education following major funding initiatives and policy reforms. Among others, the establishment of a formal degree system, abolishment of job allocation practice for graduates and funding projects like the '211' and '985' plans[5] (Yu et a., 2012). In this, the participation rate in tertiary education has increased from below 6% in 1998 to over 50% in 2017 (World Bank, 2019a). A successful transition from 'elite'- to 'mass' education, which has made China the largest provider of tertiary education worldwide (Yu et a., 2012). In this expansionary process, concerns have been raised in regard to educational inequality deriving from the configuration of the education system. Among others, introduction of tuitions fees and its subsequent rise following reforms in the 90s, but more importantly the admission quota system which discriminates subgroups[6] (Wu & Zhang, 2010).

[5] Funding projects involving both local and national government to strengthen research and build 'world-class' institutions
[6] Favours admission of local and urban students registered in large cities where universities are plentiful and most prestigious

In accordance with these conditions, dynamics and shocks altering both supply and demand of domestic high-skilled labor dramatically, there has consequently been great changes in the contribution of educational disparity to overall income inequality. As given in Figure 10 below, the contribution of intergroup dispersion based on educational attainment of the head of the household was relatively low in the early phases of China's economic liberalization. Through a Theil index decomposition of the CHIP dataset, Chuliang et al. (2018) finds that the intergroup contribution to overall inequality increased significantly at the offset of the educational reforms, followed by turnaround in the late 00s. From 1988 to 2007, the contribution of inter-group disparity between primary and below, junior middle, senior middle and higher levels of educationa increased by nearly 18%, to more than 28% of overall income inequality. Based on the same dataset from the CHIP surveys, Jain-Chandra et al., (2018) differentiates further between primary level and illiterates, whereas these estimates suggest an increased relative contribution to a staggering 32% in 2007.

Figure 10: Contribution of educational disparity to overall inequality (%)



From 2007 to 2013, the contribution dropped to 23,6%, below the levels observed in 2002. Based on the authors estimations and decomposition of Theil indices using the dataset from the China Family Panel Study (Institute of Social Science Survey, Peking University, 2018), I find a continued downward trend in intergroup contribution from 2010 to 2016 (See Appendix C). This recent development in inequality would suggest a decline in the skill premium and returns of education, which can be thought to be a result of increased supply of high-skilled labor. In this, Chan (2015) and Knight et al., (2016) finds that recent university-level graduates struggles to find suitable jobs and that unemployment within this group is rising, indicating a surplus supply. Jain-Chandra et al., (2018) further suggest that rising minimum wages could have contributed to reduced skill premium, and thereby the contribution of intergroup income disparity deriving from educational attainment differences.

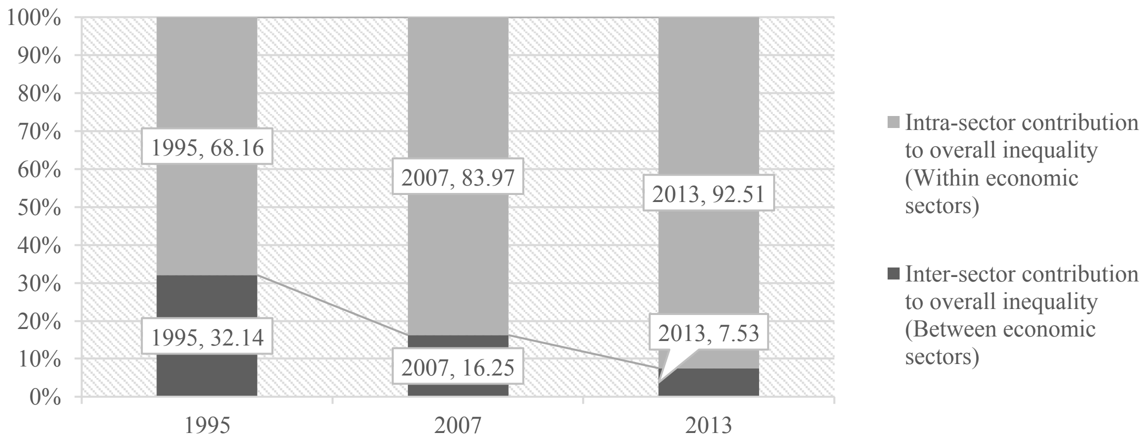
3.2.3 By sector and industry of employment

In China's transition process from a socialist planned-economy to a more market-oriented and liberalized economy, changes to employment structure has played a pivotal role in the composition of aggregate levels of income inequality (Chang, 2018; Jain-Chandra et al., 2018). The contribution and composition of income inequality based on employment structure can be categorized in terms of both sectorial and industry classifications, whereas this section will attend to both. The notion of a direct exogenous impact from shifts in employment structure as a factorial determinant of inequality will be covered in-depth in the forthcoming empirical analysis. In this section, I will focus on the composition and contribution of earnings dispersion based on differences within and between sectors and industries of employment.

By economic sectors (Non-workers, Agriculture, Secondary & Service)

The first compositional facet attends to differences in earnings based on employment by economic sector. More specifically, segregating employment by agriculture, secondary and services sectors, but also between and among non-workers. As illustrated in Figure 12 below, Jain-Chandra et al., (2018) finds that contribution of inter-sector disparity between the above-mentioned economic sectors has declined significantly from 1995 to 2013 (based on data from the China Household Income Project). In this, the contribution of between sector earnings disparity on aggregate income inequality has declined from more than 32% in 1995 to 7,53% in 2013. These finding suggests that earnings dispersion between economic sectors was a more significant factor a few decades ago and has since become less prevalent. Observations which must be seen in light of the growing importance and increased diversity in the secondary and tertiary sector since the late 70s, as industrialization and servicization progressively matured.

Figure 11: Contribution of sectorial disparity to overall inequality (%)



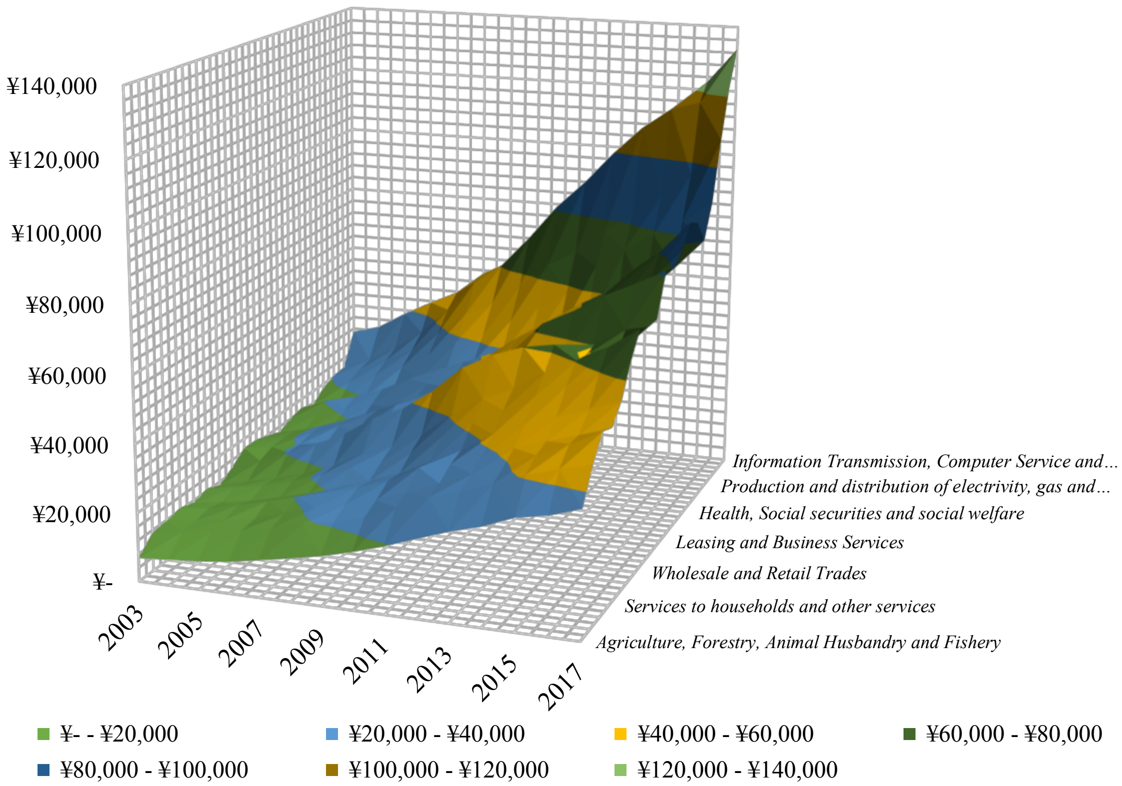
In terms of the related contribution deriving from intra-sector differences, both Chang (2018) and Jain-Chandra et al., (2018) finds that the within-sector component has increased remarkably since 1988, in both relative and absolute terms. Accounting for a majority of the in aggregate income inequality since the economic reforms. By analyzing the CHIP dataset through an income variance decomposition method, Chang (2018) finds that intra-sector income variance increased by more than 5 times from 1988 to 2013. In the same period, overall income disparity had only increased by 4 times. In relative terms, Jain-Chandra et al., (2018) finds that within-sector earnings disparity accounted for around 64% of aggregate income inequality in 1995, increasing to more than 92% in 2013.

In the same period, intra-sector contribution for individuals employed the agriculture sector had decreased the most, from 22,34% in 1995, to 4,55% in 2007 and down to 2,51% by 2013. Within-group inequality in secondary sectors has remained relatively stable accounting for around 17,5% of aggregate inequality for 1995 and 2007, whereas the share rose slightly by 2013 to around 21,7%. In terms of inequality within the service sector, there has been a marked increase in the same period, whereas both absolute and relative intra-group earnings dispersion nearly doubled from Theil's T of 0.0764 and a share of 21,6% in 1995 to 0.1321 and 38% in 2013. In terms the working and non-working population, Jain-Chandra et al., (2018) finds that inequality among non-working individuals has increased the relatively more. From 1995 to 2013, the share of aggregate income variance deriving from the non-working segment increased by a staggering 23,46%, from 6,81% in 1995, to 29,14% in 2007 up to 30.27% of overall inequality in 2013. An observation that could indicate that provision of social transfers, insurances and other welfare schemes became more unevenly distributed in the period.

By industry categorization

Given the relative importance of within-sector income disparity and its contribution to aggregate inequality, a more nuanced analysis of earnings dispersion in the industry spectrum could provide valuable insights into the intra-sectorial spread. Because of data limitations, it has not been possible to derive a direct decomposition of Theil indices based on industries as for previous sections. As an alternative, I will attend to the income gap of industry categories by examining the relevant income ratios. Figure 12 below gives a visual illustration of the related income spread in urban units based on available data on average annual wages among all 20 industry categories given by the National Bureau of Statistics (2019) from 2003 to 2017.

Figure 12: Average wage by industry categorization (urban units)



Authors illustrations based on data from National Bureau of Statistics (2019)

Following the remarkable rise in within-sector income disparity and marked contribution to both extent and rise of overall inequality, the industry income spread given in Figure 12 confirms the findings based on economic sectors. In 2003, the income gap and ratio between the lowest earning industries including agriculture, forestry, animal husbandry and fishery and the highest earning industries including information transmission, computer services and software amounted to 4.49. In line with the pattern and development in shares of contribution identified between and among economic sectors, the relative income ratio among industries dropped to around 3.65 in 2017. In absolute terms, the income gap between the top and bottom earning industries has increased significantly in the same period. In 2003, the annual average wage variance between the former and latter industry amounted to 23.013RMB. Whereas in 2017, the average income gap had increased to 96.646RMB annually, which amounts to 4.2 times increase in absolute earnings disparity. A rise in absolute industry inequality which reflects some of the structural market conditions. In this, high-tech industries and those of monopolistic nature with high entry barriers has benefited relatively more from the economic growth than that of labor-intensive industries with high competition and low entry barriers (Junqing et al., 2003).

3.2.4 By income source

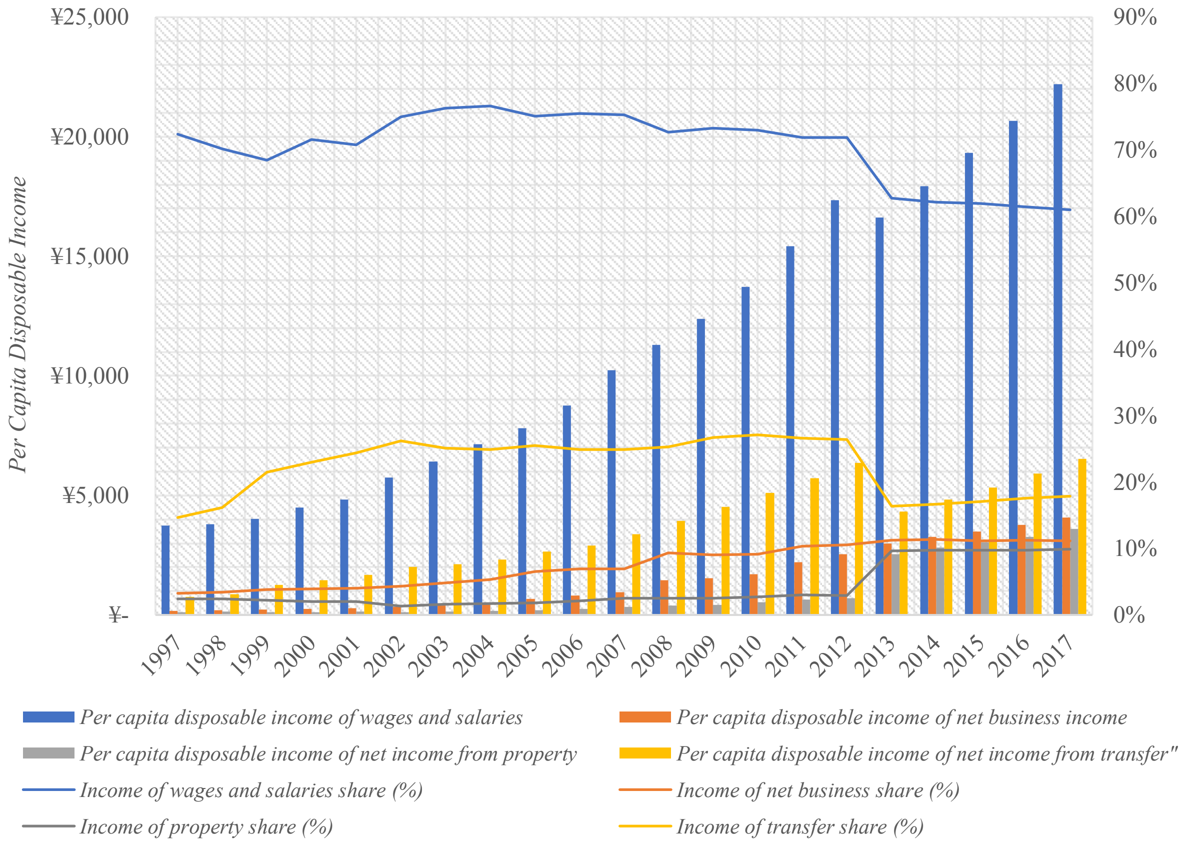
In this section, we turn to a decomposition based on sources of income among urban and rural households discretely. The purpose of this analysis to achieve a better understanding of the earnings configuration and related contribution of these income streams on aggregate inequality. In doing so, I will first attend to changes in disposable income through decomposing the proportional share of each sources based on data from the National Bureau of Statistics (2019). As urban and rural areas in China are institutionally segmented with very different income configurations, it is reasonable to analyze these spatial populations discretely. This will further include an analysis of the contribution of the various sources of income on overall inequality to understand their role in the evolution of aggregate income disparity.

Urban households

Based on data from the National Bureau of Statistics (2019), Figure 13 illustrates disposable income and relative share of income sources for urban households from 1997 to 2017. Although data limitations prevent an analysis for the whole post-reform period in the urban segment, the decomposition offers interesting results. First, wages and salaries prevail as the most important source of income, accounting for a stable share of around ¾ of income. However, from 2012 to 2013, the income from wages and salaries declined by more than 4%, whereas the related share dropped by a staggering 9%, with a continued decrease until 2017. At the same time, net income from transfers[7] declined by more than 32% in absolute terms, with a decreased share of income composition by 10% from 2012 to 2013. Even though the share of income deriving from engagement in production and business activities denoted as net business income increased steadily over the whole period, it is the share of property income that assumed the majority of the above-mentioned shift. In this, returns of financial and non-financial assets increased steadily until 2012, whereas the share spiked by 7% in 2013. As will be described in the next section, the marked drop in net income from transfer for urban households coincides with a comparative rise in net transfers for rural households. An interesting observation that indicates a significant shift in the allocation of social expenditure.

[7] Refers to regular transfer received from country, institutions and social communities such as pensions, disaster relief funds, regular donation etc. deducted for transfer expenditure such as for example taxes and expenditure for social security

Figure 13: Per capita disposable income and share (%) by source (urban households)

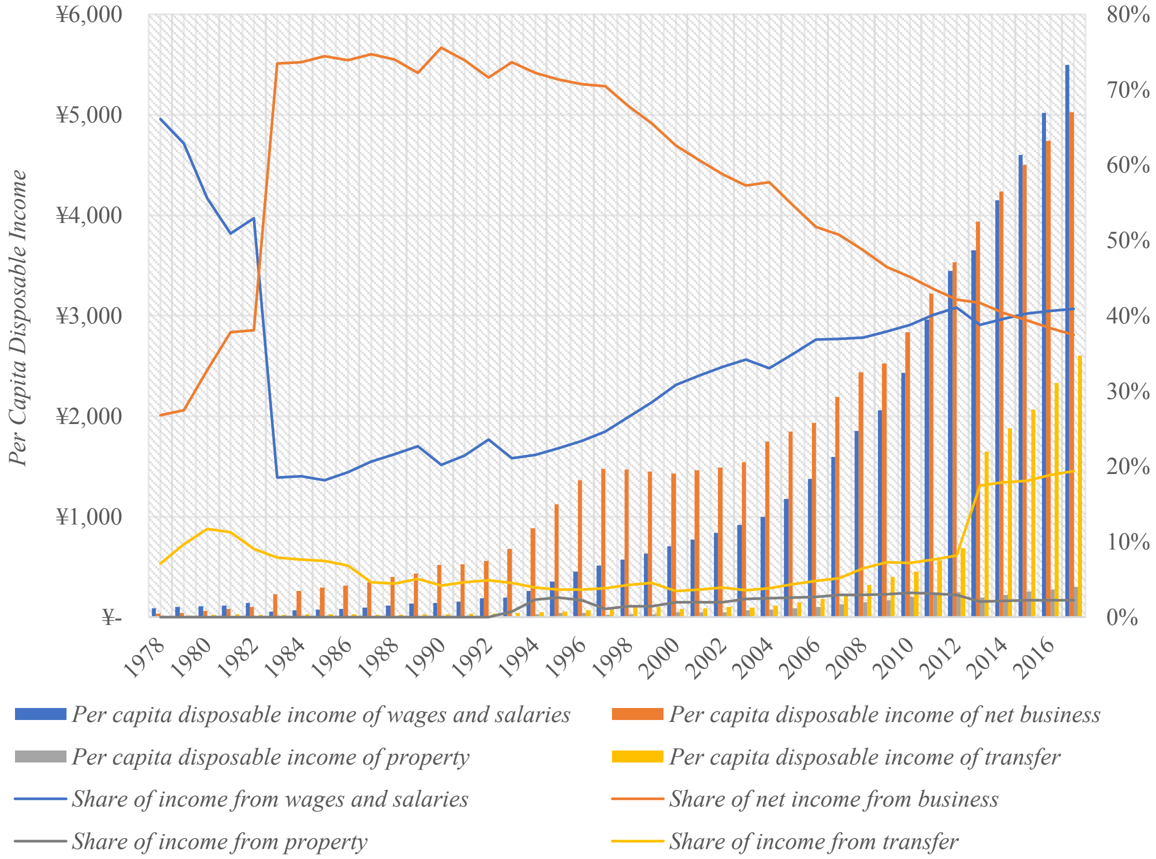


Rural households

Available data for rural households allows for an extended analysis of the income composition all the way back to the introduction of the economic reforms in 1978. From Figure 14 on the next page, we can clearly identify the recent upswing in income of net transfer and the related increase in relative share that was mentioned previously. The share of property income has contrastingly remained relatively stable at less than 1% before it rose to around 3% from 1993 to 1998, whereas the relative share has been around 2% since. The most extraordinary development in the income composition of rural households pertains to net business income and income from wages and salaries. As we can see from the graph, wages and salaries accounted for nearly 2/3 of income at the offset of the economic reforms. In the immediate years after 1978, the share of income from wage earning plunged to around 19%, before a turnaround occurred in the mid 80s. Net business income including farming, is nearly perfectly negatively correlated with the relative development for income share of wages and salaries. This dramatic shift is likely to be a result of the process of agricultural decollectivization in China following the decollectivization reforms in the late 1970s onwards. A process that dismantled collective production and brought agriculture back to small-scale family farming.

In this, almost 300 million farmers went from being wage workers that earned so-called work points[8] to being small business owners based on contractual arrangements with allocated and subsistence farmland (Zhang, 2015). In the early phases of decollectivization, the contractual agreements provided rural households with farmland in return for mandatory quotas of grain supply to the state. A quota system with tight price regulation that gradually transformed from collective to family farming by the implementation of market transaction principles.

Figure 14: Per capita disposable income and share (%) by source (rural households)



After this considerable shift of the agriculture decollectivization, there is a continuous period of rising shares of wages and salaries, with a corresponding decline in business income. Although both compositional sources of income have seen a significant rise in absolute terms, the relative growth in income from wages and salaries has been far greater from the late 90s onwards. In this, the rise has been particularly large in wage employment among non-farming activities (Zhang, 2015). The proportion of rural income deriving from wages and salaries rose from 19% in 1983 to 41% in 2017, a rise in absolute figures from 58 RMB in 1983 to 5.498 RMB in 2017. Accordingly, accounting for the largest relative portion of rural household income composition by source after 2015, as before 1983.

[8] Points that were earned and accumulated daily by farmers which would be given as kind or cash at the end of the year

Zhang (2015) argues that three trends has driven this recovery of rural wage employment; the process of rural industrialization, migration flows from rural to urban areas and an increasingly market-oriented agriculture sector. Processes that has turned industry, labor-hiring firms and household-based side-line production into the main growth engine in rural areas of China.

Contribution to overall inequality

We now turn to examine the contribution of these sources of income on aggregate inequality. Based on data from CHIP for 1995, 2002 and 2007 and CFPS for 2010, 2012 and 2014, Kanbur et al. (2017) estimates the contribution on overall inequality by a similar decomposition of Theil's T indices. In accordance with these estimations, we find that income from wages and salaries has had the largest relative contribution to accumulated levels of inequality for all years (See Appendix D.1). Accounting for nearly all earnings disparity in 1995, 88,75% in 2002 and 71,99% in 2007, before the contribution declined to 66,45% in 2010. By 2012, the relative contribution increased again and remained stable at around 77% up to 2014. Wages and salaries on the other hand, account for more than half of the increase in inequality between 1995 and 2002 (See Appendix D.2), but also for the period between 2007 and 2010. Kanbur et al. (2017) further suggest that wage income contributed to a majority of the decline in inequality between 2012 and 2014. Supporting the findings of a narrowing gap in the late 00s.

Operational income, equivalent to what has been previously denoted as net business income, contributed negatively to overall inequality by -22,77% in 1995 and -20,02% in 2002. A relative contribution that increased in 2007 and eventually turned positive, accounting for around 8% of aggregate inequality by 2010. As such, Kanbur et al. (2017) finds that the rise in operational income disparity had a significant impact on the rise of overall inequality between 2002 and 2010. Contributing to 17% of the rise up until 2007 and almost 14% to 2010, representing one of the primary components of increased inequality along with property income between 2002 and 2007. The only period where property income has contributed positively to changes in inequality, accounting for almost 12% of the change in the period, and 11,26% of total inequality by 2007. Other income, including money and gifts has had a relative stable contribution at around 5%. Contrastingly, the contribution of transfer income has been relatively high, from 14% in 1995 to more than 23% in 2002. Subsequently, the relative contribution decreased steadily until 2012, before rising again to around 3,7% to 2014. As a consequence, transfer income had a notable contribution to the rise in inequality between 1995 and 2002, accounting for almost 40% of the change, but a negligible effect the period after. A finding that emphasizes the importance of transfers in inequality dynamics of modern China.

4. Theoretical framework

From this section onwards, we turn to the second part of the research question for this thesis, which studies the determinants of aggregate levels of income inequality from 1985 to 2015. Accordingly, this chapter will present and review theoretical hypothesis that will function as the basis for the forthcoming econometric analysis of inequality drivers and off setters in post-reform China. The first part of the chapter accounts for one of the most prevalent theories on income inequality dynamics for developing countries with increased economic prosperity, namely the Kuznets curve by Simon Kuznets (1955). Despite its prevalence as one of the most famous theories on inequality dynamics, Kuznets theory has received much criticism for some fundamental limitations since the late 1970s. An empirical debate that heated up in the following decades as the Kuznets curve theory could not sufficiently account for the new-found rise in inequality following the second wave of globalization. Attending to some of this criticism and fundamental limitations of the Kuznets curve, Milanovic (2016) suggested an alternative hypothesis called Kuznets waves or cycles. A theoretical innovation with a more holistic approach to modern income inequality dynamics. These two theories will together function as instrumental and complementary frameworks for the empirical analysis.

4.1 Kuznets curve hypothesis

In his paper "Economic Growth and Income Inequality", Simon Kuznets (1955) studied the relationship between economic growth and income inequality in Germany, United Kingdom and United States in the first half of the 20th century. A study on how economic conditions and markets forces influences the level of economic inequality in a nation as the economy matures. From the findings of this work, Kuznets concluded that each of the countries that was reviewed experienced continued economic growth in per capita gross domestic product in the period, with exception of the years in military conflict. In the early phase of this economic expansion, the level of income inequality tended to increase, before the disparity in distribution levelled off at a certain point. As economic growth proceeded, income inequality eventually started to decline in all countries, but at different rates. Accordingly, the share of national income assumed by the rich decreased, while the share acquired by the poor started to increase.

Kuznets argued that the key element of this mechanism was a nation-wide process of industrialization or mechanization of agriculture. As industries begin to emerge, labor started migrating from agriculture and other low production rate sectors in rural areas to industrial sectors and higher production rate sectors in urban areas. The initial phase of this nation-wide transition entailed progressively increasing internal migration flows. This again gave rise to increased income inequality as the majority of the population remained employed in relatively poor sectors, while a minority of the labor force migrated to wealthier cities and industries.

As the economic expansion continued, the sectorial migration flow became so large that high-productivity sectors became dominant. Consequently, urban areas turned into the center of economic activity and occupied the majority of workers. At this turning point in the process of industrialization, the disparity in income distribution started to decline as the country becomes increasingly democratized, with greater demand for social transfers and reduced skill premium following increased educational attainment to the masses of the population. These factors contribute to a reduction in the earnings disparity, until the country becomes so economically advanced that it settled at a low level of income inequality. Based on these findings and the above-mentioned mechanism, Kuznets proposed an inverted-U curve hypothesis, also known as the Kuznets curve. A framework that explains the relationship between income inequality and economic growth in the process of nation-wide structural transformations. A relationship illustrated graphically in Figure 15 below.

Figure 15: Kuznets curve (Inverted-U hypothesis)

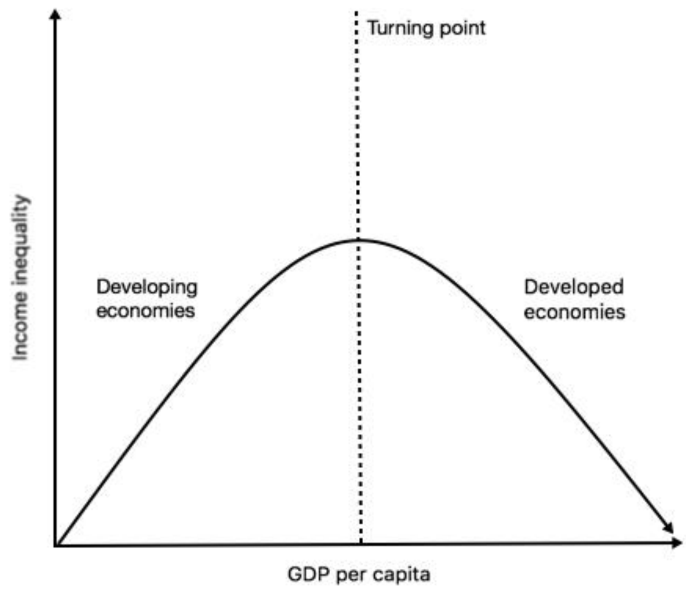


Illustration by author based on Kuznets theorem (1955)

Since it was introduced, Kuznets hypothesis has become one of the most renowned theories on the relationship between economic growth and income inequality, prevailing as a standard feature in economic literature and empirical work on income inequality. However, since the late 1980s, the hypothesis has been widely contested by critics because of certain conceptual- and data limitations in the research. Kuznets himself acknowledged the fragility deriving from data limitations, suggesting that the mechanism needed further research and more data to be confirmed. According to critics, inadequate data quality in terms of reliability and sufficiency constituted one of the primary culprits. Fogel (1987) argued that the paper only attended to a few countries in a single point in time which was characterized by wars, depression and various other extraordinary events, and that these caveats were overlooked.

Beyond the limitations in terms of data reliability and sufficiency, the validity of the suggested mechanism in itself has been subject to further debate in the academic sphere. Deininger and Squire (1998) suggested that the rise and fall of inequality derives from historical variation between countries rather than from economic progression within a country. Piketty (2014) on the other hand argued that the proposed correlation between economic growth and income inequality might be circumstantial and thus not evolutionary by nature. Similarly, Bourguignon (1995: 47) concluded that: *"If there is any parabolic relationship between income inequality and GDP per capita across countries... it is probably very weak and unstable over time... [and] longitudinal data ... seem to suggest that there is much freedom in the way distribution in a given country may change over time"*.

On a more general note, existing empirical research addressing the validity of the hypothesis is ambiguous, giving an inconclusive picture that makes it difficult to draw any clear conclusion. At the same time, it is important to note that Kuznets did not suggest that levels of economic inequality *must* rise as a consequence of growth in developing countries, but rather that inequality *tends* to rise before it decreases. A discussion related to the above-referenced empirical works will be further addressed in Chapter 5.

4.2 Milanovic's theorem of Kuznets-waves/cycles

Building on the work of Kuznets (1955) and his hypothesis of an inverted U-curve in the relationship between economic growth and income inequality, Milanovic (2016) suggested an alternative theoretical model that attended to some of the criticism of the Kuznets curve. A hypothesis that does not refute Kuznets work, but rather builds on his ideas. Milanovic's theoretical innovation construes successive periods of Kuznets curves with rising and falling inequality over time, a motion that he denotes as Kuznets waves or Kuznets cycles. From the late 1970s onwards, many developed nations embarked upon a new rise in national income inequality that Kuznets original hypothesis was unable to fully account for. Attending to this reoccurring development, Milanovic suggested that the new upswing in income dispersion could be seen as a second Kuznets wave.

The logic of the Kuznets wave hypothesis can be explained as an interplay between economic, social and political forces which drives levels of income inequality up and down in long-term cyclical motions, as illustrated in Figure 16. In contrast to Kuznets theory of a curvilinear relationship between economic growth and levels of within-nation income disparity, Milanovic's hypothesis adopts a more holistic approach that moves beyond the sole focus on economic factors in Simon Kuznets work. Milanovic argues that Kuznets approach is both naïve and insufficient in accounting for what income inequality actually is, making economic factors alone inadequate in explaining the evolution of disparity in income distribution. In this, the same logic prevails as a counterargument to Piketty's theory (2014) in his infamous book; 'Capital in the Twenty-First Century', which focus on political factors as exogenous drivers.

Figure 16 Expected pattern of changes in inequality versus income per capita

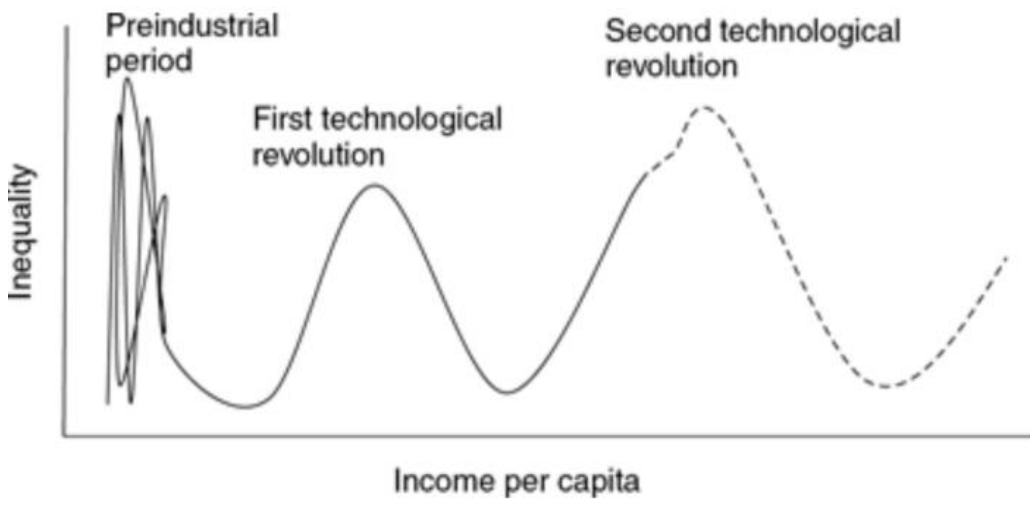


Illustration by Milanovic (2016)

As previously mentioned, Milanovic theory (2016) does not reject Kuznets hypothesis, but rather acknowledge important facets to his theoretical construct and builds upon it. Herein, Milanovic supports the proposed dynamic of a rising income inequality in developing nations whereby mean income is increasing with the process of economic growth, substitution of labor to capital and transfer of labor from one sector to another. However, he recognizes that these structural mechanisms cannot be seen as segregated effects, and thereby cannot be interpreted in isolation nor be overgeneralized. The level of income inequality must be seen as a result of the interplay between economic, social and political factors that affects inequality trends. An interdependence and complexity that moves beyond the original hypothesis of Kuznets. In order to attend to these fundamental dynamics of Milanovic's theoretical construct and apply his ideas in the forthcoming empirical analysis, I will now turn to review the specific determinants suggested by the theorem in the upward and downward portion respectively.

4.2.1 Drivers of the upward portion of a Kuznets wave

In terms of exogenous factors driving the upward potion of a Kuznets wave, Milanovic distinguishes between pre-modern and modern societies, which can also be described as pre- and post-industrial economies. This is an important distinction, because the fundamental logic of the determinants and related dynamics in national inequality is very different. For pre-modern societies, where mean incomes were stagnant, Milanovic argues that there is no relationship between mean income and levels of inequality. Changes in inequality is driven by non-economic factors and idiosyncratic events, such as wars and epidemics. Given that this thesis only attends to the 'modern era' in Milanovic's wording, the focus will be on the latter.

For modern societies, Milanovic suggests that the upward portion of Kuznets waves is driven by technological revolutions and structural transformations under the condition of globalization. In this, Milanovic suggest that there have been two Kuznets cycles over the last two centuries in a global perspective. Whereas the first wave was triggered by the industrial revolution and the transition process of economies from agriculture to industry. These proposed dynamics of the rising levels of within-nation income inequality closely aligns with the reasoning of the Kuznets original U-curve theory. The distinction is rather the focus on technological change as the exogenous trigger for the rising levels of inequality in societies that experience rising levels of mean income. In addition to the amplification of these triggers through the conditional process of globalization, which accompanied the industrial revolution.

The second Kuznets wave in the modern era, builds on the same fundamental logic and dynamic as for the first wave among modern societies. This cycle was triggered by the information technology revolution and a new wave of globalization, which started around the 1980s for many post-industrial societies. In accordance with the dynamics of the first wave, this entailed migration of labor from homogenous manufacturing jobs to more skill-intensive and heterogenous service occupations. A process which rewarded high-skilled labor more in both absolute and relative terms, but also bolstering the relative share of and return to capital.

Accordingly, Milanovic argues that the forces driving up the level of inequality in a modern society could be explained by 'TOP elements' which is an abbreviation for; technology, openness/globalization and policy. He further argues that these elements are mutually dependent and cannot be disentangled in any meaningful way, whereas policy is considered to be exogenous with respect to globalization and economic preconditions. Milanovic suggests that by removing only one of the elements, one could discourage almost the whole rise in income inequality for either of the two Kuznets waves. At the same time, he argues that the three elements combined could explain nearly the whole upward motion of both the first and the second Kuznets cycle. I will now attend to the functional mechanism of these elements.

Technological change

The principal logic of how technological revolution drives up levels of within-nation inequality derives from a process of increased demand and productivity for capital and high-skilled labor. On the capital income side, creation of various technological rents takes places, which is then assumed by the technological leaders and those with political power to ensure monopoly power or political protection. On the labor side, the endogenous technological change has been skill-biased, meaning that it has rewarded high-skilled labor relatively more. The type of inventions has also been an important factor, whereas much of the technology has been made to replace relatively more expensive production factors such as labor. More specifically, low-skilled labor in agriculture for the first wave and heterogenous manufacturing jobs for the second wave. As a consequence, wages and job prospects for individuals employed in the relevant economic sectors has been diminished. A process which has augmented the skill premium and thus earnings gap between high- and low skilled workers. Still, Milanovic suggest that such conditions does not guarantee their 'victory', as these factors needs to be supported by conditions of globalization and endogenous policy that amplifies inequality.

Openness/Globalization

Accordingly, the condition of globalization or openness has been indispensable for these triggers, interplays and complex inequality dynamics leading to the rising motion of the waves. Whereas the triggers and effect of technological innovation are amplified by the scope of operations, which was brought to a global scale under the first and second Kuznets wave. Herein, the emergence of broader production networks and greater access to supply of cheap and low-skilled labor augments the effect through reduced production costs. A process that in turn weakened the labor's position further and reduced the importance of trade unions, which again allowed capital owners to assume more of the technological rent. Beyond increased access to cheap and low-skilled labor, technological rents were further amplified by the global scope of operations in terms of greater access to exploitable resources, capital and markets.

Policy

As previously described, Milanovic portrays the political forces driving the upward portion of a Kuznets wave as being endogenous to globalization and economic preconditions. Factors including policies and political forces in a broader economic perspective, whereas parameters such as degree of globalization, supply of skilled labor, access to capital and exploitable resources is included. Political changes and battles along these dimensions set the context for potential growth in levels of national income inequality, a mechanism that gain traction if the general market trends also work in favor of some dimensions. In this, Milanovic emphasizes the tendencies of reduced marginal tax on high income and capital, but also the increasingly free global movement of capital to have been particularly forceful drivers in the second wave. As a consequence, he argues that from the 1980s onwards, the redistributive function in most modern and developed societies has weakened or stagnated. In rare cases of increasing redistribution, Milanovic suggest that the rise has been inferior to the rise in market inequality.

Given the complex interplay between economic and political factors, the size and peak of a wave tend to diverge markedly among nations, but the shape of the cycle remain fairly similar. In view of this finding, the post-reform development in China is a highly interesting case. By Milanovic's definition, China could be perceived as a pre-modern society up until only a few decades ago. Despite its delayed process of industrialization, the latter information technology revolution has undoubtedly unfolded in modern China under the condition of globalization. Therefore, we could be looking at a scenario whereas the suggested triggers and conditions of two technological revolutions take place in the same country simultaneously. Accordingly, the forthcoming empirical analysis needs to address the upward portion of both Kuznets cycles.

4.2.2 Forces offsetting rising levels of within-nation income inequality

Beyond the suggested forces driving up the level of within-nation income inequality, Milanovic (2016) identifies various economic, social and demographic forces that have contributed to the 'Great Levelling'[9] after the first world war. In this, he argues that many of the same forces could play an important role in the future, i.e. driving down the second Kuznets wave. Following Milanovic's wording, these forces result in *benign* and *malign* mechanisms, which reduces national income inequality. In this, benign forces include increased social transfers, progressive taxation and more widely accessible education. Malign forces on the other hand consist of wars, civil conflict, natural catastrophes and epidemics. According to his theory, these are the two ways in which income inequality can be reduced in modern societies. The principal differences between these two mechanisms or types of inequality reducing forces is that nations with stagnant mean income will not be affected by benign forces. In this, Milanovic argues that only growing economies experience increased educational attainment, higher political participation and encounter downward pressure deriving from an aging population. The same principal does not apply to malign forces, which are more similar, because conflicts and wars is influential in both expanding and stagnant economies.

Accordingly, Milanovic does not refute Kuznets' notion in that the downward slope in inequality was a product of economic and demographic forces and structural transitions - such as increased supply of more-educated labor, demand for redistribution and return on capital. Instead, he emphasizes the importance and neglection of malign forces in Kuznets theory for explaining the downward portion of the first Kuznets wave - such as wars, revolutions and epidemics. Beyond the neglection of malign forces, Milanovic suggests that the effect of low-skill-biased technology change has not been adequately studied and could potentially put downward pressure on income inequality in the future. Following his argument, history has led to a common perception of technological progress as capital-driven, raising demand for highly skilled labor and thus wage premium, but also as a factor which has replaced low-skilled labor through automation. However, Milanovic claims that there is a possibility that future technological innovations will be biased towards the poor by bolstering productivity levels among low-skilled labor. That being said, the standing lacks a line of empirical support and remains speculative postulation, which this paper will not attend to in any further detail.

[9] The significant decline in income inequality that occurred in most of the western world in the twentieth century

Accordingly, Milanovic's theorem takes a more holistic approach in that he portrays the downward pressure on income inequality to derive from the interplay between political, economic, social and demographic factors. In line with his argument, a narrow perspective focusing solely on benign economic forces becomes inadequate in accounting for the complex and dynamic nature of income inequality. As such, Milanovic recognizes the interdependence of these mechanisms as a dynamic system rather than viewing these processes in isolation. A summarization of these proposed benign and malign forces for societies with stagnant and rising mean income is presented in table 1 below.

Table 1 Malign and benign forces reducing within-nation income inequality

Type of society	***Malign forces***	***Benign forces***
Societies with stagnant mean income	Idiosyncratic events Wars (through destruction) Civil conflict (state breakdown) Epidemics	
Societies with a rising mean income	Wars (through destruction and higher taxation) Civil conflict (state breakdown)	Social pressure through politics (socialism, trade unions) Widespread education Aging population (demand for social protection) Technological change that favors low-skilled workers

Source: Milanovic (2016)

5. Empirical review

In this chapter, I will present and review empirical research and evidence related to determinants and drivers of within-nation income inequality. The purpose of this empirical review is to shed light on existing research of structural mechanism and their net effect on national levels of disparity in income distribution. Furthermore, to draw insights and inspiration from the empirical work in the specification of hypotheses. In that, ensuring a holistic and pragmatic approach in the regression modelling by complementing the theoretical framework. The empirical support will also have a guiding function in terms of measurement technique and specification related to the variable construction for the regression analysis.

5.1.1 Economic growth

As previously described, the existing empirical evidence for the Kuznets curve hypothesis is inconclusive and ambiguous at best. By examining changes in income distribution in industrialized economies, Paukert (1973) found supporting evidence for curvilinear relationship between economic growth and income inequality. Londoño (1990) found evidence for an inverted-U shape in the long-term development of inequality in Colombia, while Williamson and Lindert (1980) found support for the hypothesis in United States and Great Britain over several decades. Several other empirical investigations from the likes of Oswang (1994), Ali (1998), Milanovic (1994) and Fishlow (1995) has also provided some support for Kuznets theorem. Barro (2000) on the other hand, finds that the Kuznets curve is an empirical phenomenon, but the theory is unable to explain most of the variation in income inequality over time. Anand and Kanbur (1993) found a weak relationship depending in the functional form, while Deininger and Squire (1998) found no empirical support for Kuznets hypothesis. Fields (2001) reviewed available empirical evidence on Kuznets hypothesis based on large panels of countries and time series. In this, no empirical tendency was found either for the rise of inequality in developing countries, the fall of inequality in developed countries, nor any significant link to the rate of economic growth. At the same time Dumke (1991) and Thomas (1991) could not find evidence for a Kuznets curve in neither Germany nor Australia. A notable divergence in findings which again underlines the lack of any empirical consensus.

5.1.2 Sectoral transformation

Sectoral transformation can be described as shifts in domestic employment structure through changes in the share of employment in an industry or sector. Specifically, this thesis will attend to sectoral shifts related to the transition processes from agriculture to industry, also known as industrialization, but also the shift from industry to service, denoted as servitifization. These broad sectoral changes are often described as indispensable to the processes of urbanization and long-term economic development, which again are all related to Kuznets' (1955) inverted U-curve hypothesis described in the previous chapter. Interestingly, Jain-Chanda et al. (2018) finds that sectoral changes had an offsetting effect on income inequality in China over the last decades. According to their study, within-sector inequality rose, but this effect was offset by the fall in between-sector inequality which is attributed to the general equilibrium effects. Wan et al. (2016) specifically investigated the relationship between structural change and income inequality in China from 1952 to 2012. According to their research, they found empirical evidence that confirms the theoretical prediction of an inverted U-shape relationship. They also found that sectoral transformation represented the main driver of regional inequality in China from 1978 up until 2004. Another interesting finding in their study is that the agriculture sector has had negative effect on inequality, while the service sector has increased inequality.

5.1.3 Urbanization

In accordance with Kuznets' (1955) inverted U-curve theory, the process of urbanization referring to population shifts from rural to urban areas will increase income inequality in the early phases of structural transformations (e.g. industrialization). Herein, the process of urbanization has often been described as one of the primary drivers of widening disparity in the income distribution (Behrens and Robert-Nicoud, 2014). As for the impact of sectoral transformation, the relationship between urbanization and income inequality is found to follow an inverted U-curve (Rauch, 1993). Jain-Chandra et al. (2018) found that the rapid process of urbanization in post-reform China has been a significant driver of the rising levels of income inequality in recent decades. An impact that is reflected in the considerable spatial disparity between urban and rural areas, but also in the rise of within-group inequality in urban areas. Another study by Chen et al. (2016) looks specifically at the causal relationship between urbanization and income inequality in China from 1978 to 2014. In this, they find that the process of urbanization in China has had an immediate reductive on the levels of domestic income inequality. However, by lagging the effect by only one period (one year), they find that urbanization has a significant aggravating effect on disparity in the income distribution.

5.1.4 Technological progress

In accordance with Milanovic's theorem of 'Kuznets cycles', technological change is found to have a significant effect in rising skill premium, which then again results in widening disparity in labor income distribution (Dabla-Norris et al. 2015). There is two principal mechanisms and transmission channels in which the technological progress affects the level of income inequality. First, significant technological advances increase demand for capital and skilled labor, which in turn reduces demand for low- or unskilled labor. Secondly, the nature of the recent technological revolutions has entailed a high degree of both automation, digitization and robotization. These advancements have in many cases eliminated the need for labor, job functions that previously were held by low- or unskilled labor (Card and DiNardo, 2002; Acemoglu, 1998). Accordingly, it is not technological progress itself that widens the gap in income share, but rather the nature of the advancements and its skill-bias. Staggeringly, OECD (2011) has found that almost a third of the rise in income inequality between the 10th and 90th percentile can be attributed to technological progress in the last 25 years among OECD countries, making it the most significant driver of income inequality in the same period. Jaumotte et al. (2008) at IMF finds that rising inequality in developed and developing countries over the past two decades can largely be attributed to the impact of technological change.

5.1.5 Trade openness

Following Milanovic's proposed dynamic of Kuznets waves, liberalization of trade ought to make up a significant amplifier for the upward motion of a cycle. Yet, the empirical evidence for the causal relationship between trade openness and income inequality seems to be ambiguous and inconclusive. Based on household surveys from 18 Latin-American countries in the period 1977 to 1998, Behrman et al. (2003) finds that a trade index explains 10-12% of earnings disparity between employees with different schooling. Lundberg and Squire (2003) finds that inequality is significantly positively correlated to the Sachs-Warner openness indicator, suggesting that trade liberalization widens the gap in national income distribution. A similar relationship was found by Barro (2000) showing a positive and long-term connection between openness for trade and income inequality. Cragg and Epelbaum (1996) found that trade give rise to skill intensification which resulted in 0,1% rise in earnings premium in the traded manufacturing sector, based on micro-level data from 1 million workers in Mexico between 1987 and 1993. For advanced economies, Feenstra and Handson (1996; 1999; 2003) finds that companies' ability to offshore and adopt labor-saving technologies has been an important driver for rising skill premiums and the decline in manufacturing.

On the other hand, Faustino and Vali (2011) conversely finds that increasing trade openness leads to a decline in the disparity in income distribution for 24 OECD countries between 1995 to 2007. Supporting this premise, Zhou et al. (2011) similarly finds that globalization has reduced domestic inequality in 60 countries, while Jaumotte et al. (2008) finds that increased trade tends to reduce income disparity. Herein, increased competition, specialization and incentives to up-skill has been some of the suggested channels through which increasing levels of trade openness can reduce national income dispersion (Birdsall, 1998; Blanchard and Giavazzi, 2003; Francois and Nelson, 2003). The lack of empirical consensus for the relationship is further accentuated by a myriad of inconclusive and mixed findings. In this, Franco and Gerussi (2013) found that trade was not relevant in explaining the variation of inequality in 17 transitional economies. Similarly, Edwards (1998) and Roine et al. (2009) found no evidence for a distributional effect linking trade liberalization to inequality. On the contrary, Wood (1999) found that trade liberalization may increase or decrease domestic earnings dispersion by examining surveys from Latin-American and East-Asian countries from the 1960s to 1990s. Findings from Munch and Skaksen (2009) lend support to this, saying that trade openness could have mixed effects on earnings of unskilled labor in advanced economies, whereas skill premium rise, but real wages increase as import prices are lowered.

5.1.6 Financial openness

Financial openness or integration pertains to financial flows and foreign direct investment which has been extensively researched for its impact on income inequality. A variable that can be perceived as a subfunction of Milanovic's suggested globalization parameter alongside trade liberalization. Even though there is a lack of a clear empirical consensus related to the effect of increased financial integration on domestic income inequality, the impact seems far less dubious than that of trade openness. This is well reflected by the study of Lee (2014) which is based on cross-country regressions from 1976 to 2004. In this, he finds that the relationship between trade liberalization and inequality is conditional, while financial openness generally increases income inequality. Freeman (2010) further finds that increased financial flows leads to wider disparity in the income distribution, both for emerging market economies and for more advanced economies. Results that further indicated that the effect from foreign direct investments and portfolio flows was particularly strong. Dabla-Norris et al. (2015) argues that a possible explanation for this effect derives from a concentration of foreign assets and liabilities in sectors that can be perceived technology- and skill-intensive.

A premise that is supported by Jaumotte et al. (2008), finding that increased stock of inward FDI as a ratio of GDP increases income inequality in both developing and developed countries. Larrain (2015) further finds that increased capital inflows raise the skill premium, and thereby the overall earnings gap. Choi (2006) on the other hand, finds a more detrimental effect of outwards FDI stocks in his research of the impact in 119 countries from 1993 to 2002. Findings that lend further support to the premise of a significant distributional effect of increased foreign direct investment. Based on a UK panel data, Taylor and Driffield (2005) found that the skill demand effect deriving from FDI explained around 11% of earnings dispersion in the British manufacturing sector from 1983 to 1992. Looking specifically at China and 10 other Asian countries from 1980 to 2014, Bukhari and Munir (2016) finds that financial globalization had a significant effect in increasing domestic income inequality. That being said, Lim and McNelis (2016) still suggest that the impact of financial openness is likely to depend on the nature of the production structure and how advanced the economy is.

5.1.7 Redistributive policies

The effect of redistributive policies such as government spending, social expenditure and progressive taxation on disparity in income distribution seems rather intuitive and straight-forward. By definition, redistributing policies will naturally benefit the low-income earners relatively more than high-income earners, and by purpose it will aim ensure greater equality. Howbeit, the predicted theoretical impact is less obvious if we account for indirect second-round effects or behavioral adjustments by economic agents (Doerrenberg & Peichl, 2012).

Empirical evidence confirms a direct reductive effect of social policies on domestic income inequality (Garfinkel et al., 2006; Fuest et al., 2010). Herein, the effect of government spending on health, education, infrastructure and other social benefits is found to have a negative impact on disparity in income distribution (Gradstein and Justman, 1997; Benabou, 2000; 2002). Based on panel data from industrialized OECD countries Doerrenberg and Peichl (2012) found that a 1% increase in government spending or social expenditure decreases income inequality by 0,3%. However, in accordance with their findings, the causal effect of tax progressivity remains inconclusive. It is however important to note that the effect of both social policies and progressive taxation is highly dependent on both targeting and coverage (Alesina, 1998; Davoodi et al., 2003; Rhee et al., 2014).

Despite the empirical consensus of direct negative effect of redistributive policies, indirect second-round effects could offset and even overcompensate the initial equalizing impact (Sinn, 1995; Poterba, 2007; Chu et al., 2000). Doerrenberg and Peichl (2012) argues that certain redistributive policies including social benefits and progressive taxes diminish the incentives either to work or to make investments. Herein, Roed and Strom (2002) has found labor supply to be relatively more elastic among low-income earners, which could give a relatively more significant reduction of labor supply among low-income earners. Wage-setting behavior of employers could further induce second-round indirect opposing effects, in which employers could expect inequality to be a responsibility of the government. In accordance with this argument, employers would avoid any social responsibility by adopting lower grow-wages for employees, which would see higher profits absorbed by employers (Doerrenberg & Peichl, 2012). Following these potential second-round effects, the causal relationship between redistributive policies and domestic income inequality might not be as clear and intuitive as one would expect at first glance.

5.1.8 Educational attainment

Educational attainment can generally be seen as important factor for the degree of domestic income inequality as it is decisive for individual occupational choices, job eligibility and income level from wages, therefore also for the income distribution structure at a macro level. Herein, relevant literature suggest that education represents a significant determinant of income inequality (Atkinson, 1997; Acemoglu, 1997; Becker and Tomes, 1986; Benabou, 1994; Durlauf, 1996 i.a.). Despite the intuitive impact, theory suggest that the relationship might not be clear. According to the human capital model of income distribution, the effect of domestic educational attainment on within-nation income dispersion is determined by the rate of return to education or skill premium, which could be both positive and negative (Mincer, 1958; Becker and Chiswick, 1966). The theoretical relationship and effect of increasing domestic educational attainment can be somewhat ambivalent given two opposing forces. First, the ‘composition’ effect, which gives the increased share of high-income earners, predicts an inverted u-curve relationship of income inequality plotted along the extent of educational attainment. Herein, inequality will rise in the early stages and subsequently decline after reaching a certain extent of educated individuals. The other effect known as ‘wage compression’, giving the relative decline in returns of higher education compared to lower education, suggest that income inequality and skill premiums declines following an increase in the relative supply of skilled and educated individuals (Knight and Sabot, 1983).

In terms of the empirical evidence, there is manifold of studies illustrating a negative relationship between increased domestic educational attainment and income inequality (De Gregorio and Lee, 2002; and references therein). Gregorio and Lee's (2002) comprehensive study finds that countries with relatively greater educational attainment have relatively greater equality in income distribution. Their findings suggest that increased educational attainment by one standard deviation, between 2,5 and 2,9 years, gives a reduction in the Gini coefficient by approximately 3 percentage points. At the same time, educational inequality is found to have a significant positive impact on income dispersion. Other empirical findings seem to indicate that the relationship depends on several other factors, including rate of return on education and educational investments from both individuals and government (Dabla-Norris et al., 2015). A complexity that is supported by cross-country studies showing that increased educational attainment decreases income inequality, but that the effect is intricate and dependent on both type, quality and distribution of education (Barro, 2000; Checci, 2000).

5.1.9 Financial deepening

In the comprehensive IMF study on causes and consequences of income inequality by Dabla-Norris et al. (2015), they find financial deepening referring to increased provision of financial services could be an important factor to consider for the variation of income dispersion. In accordance with their study, they argue that financial deepening could induce greater access of financial services to both households and companies, which facilitate retirement savings, educational investments, capitalization on market opportunities, but also better protection against economic shocks. In this, they find that financial deepening could reduce income inequality and improve allocation of resources if the provision is accompanied by a more inclusive financial system. The theoretical standpoint by Greenwood and Jovanovic (1990) suggest that such financial development is relatively more beneficial for high-income earners in the early phases, whereas it becomes more inclusive as the economy becomes more developed. Empirical work from Deng and Su (2012) lend support to the evidence from Dabla-Norris et al., finding that financial deepening spur income growth among low-income earners which contributes to reduced income inequality. Financial services could further expand at the extensive margin, broadening the inclusion groups that are marginalized, but also enable these groups to invest more in both physical and human capital. This mechanism could in turn narrow the gap in income distribution (Becker & Tomes, 1979; Banerjee & Newman, 1993).

However, some empirical findings seem to contradict the evidence from Dabla-Norris et al. (2015). Claessens and Perotti (2007) finds that financial deepening may transpire at the intensive margin, which would enhance the financial services of groups that already have access to these services. Seeing as these groups are more likely to be high-income earners, higher assets or established companies, this could raise income inequality by increasing skill premiums and possibly return to capital. Roine et al (2009) further found that financial development measured by the relative share of the banking sector in the economy could increase inequality in the early phases as it disproportionally benefits the top income earners. The empirical evidence related to the causal relationship between financial deepening and income inequality is therefore not without ambiguity. Yet, available findings provide appropriate justification for testing the factor against variation in income inequality in China.

5.1.10 Population aging

In contrast to the suggested determinants mentioned above, the impact of population aging on income inequality has received far less theoretical and empirical attention. Yet, a nation's age structure and composition has long been regarded as an important determinant for the level of disparity in income distribution (Jain-Chandra et al., 2018). A premise that makes China's rapidly aging population a highly interesting phenomenon. Existing research has predominantly attended to the relationship for economically developed countries, whereas most of empirical evidence finds that population aging only accounts for a small share of overall income dispersion with little impact on the gap in distribution (Barret et al., 2000; Bishop et al., 1997; Jantti, 1997). Conversely, Deaton and Paxson (1994; 1997) has found that income inequality increases following a process of population aging in accordance with the behavioral predictions of the permanent income hypothesis. Further, Ohtake and Saitho (1998) found that nearly half of the dramatic rise of consumption inequality in Japan in the 1980s could be attributed to population aging. Cameron (2000), found that 5,8% of the variation in income inequality in Java for the period 1984 to 1990 could be explained by the impact of an aging population A premise that was supported by Chu and Jiang (1997), finding that population aging significantly affected domestic income inequality in Taiwan in the period between 1978 and 1993. Empirical evidence from rural China has already established that population aging has significantly increased dispersion in the income distribution for rural areas in recent years (Zhong, 2011). Further empirical support is given by Jain-Chandra et al. (2018) who found that both the fall in fertility and the process of population aging has had a significant contribution in widening domestic income inequality in China in recent decades.

5.1.11 Privatization

A central aspect to the transformative economic reforms introduced in the late 70s and early 80s was the process of increasing marketisation and privatization (Bakkeli, 2017). Herein, the former refers to a process in which economic activities and resources allocation that was previously controlled by the state becomes directed by market mechanisms (Wu and Xie, 2000). The ladder describes a process of transferring ownership of enterprises and assets from the state to private actors, but also a withdrawal process of public services being replaced by private service providers (Bailey, 1987). In this, the process of privatization has often been associated with increased disparity in the income distribution (Bandelj and Mahutga, 2010). An intuitive perspective would be changes in the income structure of transitional economies, whereas the share from wages fall relative to capital and entrepreneurial income (Honkkila, 1997). Howbeit, existing theoretical literature suggest that there are numerous ways in which privatization could impact the distribution of income, which makes the distributional effect rather ambiguous. As a consequence, Ceriani et al. (2016) argues that the net effect of privatization on income inequality becomes "*an empirical matter of relative magnitudes*".

According to the Honkkila (1997), empirical evidence has found that income inequality rises in transitional economies, and that the rising share of capital income can account for some of the rise in income inequality. At the same time, McKenzie and Mookherjee (2003) found that privatization has a very limited effect on income inequality in developing countries. Birdsall and Nellis (2003) shows that privatization programs widen inequality in the distribution of income, at least in the short run. A premise which is supported by Chao et al. (2006), finding that partial privatization could lead to increase earning dispersion between unskilled and skilled workers, higher unemployment ratio, higher prices of goods and lower social welfare. Based on survey data, Bakkeli (2017) established that privatization has had a significant impact on income inequality in the Western regions of China. Still, it has been argued that the distributional effect of a privatization process depends on various other factors, including the regulatory regime and market competition (Florio and Puglisi, 2005; Birdsall and Nellis, 2005). An argument that is in line with findings from the comprehensive study by Ceriani at al. (2016). Based on a panel dataset of 80 developing countries from 1988 to 2008, they found that privatization has a contributes significantly to increased income inequality in countries where political institutions could be described as 'unmatured'. At the same time, they find a significant positive relationship between privatization and income inequality in countries where the so-called democratic institutions are effectively consolidated.

6. Methodology

In this section, I will present the research methodology applied in the empirical analysis of this dissertation. A methodological mode that is selected and designed to estimate the relationship between disparity in income distribution and the determinants given by the predictors presented in chapter 7.1. The first part of this section will describe the relevant regression estimation method for time series that is adopted for the empirical analysis. Followingly, I will give an account for the necessary statistical assumptions that needs to be satisfied in order to obtain a best linear unbiased estimator, but also the relevant diagnostics test to control for these assumptions. The last subsection of the chapter will attend to properties of time series data that needs to be accounted for in order to avoid spurious regression results.

6.1 Regression Analysis

Regression analysis can be described as an analytical technique used to study how the mean value of a given variable covaries with one or more independent variables. A technique that allows for and enables control for potential disturbing variables that may lead to spurious causalities or relationships (Johannesen et al., 2011). Accordingly, the properties of a regression analysis make the technique a suitable and appropriate mean for analyzing and identifying the relationship between two or more variables. At the same time, Osmundsen et al (2002) underlines that a common misinterpretation of the relationship between variables is to assume that a correlation, which only indicates the variables covaries, is equivalent to a cause-effect relationship. Accordingly, the empirical analysis of this paper will not be able to conclusively determine any robust causal mechanisms, but rather identify relationships based on coefficient estimates from an ordinary least squares regression, denoted as OLS. The simplest and most fundamental OLS estimation method is known as a bivariate linear regression or a simple linear regression model. Whereas the purpose is to describe the relationship between a dependent and one independent variable, given in equation 6.1 below.

$$y = \beta_0 + \beta_1 x + \mu \tag{6.1}$$

In this, y expresses the dependent variable or regressand, while x represents the independent variable or regressor. β_0 gives the relevant intercept parameter, also denotes as the constant term. β_1 represents the slope parameter that explains the relationship between the dependent variable y and the independent variable x, given that the error term μ is fixed. Herein, the error term reflects the unobserved factors that affect y (Woolridge, 2016).

6.1.1 Multiple Linear Regression

In contrast to a bivariate regression, a multiple linear regression model explicitly allows for control of two or more independent variables that simultaneously affect the regressand. Consequently, a multiple regression analysis enables composition of better and more suitable models to draw conclusions and predict the dependent variable. An inherent advantage as most regressand is affected by more than one regressors. Therefore, adding additional factors to the model helps to explain more of the variation in the dependent variable (Wooldridge, 2016). The general relationship can be illustrated by equation given below.

$$y_i = \beta_0 + \beta_1 x_{i1} + \beta_2 x_{i2} + \ldots + \beta_2 x_{i2} + \mu_i \quad (6.2)$$

In this, the vehicle of a multiple regression model prevails as one of the most commonly used empirical analysis techniques in both economics and various other social sciences. In the application of a multiple regression analyses, OLS estimation similarly prevails as the primary method for estimating the parameters in the model. Accordingly, these preeminent econometric techniques in studying relationship between variables facilitates a well-suited methodological approach for an empirical analysis in the determinants of income inequality. In order to justify the predominance of the OLS method over comparable estimators and to obtain reliable, valid and unbiased estimation results certain assumptions needs to be satisfied.

6.2 Classical linear model assumptions for time series

According to the Gauss-Markov theorem, OLS estimators is considered the best linear unbiased estimator (BLUE) given that a standard set of assumption holds (Wooldridge, 2016). I will now attend to each of the six assumptions that is relevant for time series regression models with related consequences. In this, I will also elaborate on relevant diagnostics procedure to test and mitigate potential violations of the necessary assumptions.

1st Assumption – Linear in parameters

The first of these assumptions states that the dependent variable must be a linear function of the independent variables. In other words, that the stochastic process follows a linear model that is linear in parameters $\beta_0, \beta_1, \ldots, \beta_k$. If the model does not satisfy this assumption (i.e. non-linearity in parameters), the estimation method described above will still estimate a linear relationship between the variables. Such a condition will lead to unreliable regression results and biased coefficient estimates. A violation of this assumption would need to be addressed by transforming the predictor variable to the appropriate functional form (Wooldridge, 2016).

2nd Assumption – No perfect collinearity

The Gauss-Markov theorem further assumes that none of the explanatory variables are perfectly correlated with one or more of the other explanatory variables. Even though a high degree of multicollinearity does not violate the necessary assumption, elevated levels of correlation between regressors entails disruptive effects on regression results as the estimates produce unreliable coefficients. This encumbers interpretation of relationships, making it difficult to distinguish the distinct effect of each regressor on the dependent variable (Kraha et al., 2012). To control for the level of multicollinearity in the dataset employed for this analysis, I will make use of both a correlation matrix and a variance inflation factor test (VIF).

3rd Assumption – Zero conditional mean

The assumption of a zero conditional mean entails that the value of the error term u_t for each period of time, should have an expected value of 0 given the independent variables value for all periods. In other words, the error term for each period is uncorrelated with the regressors for all of the time periods (Wooldridge, 2016). This can be given mathematically as follows:

$$\mathrm{E}(\mathrm{u_t}|\mathrm{x_{1t}}, \dots, \mathrm{x_{tk}}) = \mathrm{E}(\mathrm{u_t}|\mathrm{x_t}) = 0, \mathrm{t} = 1,2, \dots, \mathrm{n}. \quad (6.3)$$

If equation 6.3 holds, the explanatory variables in the model can be described as contemporaneously exogenous because the regressors and error terms are contemporaneously uncorrelated. However, for the assumption of zero conditional mean to be satisfied and for OLS to be unbiased, the independent variables need to be strictly exogenous across all time periods. Accordingly, the regressors cannot be reactive to previous changes in the dependent variable, which poses a typical problem in social sciences because many explanatory variables cannot be considered strictly exogenous by nature. This broader issue will followingly be a concern for my regression model as well, for example when testing for certain types of variables, such as policy. If the assumption is violated, estimations will be both biased and inconsistent. Issues of endogeneity can derive from several conditions in the data or the model specification, but the most common reason for a violation is either measurement errors, misspecification of regressors, omission of central variables or endogenous variables (Wooldridge, 2016). Accordingly, any mitigative techniques must be based on the specific reason for the violation of the assumption.

4th Assumption – Homoskedasticity

The fourth assumption that needs to be satisfied in order for the OLS estimation to be BLUE is that the error terms u_t are homoscedastic. This means that the variance of the error term must remain constant for all time periods, but also that they are independent of the explanatory variables (Wooldridge, 2016). A condition illustrated mathematically in equation 6.4 below

$$Var(u_t|x_{1t}, \dots, x_{tk}) = Var(u_t) = \sigma^2, t = 1,2, \dots, \mathrm{n} \quad (6.4)$$

If the errors violate this assumption, they are denoted as heteroscedastic. Even though the properties of the OLS estimators remain unbiased and consistent if this is condition is violated, they will no longer be efficient or of minimum variance. Accordingly, they will no longer be the best linear unbiased estimators, and OLS will no longer be a good estimator. Furthermore, this will induce invalid inference in that standard errors, level of significance and thus related *F*- or *t*-test will be invalid and unreliable, which again leads to erroneous conclusions (Gujarati, 2015). There could be several reasons for unequal variance in the error terms, such as outliers in dataset, incorrect functional form or transformation of data. In the forthcoming diagnostics procedure, I will test control for the presence of heteroscedasticity in the error term by a conventional Breusch-Pagan test, which will be supplemented by a graphical diagnostic of analyzing a plot of the residuals against the fitted (predicted) value.

5th Assumption – No autocorrelation

Followingly, the theorem assumes that the model does not suffer from autocorrelation. This necessary statistical property entails that the errors of two different time periods are uncorrelated and equal to zero, conditional on the explanatory variables. In other words, if the error terms correlate over time, they can be denoted as autocorrelated (Wooldridge, 2016). Accordingly, to satisfy the fifth assumption, the following criterion must not be violated:

$$Corr(u_t, u_s|X) = 0, for\ all\ t \neq s \quad (6.5)$$

Autocorrelation is a common issue when working with time series, which could have consequences for the regression results in that the OLS estimators no longer are efficient. In this, the standard errors will become unreliable and often underestimated, which again will lead to inflated t- or F-values and increase the probability of incorrectly rejecting the null hypothesis (Type 1 error) (Gujarati, 2015). There are several reasons why autocorrelation in the error term might occur, including omitted variables absorbed in the error terms and misspecification of variables.

In this, there is several methods to control for the presence of autocorrelation in the model. For the regression analysis of this paper, I will make use of as a Durbin-Watson *d* test, which will be supplemented by a graphical analysis of a correlogram. In the presence of autocorrelated error terms, the preferred remedial measure depends on both the nature of the problem and the size of the sample. Examples of mitigative techniques for autocorrelation include first-difference transformation, lagging of the dependent variable, a more generalized functional form transformations (Gujarati, 2015).

6th Assumption – Normality

The final assumption in the Gauss-Markov theorem attending to time-series regression model implies that the error terms are normally distributed with an average value of zero and constant variance, but also that they are independent of the explanatory variables (Wooldridge, 2016).

$$u \sim N(0, \sigma^2) \tag{6.6}$$

If the assumption of normality in distribution of error terms is violated, this will result in issues in the construction of confidence intervals, which directly affects the validity of significance in results deriving from t- and F-tests. To test control for normality in the distribution of residuals, I will perform a skewness/kurtosis test which will be supplemented by a histogram plot of the predicted residuals for each of the models.

6.3 Stationarity

The use of time-series data in econometric analyses facilitate research of dynamic effects between two or more variables across time. Howbeit, time-series data is often fraught with more difficulties than a cross-sectional analysis because it allows for observations to be correlated over time. These temporal correlations require certain properties of the data to be further attended to when performing a regression analysis. In this, the notion of stationarity is critical, reflecting an assumption that statistical properties of processes remain time invariant. If the relationship between two variables change from period to period, it becomes difficult to estimate any meaningful relationship. The inclusion of one or more non-stationary time-series can lead to spurious regressions results, meaning that the regressors seems to explain more of the variation in the regressand than it actually does. Herein, t-statistics and R-square values becomes inflated as they do not follow a usual distribution (Granger & Newbold, 1974).

A time-series can be denoted as *weakly stationary* if the two first moments given below are regarded as time invariant. These include a constant mean (6.7) and variance (6.8) over time, but also that the autocovariance function between two time periods only depend on the interval (6.9) and not the actual time at which the covariance is computed (Gujarati, 2015). In other words, we can generally say that a stationary process represents a series with statistical properties that do not change over time. These conditions can be described formally as follows:

$$E(x_t) = \mu \tag{6.7}$$

$$V(x_t) = E((x_t - \mu)^2) = \gamma_0 \tag{6.8}$$

$$Cov(x_t, x_{t-k}) = E\big((x_t - \mu)(x_{t-k} - \mu)\big) = \gamma_0 \quad \text{for } k = 1,2,\ldots \tag{6.9}$$

In order for a stochastic process to be regarded as *strictly stationary*, all moments of its probability distribution must remain constant over time. Accordingly, in a sequence of random variables the joint probability distribution must remain unchanged if the sequence is shifted ahead of any given time periods. In practical cases, strict stationarity could often be too strict. In this, Wooldridge (2016) suggest that for multiple regression models, we assume a certain form of stationarity by assuming that the beta coefficient estimates do not change over time.

If a stochastic process does not satisfy all of the above-mentioned conditions, the times series is denoted as non-stationary. In other words, the statistical properties are not time-invariant and the value at a given time is affected by the value from previous time periods. Accordingly, if there is a shock at any point in a non-stationary process, the effect of this shock will influence the forthcoming values in time series. There are several ways in which the stationarity assumption can be violated, whereas some of the most typical deviations include a *deterministic trend* (trend stationary), *unit roots* (stochastic trends/difference stationary), *level shifts* (structural breaks) and *changing variances*. The two ladder examples of non-stationarity are rather intuitive, deriving from change in parameters or changes in the variance. If a stochastic process is trend stationary, there is fluctuations around a deterministic trend that reflects a stationary disturbance term. This leads to a trending mean that continually increases or decreases over time which violates the assumption. In the case of a difference stationary process, the trend is denoted as stochastic and possess one or more-unit roots. An important distinction between unit root processes and trend stationarity is the effects of shocks on the long-term behavior of the data. Herein, processes that are trend stationary will be mean reverting, implying that shocks will only induce transitory effects on the data series. Whereas for unit root processes, shocks will have a permanent effect. (Tabor, 2018).

The simplest example of a stochastic time series is a random walk, whereas the value of one period is given by the value of the previous period in addition to an unpredictable change of a pure random process. An extension to this model is a random walk with drift, which represents a random walk with a constant added to the equation. If the process entails a positive constant it will have an upward tendency, whereas a negative constant induces a downward tendency. Accordingly, a random walk with drift entails a stochastic trend, while a trend stationary process alters deterministic in time. Additionally, a process could be non-stationary through a combination of these. In this, a random walk could entail both a drift component and a deterministic trend. Such a combination would specify a value at one period based on the value of the previous period including a drift, a trend and a stochastic component (Gujarati, 2015).

6.3.1 Test of stationarity

In accordance with the reasoning mentioned above, it is critical to determine whether the time series in the regression model is stationary or not. There are several methods of examining whether the stochastic processes are stationary. The most commonly used statistical test for stationarity by a unit root analysis is the 'Dicky-Fuller test', which Stock & Watson (2015) claim to be to most reliable of sorts. In accordance with the reasoning mentioned above, this will be the preferred controlling option for stationarity in the forthcoming regression analysis.

Augmented Dickey-Fuller test

The Dickey-Fuller (DF) test is a unit root test that was first put forward by statisticians David Dickey and Wayne Fuller (1979). In this procedure, we run a hypothesis test, whereas the null hypothesis or the unit root hypothesis is that the variable contains a unit root. The alternative hypothesis is that the stochastic process is generated by a stationary process (Gujarati, 2015). An issue with the standard DF-test is that only offers a simple autoregressive model, which is unable to capture the dynamic and complex structure of most economic time series. A way to mitigate this limitation is to apply an extended version of the DF-test known as an Augmented Dickey-Fuller test (ADF), which allows for higher-order autoregressive process. An extension which is based on fitting of the following regression can be described formally as:

$$\Delta y_t = \alpha + \delta t + \beta y_{t-1} + \zeta_1 \Delta y_{t-1} + \cdots + \zeta_k \Delta y_{t-k} + \epsilon_t \tag{6.10}$$

Herein, α indicates the constant term and δt gives the time trend, which are optional terms that must be included if the process follows a linear or quadratic trend. k represents the number of specified lags, and the optimal lag order can be identified through information criterions.

The augmented version of the Dickey-Fuller test is applicable for four different cases in accordance with the various examples of non-stationary processes mentioned previously. In this, the null hypothesis for each case will always be that the variable contains a unit root. The difference between the four applications is if the null hypothesis includes a drift term and if the employed regression includes a constant term and a time trend. For the first, there is a null hypothesis that the process follows a random walk without drift, whereas the fit does not include a constant nor a time trend. The difference to the second case is merely the inclusion of a constant term. For the thirds case, there is a null hypothesis that the process contains a unit root with drift, but there is no time trend in the fitting. Lastly, the fourth case gives a null hypothesis of a random walk with or without drift, whereas the constant is unrestricted, and the fit includes a time trend (Hamilton, 1994). The four cases are summarized in Table 2.

Table 2: Application cases of the Augmented Dickey-Fuller test

Case	Process under null hypothesis	Regression restrictions	Options
1	Random walk without drift	$\alpha = 0, \delta = 0$	No constant
2	Random walk without drift	$\delta = 0$	Default
3	Random walk with drift	$\delta = 0$	Drift
4	Random walk with or without drift	None	Trend

In order to decide the best fit for the regression diagnostics procedures, the selection needs to be based upon a combination of economic theory and a graphical analysis of the time series. Still, if there is solid theoretical support or an identification of a distinct patterns in the visual inspection that do not contradict each other, that can be seen as sufficient reasoning for selecting one of the cases. For instance, if a process that shows a clear upward trend over time gives a good indication that the fourth case could be an appropriate choice of mode. Alternatively, a process that does not entail a clear trend component and still has a nonzero mean would suggest that the second case application should be the preferred option.

6.3.2 Stationarization

In order to conduct regression analyses with non-stationary processes, avoid spurious regression results and satisfy the assumption of traditional regression modelling, the time series needs to be transformed in order to achieve stationarity. Herein, there is several techniques of stationarization which can be adopted, and the best fit will depend on the findings from the diagnostics procedure and on related economic theory. Given the type of data the empirical analysis of this thesis attends to, I will only account for two relevant procedures of stabilization; *detrending* and *differencing*. As a first step, it can be reasonable to logarithmically transform the time series, which may also stabilize non-constant variance.

Detrending

If a process is trend stationary and contains a deterministic trend, the time series can be made stationary by estimating and subtracting the trend component to work with the deviation from the trend. This can easily be done by regressing the time series against time in statistical packages such as Stata, whereas the residuals from the regression represent the series without a linear trend (Gujarati, 2015). For quadratic detrending, the procedure is similar, but a squared time component is added to the regression producing the residuals, which supposes an exponential-type behavior. Another option is to decompose the time series nonparametrically by making use of filtering techniques and moving averages.

Differencing

If the time series is found to have a stochastic trend, the process can be differenced one or more times to be made stationary, depending on which order the time series is integrated of, as shown in equation 6.11 below. Another benefit from differencing the time series is that it removes any linear time trend, which means that for series with obvious trends we can take the difference of the variable rather than including a time trend (Wooldridge, 2016).

$$\Delta \log(y_t) = \log(y_t) - \log\,(y_{t-k}) \tag{6.11}$$

In this, the time series is integrated of order k equal to the k of unit roots and the term could be seen as the inverse of differences, therefore a stationary process is integrated of order zero. If the series is integrated of order one, it can be made stationary by differencing it once. For time series integrated in order two, it must be differenced two times to become stationary and so forth (Gujarati, 2015). In practice, most nonstationary economic and strictly positive time series are either integrated of order one or two, with the latter being an exception.

7. Data description

The following chapter will give a description of the dataset that will be employed in the forthcoming regression analysis. This will include a presentation of the variable identification, related development of the different processes, the sources of data and the measurement techniques applied for variable construction. In the final sections of this chapter, the preliminary model specifications will be presented, followed by a brief a discussion related to limitations of the relevant measurement techniques applied for the variable constructions.

7.1 Data set and variable construction

In accordance with the theoretical predictions and comprehensive empirical review of structural determinants, the regression models will test for 13 distinct predictors of income inequality, including their related polynomial terms based on the predicted relationship. These predictors follow an annual periodicity in the period from 1985 to 2015, which gives a small sample size of 30 observations, a limitation that will be discussed further in chapter 8.4.2.

7.1.1 Dependent variable

In accordance with the findings presented in Chapter 3, the arguments and empirical evidence presented by Palma (2011; 2016), there is valid and compelling reasons for selecting an alternative measure of income inequality than the conventional Gini coefficient. As such, the dependent variable will follow the methodological approach introduced by Palma in measuring aggregate national income inequality as the share of national income assume by the 10th percentile at the top of the distribution over the acquired income of the bottom 40%. The data employed for the variable construction is sourced from Piketty et al. (2017) through the World Inequality Database, measured as the percentage share of assumed national income. These estimations are constructed based on a combination of national accounts, income surveys and tax data. From the graphical illustration in Chapter 3 and the relevant ADF-test results given in Appendix E.1, we find that process is non-stationarity with a unit root and a first order integration. In accordance with these findings, the variable has been logarithmically transformed and differenced once to achieve stationarity, giving the following formulation:

$$Income\ inequality = \Delta_1 ln(Palma\ ratio) = \Delta_1 ln\ (\frac{p0p10}{p60p100}) \qquad (7.1)$$

7.1.2 Independent variables

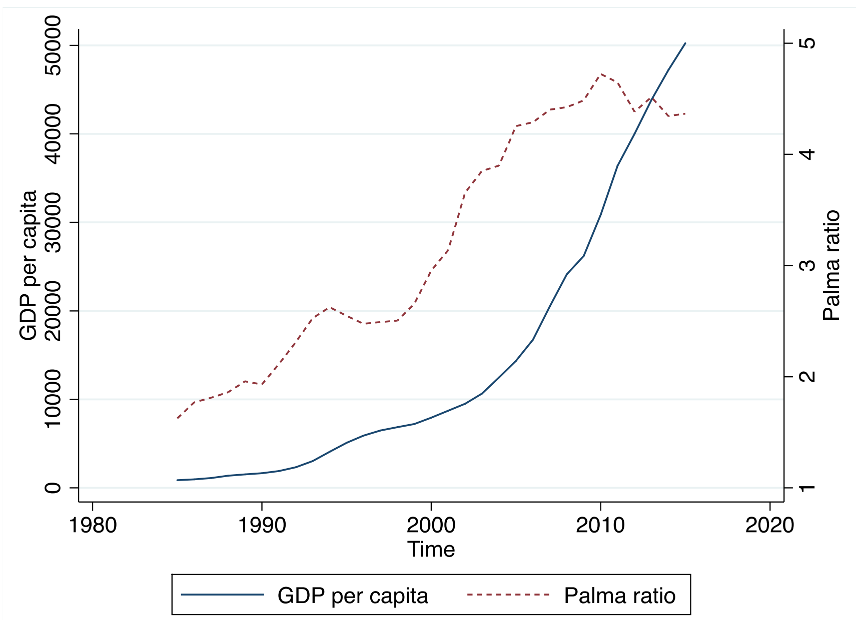
Economic growth

In order to test for Kuznets' prediction of an inverted U-curve relationship between economic growth and income inequality, I will test for changes to GDP per capita in accordance with the original theoretical construct. The time-series is collected from the World Bank Database (2019b) and is measured in current local currency unit. To account for the non-linear relationship, the variable will be transformed logarithmically. The relevant ADF-test results given in Appendix E.2 indicates the presence of a unit root and the variable will accordingly be differenced once in line with dependent variable. To control for the parabolic relationship as suggested by theory, a quadratic term of the function will be added to the regression models.

$$Economic\ growth = \Delta_1 ln(Gross\ domestic\ product\ per\ capita) \tag{7.2}$$

From Figure 17, the development in gross domestic product per capita is plotted against variation in inequality by the Palma ratio to give an impression of the covariance over time. From this illustration, we can clearly observe the exponential nature of the economic expansion following the economic reforms, particularly from the mid- to late-00 onwards. Over the whole period, China represented the fastest-growing major economy in the world with an increase in GDP per capita from 866¥ in 1985 to 50.251¥ by 2015 (IMF, 2018; World Bank 2019b). Even though we cannot draw any conclusions related to correlation or causality from the observed illustration, the covariance of the processes over time is greatly interesting at first glance - in consideration of Kuznets theoretically predicted relationship.

Figure 17: GDP per capita against Palma ratio



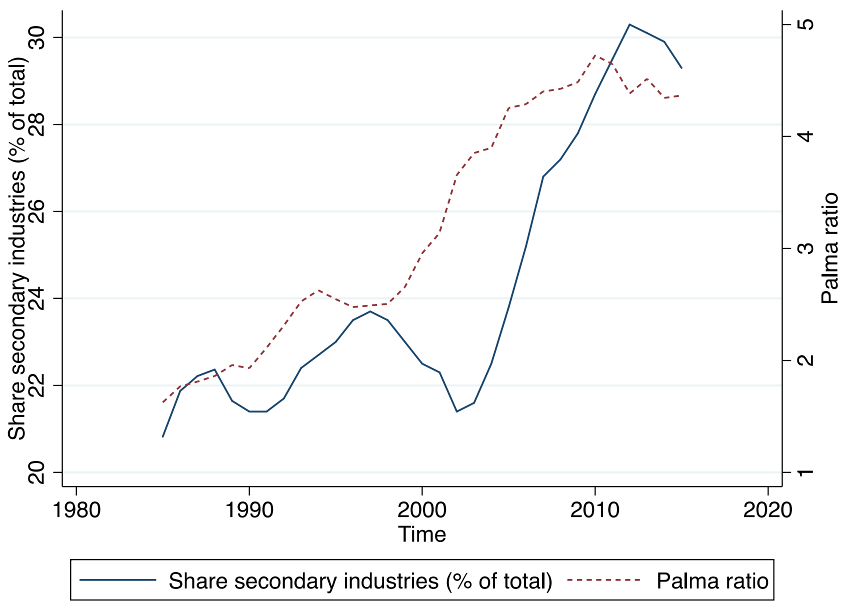
Industrialization

A process which is interrelated with the impact of economic growth according to the Kuznets' and Milanovic's theorem is the effect of the structural transformation following a process of industrialization. To control for this effect, I will test for the share of employment in secondary industries in China as a percentage of total employment. This data is obtained from the databank of the National Bureau of Statistics (2019). In accordance with the theoretical prediction, we would expect an inverted to U-curve relationship between the process of industrialization and inequality over time, supported by previous empirical research in post-reform China (Wan et al., 2016). Accordingly, to test for this parabolic relationship, a quadratic term for the process will be included in the final regression model. As for the process itself, we can identify a trending mean following stochastic trend component from the graphical illustration in Figure 18. The presence of a unit root is confirmed by the ADF-test given in Appendix E.3. As such, the variable will accordingly be logarithmically transformed and differenced once to achieve stationarity, giving the following formulation:

$$Industrialization = \Delta_1 \, ln\left(\frac{No. of\ people\ employed\ in\ secondary\ industries}{Total\ number\ of\ people\ employed}\right) \quad (7.3)$$

Interestingly, figure 18 shows that share of employment in secondary industries remained relatively stable between ~21 and ~24% from 1985 to 2005, before it increased significantly until 2012 and then declined. This observation could indicate that a transformative industrialization process occurred before 1985 and a new shock took place at around 2005.

Figure 18: Share of employment in secondary industries



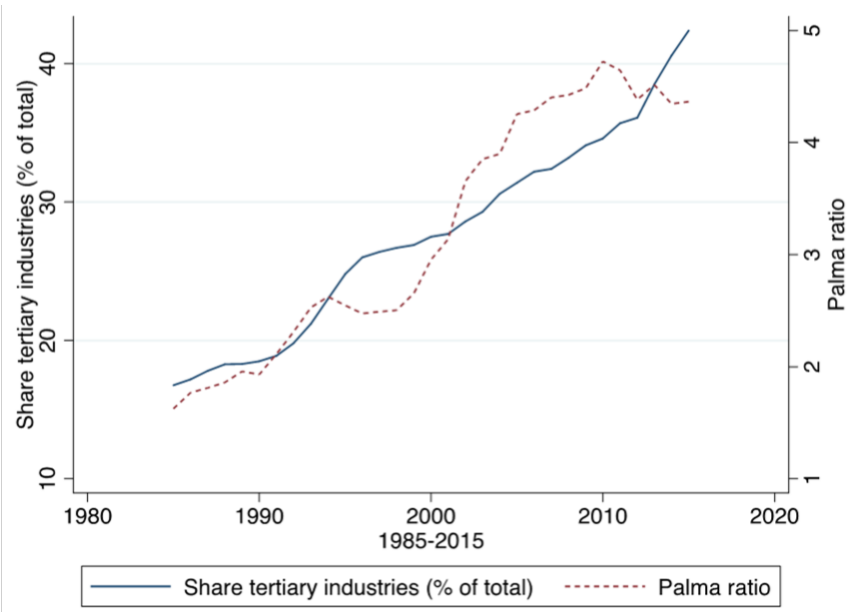
Servicization

Building on Kuznets premise of the impact of nation-wide structural transformations, Milanovic suggested that mass transfers of labor from homogenous manufacturing jobs to skill-intensive heterogenous service occupations represents one of the key drivers in the second 'Kuznets wave through rising skill premium and increased share and return to capital. To account for this effect of servicization, I will test for the share of employment in tertiary industries as a percentage of total employment. The data is similarly collected from the National Bureau of Statistics (2019), ensuring consistency with the data on industrialization. Based on the same reasoning as for the previous variable, the series will be logarithmically transformed and difference following the ADF-results given in Appendix E.4. Further, the predicted quadratic relationship will be tested for by including a squared term of the variable.

$$Servicification = \Delta_1 \, ln\left(\frac{No. of\ people\ employed\ in\ tertiary\ industries}{Total\ number\ of\ people\ employed}\right) \qquad (7.4)$$

As given in Figure 19, relative employment in tertiary industries has increased steadily and significantly over the whole period from ~16,8% in 1985 to more than 42% in 2015. In fact, tertiary industries became relatively larger than secondary industries already by 1994 and overtook primary industries as the largest sector after 2010, which coincides with the trend shift in the development of income inequality. Even though Kuznets original work did not attend to servicization specifically, he predicted that once the high-productivity sectors occupied the majority of labor, domestic income inequality would turn and start to decline.

Figure 19: Share of employment in tertiary industry



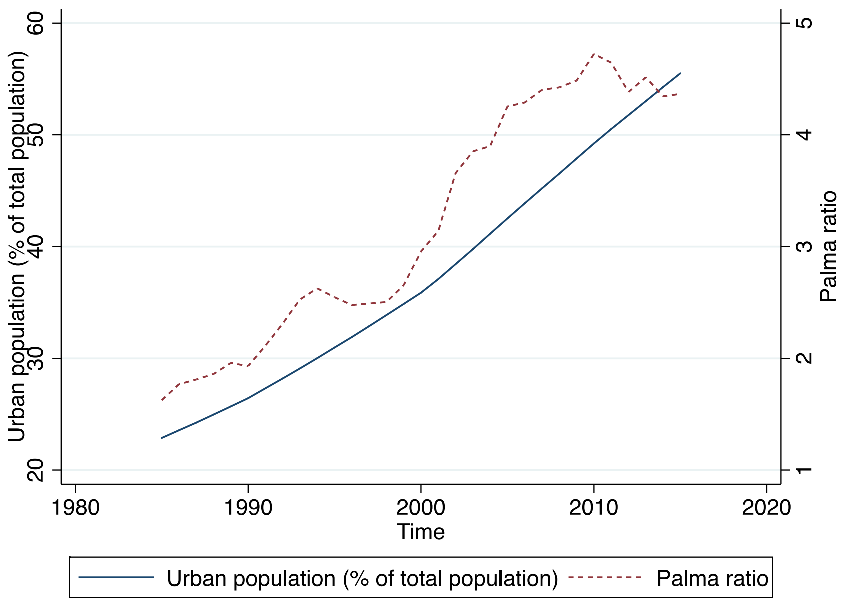
Urbanization

Urbanization represents another key component of both Kuznets and Milanovic's hypothesis. In this, mass internal migration flows from rural to urban areas following structural transitions is predicted to induce an initial rise in domestic income dispersion, which will turn to a negative effect at later stages of urbanization. The variable that will be employed to test this effect is given by the share of urban population, reflecting people living in urban areas[10], as a percentage of the total population sourced from the World Bank databank (2019k). A series that is collected and smoothed by United Nations Population Division. In accordance with the illustration given in Figure 20, we can observe a distinct deterministic trend component. However, given the order of integration for the previous processes, we should adhere to the highest order of integration. The variable will therefore be difference once instead of subtracting the mean. To test for the quadratic relationship, a related squared term is included.

$$Urbanization = \Delta_1\left(\frac{Population\ in\ urban\ areas}{Total\ population}\right) \tag{7.5}$$

As we can observe from figure 20, the process of urbanization reflects an uninterrupted and considerable migration flow from 1985 to 2015. In this period, the urban population rose from 23% to 55%. Whereby the decline in overall income inequality coincides with the urban population exceeding the 50% mark. However, the aggregation of rural and urban population may not equal the total population, which I will come back to in the limitations of the dataset.

Figure 20: Urban population as % of total population



[10] Urban areas as defined by national statistical offices

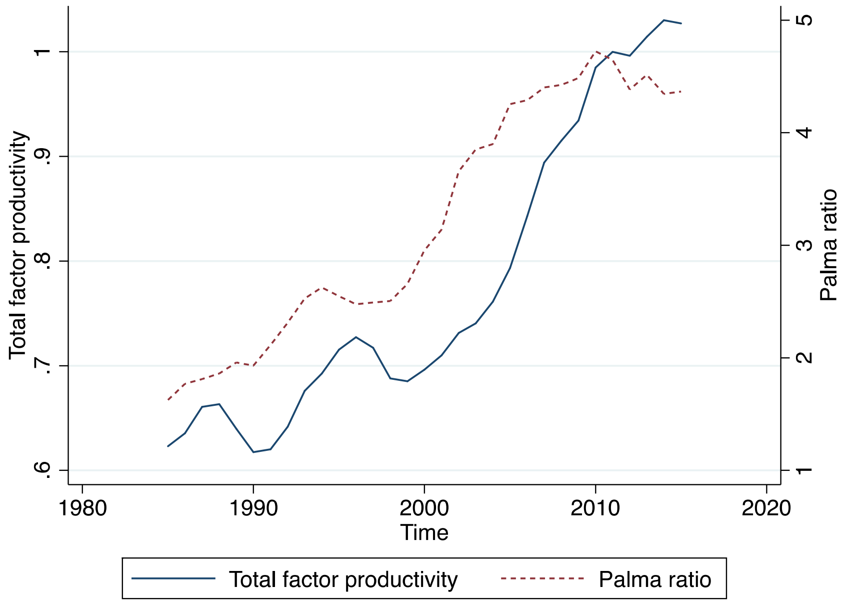
Technological progress

In accordance with Milanovic's theory of Kuznets waves, technological progress under the conditions of globalization and endogenous policy changes represents one of the key drivers of the upward motion of a cycle. A premise that is widely supported by empirical work and impacts both capital income through creation of technological rents and labor income through raising demand for high-skilled labor and substitution of labor in manufacturing processes. Measuring such technological progress directly is however a cumbersome endeavor. An indirect approach commonly applied by economist is to measure total factor productivity growth (TFP), giving the relative efficiency of an economy in producing goods and service for given aggregate input of capital and labor. In this, measuring technological change through attributing income growth which is not explained by increased labor supply or investment to the technological progress (World Bank, 2008). The link has been disputed in the academic sphere, which I will come back to in the limitations of the dataset. Still, given data limitations, this function of TFP offers as a reasonable proxy for technological change in China. The proxy will be modelled from total factor productivity estimates at constant national prices (Index 2011=1) by Feenstra et al. (2015). Following the ADF-results given in Appendix E.5 and the previously described rationale, the process will be logarithmically transformed and differenced once in to achieve a stationarity process. This gives the following formulation:

$$Technological\ progress\ = \Delta_1 ln\ (Total\ factor\ productivity) \tag{7.6}$$

From figure 21 below, we can observe that the productivity growth in China has risen significantly from the mid 1980s to 2015, especially from late 90s onwards. The productivity performance in China from 1990 to 2008 ranked on top of the international TFP growth ranking (The Economist, 2009). Interestingly the productivity growth show signs of slowing down from 2010 onward, a break that coincides with the turning point in the development of overall income inequality. Across the whole period, the covariance between the two structural variables is notable. At the same time, the forthcoming regression results should be interpreted with great caution, given the variable construction, which merely gives a proxy of the process. It is difficult to estimate how much of the productivity growth that can be attributed to technological progress and technical efficiency. However, by becoming the largest telephone market in the world in 2003 with the largest number of internet users and representing the largest supplier of IT goods by 2008, there is no doubt that China has undergone a transformative technological revolution in the last decades (Zheng & Zheng, 2009).

Figure 21: Total factor productivity at constant national prices



Openness

In accordance with Milanovic's hypothesis, openness represents an indispensable amplifier for the effects of technological progress on domestic income inequality, but also a factor that could induce single-handed effects through weakening the position of labor and trade unions. In literature, the notion of openness is discussed primarily along two dimensions; trade liberalization and financial integration. Herein, empirical evidence gives a dubious and mixed picture in regard to the long-term impact on within-nation inequality. This is especially true for trade openness, whereas there seems to be more consensus among researchers that increased financial integration has a significant effect in raising domestic income dispersion.

In order to test Milanovic's predictions in accordance with his hypothesis, I will construct an openness indicator composed of a non-weighted average between the representative variables for trade liberalization and financial integration. In addition to this specification, separate regression models will test for these compositional factors discretely, to account for potential diverging effect between the two processes. Trade openness will be measured as the relative trade dependence, which gives the aggregate value of total imports and exports as a percentage of the total gross domestic product. Herein, export FOB (Freight on board prices) and import CIF (Cost, Insurance and Freight prices) is sourced from CEIC (2019a; b) and reported by General Administration of Customs. Data for nominal GDP is collected from the World Bank (2019c) whereas all subcategory variables are measured in US dollars.

Financial integration or openness will be measured as total external assets and liabilities outstanding as a percentage of GDP. Herein, data for net foreign assets and gross domestic products is sourced from the World Bank (2019d; b), while the data on external debt is provided by the State Administration of Foreign Exchange and sourced from CEIC (2019c). This gives the following measures of openness, trade dependence and financial integration, which has been logarithmically transformed and differenced once (See Appendix E6, E7, E8):

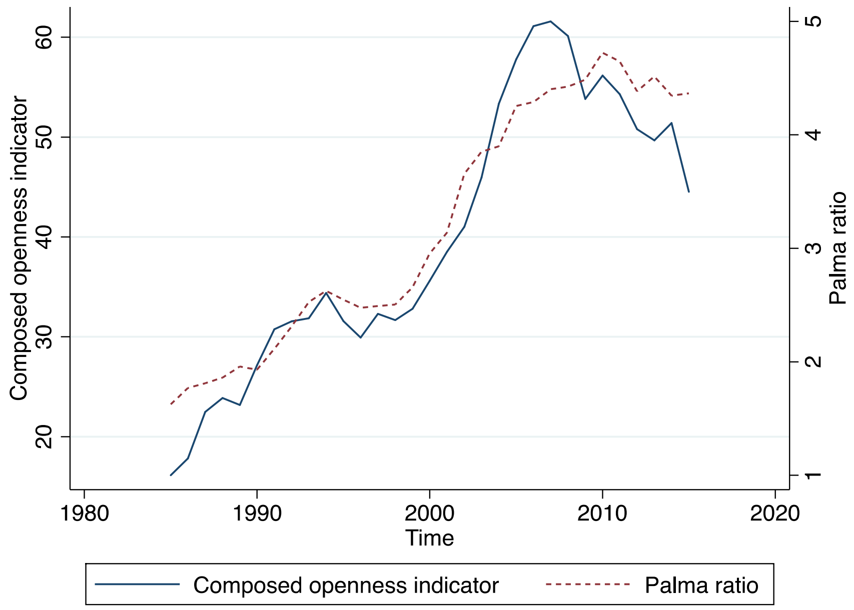
$$Openness = \Delta_1 ln\left(\frac{Trade\ dependence + Financial\ Integration}{2}\right) \tag{7.7}$$

$$Trade\ dependence = \Delta_1 ln\left(\frac{Export\ FOB + Import\ CIF}{Nominal\ GDP}\right) \tag{7.8}$$

$$Financial\ integration = \Delta_1 ln\left(\frac{External\ assets\ +\ Foreign\ liabilities\ outstanding}{Nominal\ GDP}\right) \tag{7.9}$$

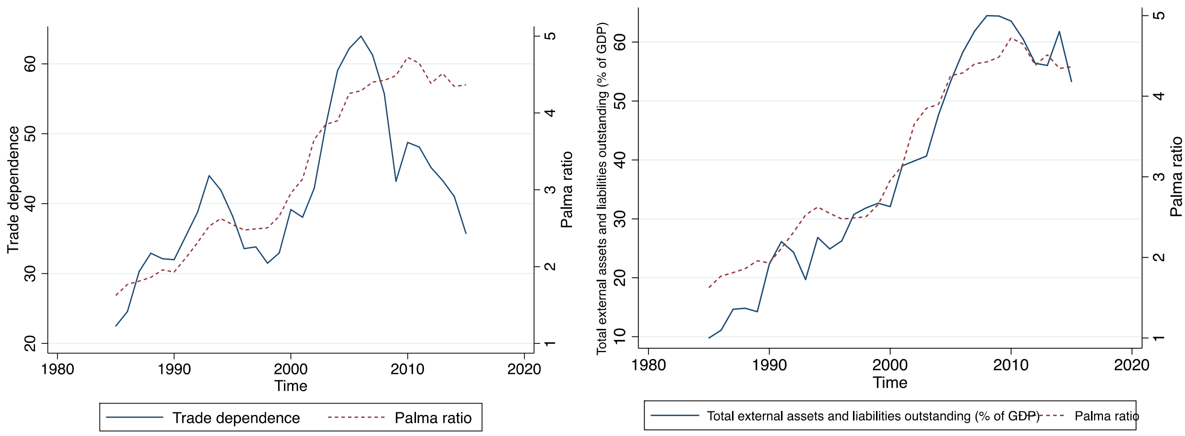
As illustrated in figure 22, we can observe the considerable change in 'openness' as the Chinese economy broke into the global market following the market-oriented reforms over the last couple of decades. In the period between 1985 and 2015, foreign direct investment increased by around 182 times (World Bank, 2019e; f), while the scale of foreign trade increased by about 119 times in the same period (CEIC, 2019a; b). At the same time, we can see that the constructed openness indicator closely covaries with the Palma ratio over time, with a corresponding a structural break in the process around the mid- to late 00s.

Figure 22: Openness indicator



Looking further at the two components of the openness indicator in figure 23, we see that the trade dependence given on the left has markedly more fluctuant over time than the process of financial integration. Herein, we find two periods of considerable increase in the relative importance of international trade and correspondingly two periods of significant decline. Without going into detail changes to the trade policies, it is important to note that these relative cycles are determined by the relative development in GDP, and that absolute value of aggregate imports and exports only declined for observation years 2009, 2014 and 2015. As for financial integration, we can observe a steady growth in both external assets and liabilities outstanding relative to the economic growth. At the same time, we observe a similar structural break in the series, which is far less distinct for financial integration than for trade dependence.

Figure 23: Openness ind. Composition (Trade dependence & financial integration)



Redistributive policies

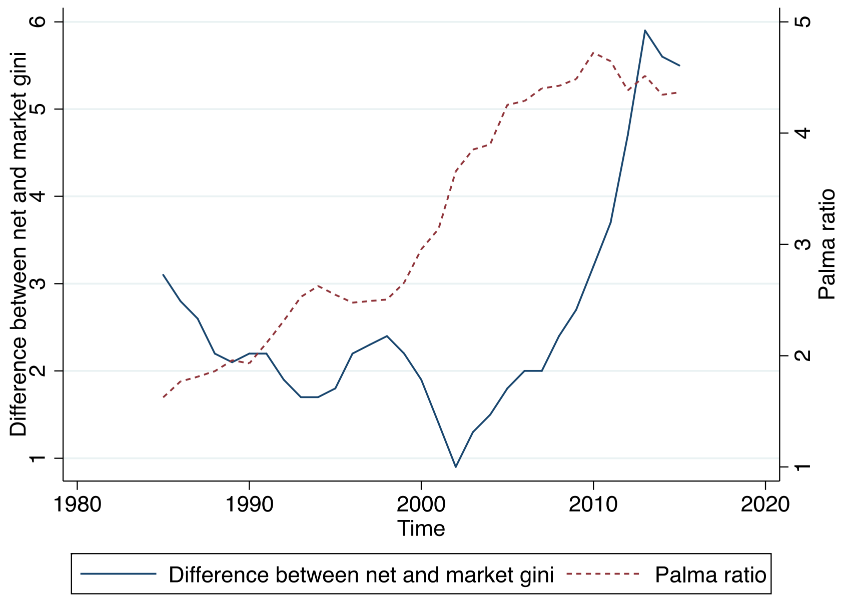
In order to measure the effect and efficiency of redistributive policies on the levels of disparity in income distributions, there is numerous dimensions that needs to be accounted including public spending, social transfer, taxation etc. Because of data limitations, I will employ a proxy that embodies these mechanisms by measuring the efficiency of redistributive policies in reducing inequality. This proxy variable will be constructed as the difference between the market Gini, measure before transfers and taxes, and the net Gini. The data employed for the variable construction is sourced from SWIID (Solt, 2009; 2016). The process is similarly found to entail a stochastic trend component and will therefore be transformed logarithmically, and first order differenced (See Appendix E.9), giving following variable measurement:

$$\begin{aligned} Efficiency\ of\ redistributive\ policies &= \Delta_1 \ln\left(Absolute\ redistribution\right) \\ &= \Delta_1 \ln\left(Market\ Gini - Net\ Gini\right) \end{aligned} \tag{7.10}$$

From figure 24, we can clearly observe the dramatic increase in efficiency of redistributive policies from 1985 to 2015, with a notable break in the trend around 2002. From 1992 onwards, there has been radical changes to the role of the Chinese government in providing welfare, collecting and distribution of tax revenues (Li, 2012). Since the late 90s, several rounds of social policy reforms have seen the introduction of unemployment insurance, medical insurance, workers compensation insurance, maternity benefits, communal pension funds, individual pension accounts and universal health care among others. Redistribution through taxation has also been gone changed dramatically over the last couple of decades. Even though the Chinese tax system has existed since 1949, individual income tax was not introduced until 1980 and a tax assignment system as late as 1994 (Jianxiong, 1998). A refinement process that has continued ever since with various other tax reforms.

Without having sufficient data to estimate the specific effect of these policy changes discretely, we can firmly conclude that the redistributive efficiency of social policies has improved significantly following these initiatives. Interestingly, we can also find that the structural break coincides with the implementation of the previously mentioned 'Western Development Strategy', which has been suggested to have contributed to a decline in income dispersion between western and coastal regions from the mid-00s onwards (Li et al, 2014).

Figure 24: Proxy for absolute redistribution



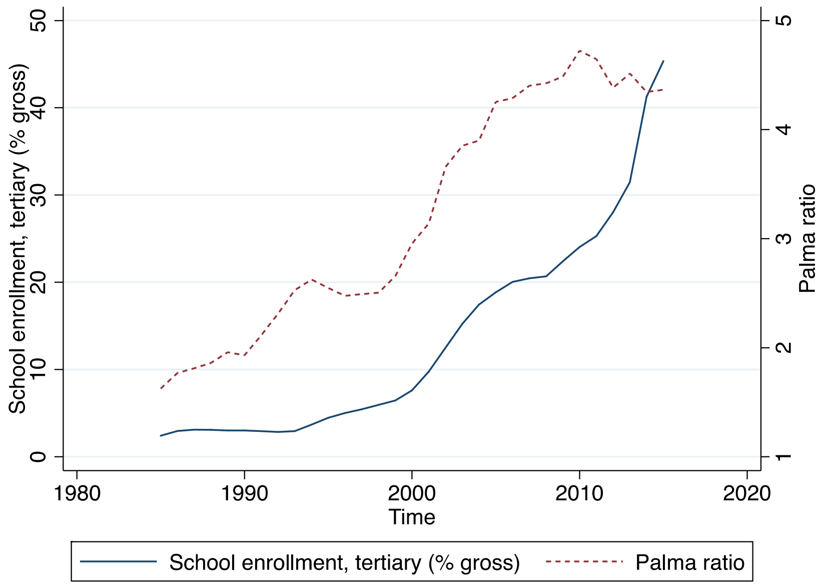
Educational attainment

In accordance with the theoretical standpoint and empirical evidence, educational attainment plays a decisive role in determining the level of disparity in income distribution. Following Kuznets original hypothesis, we would expect educational attainment to have a parabolic relationship with income inequality over time. To measure the effect of changes in educational attainment, it would be desirable to test for cumulated mean or average years of schooling. Seeing that this data is unavailable for the entire period, the most appropriate open-source measure is given by the gross enrollment rations at various educational levels. Considering that China has maintained a notably high enrollment ratio in junior middle and secondary schools (National Bureau of Statistics, 2006; 2019), tertiary enrollment is found to be the most effective representation of changes to overall educational attainment. The measure will describe the ratio of total enrollment to the age group of the population corresponding to the tertiary levels of education, whereas tertiary education denotes levels of education that require completion of secondary level of education as a minimum. The data employed for this variable construction is sourced from UNESCO Institute for Statistics (2019a). In line with previous findings from the ADF-test presented in Appendix E.10, the process will be transformed in accordance with the previously described procedure, giving the following formulation:

$$Educational\ attainment = \Delta_1\ ln(Gross\ enrollment\ ratio\ in\ tertiary\ education) \qquad (7.10)$$

From figure 25 below, we can observe that educational attainment has increased dramatically since 1985, and especially from the late 90s onwards. Gross enrolment in tertiary education in 1985 was around 2,42%, increasing to more than 45% by the end of 2015. The new upward trajectory around the millennium coincides with growth in educational investment following the educational reform from 1998; *'Action plan for Invigorating Education for the 21st century'* – which saw a dramatic rise in the enrolment of new students in higher education. In a more holistic perspective, we find that mean years of schooling has increased from 3,97 years in 1982 to 7,33 by 2010 (UNESCO, 2019b). Consequently, policies aimed at promoting education has been remarkably efficient in increasing the general educational attainment. At the same time, inequality in opportunities for education remain a significant problem in China, as institutional barriers, unequal quality of education and distribution of resources has put certain groups at a disadvantage (Yang et al. 2014). In line with this finding, it would reasonable to assume that changes to the difference in educational opportunities could induce an effect on income dispersion. However, despite this prevailing gap, Yang et al. (2014) found that the policy reforms been effective in reducing the related dispersion in such opportunities.

Figure 25: Gross enrollment ratio in tertiary levels of education



Population aging

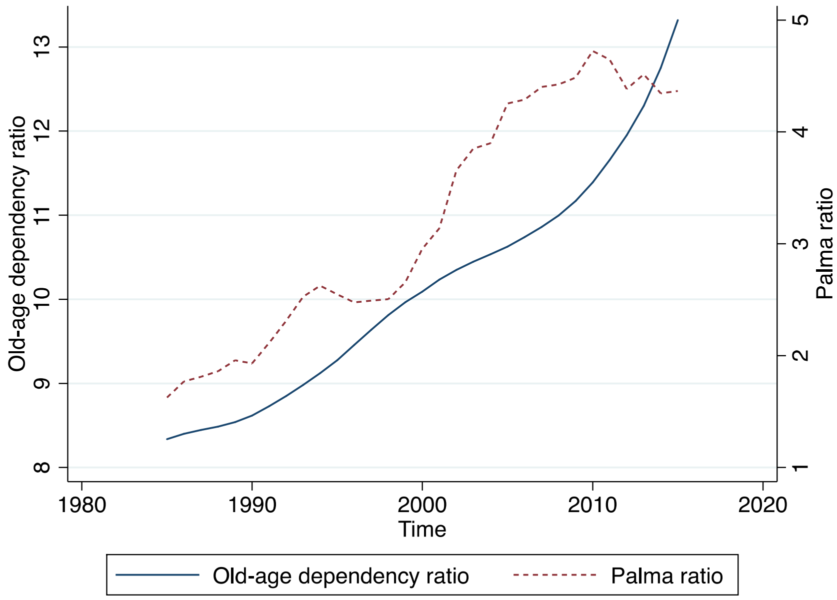
Following Milanovic's hypothesis, we would expect an aging population to increase the demand for social services and redistribution in developing nations, which would induce a negative effect on income disparity. At the same time, the empirical review has found population aging could have significant positive effect on inequalities in developing countries. To account for the impact of China's rapidly aging population on income inequality, I will test for an estimated old-age dependency ratio. This variable describes the ratio of so-called old-age dependents to the working-age population, giving the proportion of the population older than 64 years per 100 of the working-age population aged 15 to 64. The data is sourced from the World Bank database (2019g) and based on age distribution estimates United Nations Population Division's World Population Prospect. The process is further found to be difference stationary (See Appendix E.11) and will be transformed accordingly:

$$Population\ aging = \Delta_1 \ln\left(Old\ age\ dependency\ ratio\right)$$
$$= \Delta_1 \ln\left(\frac{Dependents\ aged\ 64\ and\ older}{Per\ 100\ working\ age\ population}\right) \tag{7.11}$$

China is facing one of the most rapid aging populations in the world, whereas the population older than 60 is expected to double from 2010 to 2040 (UN DESA, 2013a). Furthermore, the elderly population in China is expected to live far longer than previous generations, with estimates projecting the number of people older than 80 years to quadruple from 2013 to 2050 to over 90 million - to become the largest most-elderly population segment in the world (UN DESA, 2013b). These demographic trends can be seen as a result of improved life expectancy, low fertility rates, but also the cumulative effect of previous changes to birth and death rates.

In the period between 1979 and 2015 when the one-child policy has been in effect, life expectancy in China has improved from 67 to 75 years, following considerable improvements in health care (World Bank, 2019h). Simultaneously, the estimated birth rate has dropped from around 2.8 to about 1.7 under the strict family planning policy regime (World Bank, 2019i). As a consequence, the relative share of dependents is expected to skyrocket in the forthcoming decades. As illustrated in Figure 26 below, the old-age dependency ratio has been rising continually over the period under investigation, from around 8,34 in 1985 to more than 13,3 by 2015. A relative growth in the proportion of old-age dependents that has remained relatively stable below 2% up until around 2010, from where we can observe an exponential growth rising to nearly 5% annually by 2015. Consequently, the effect of population aging needs to be understood in accordance with the stage of the demographic transition over the period, which has just recently seen the peak in the growth of the working-age population.

Figure 26: Old-age dependency ratio



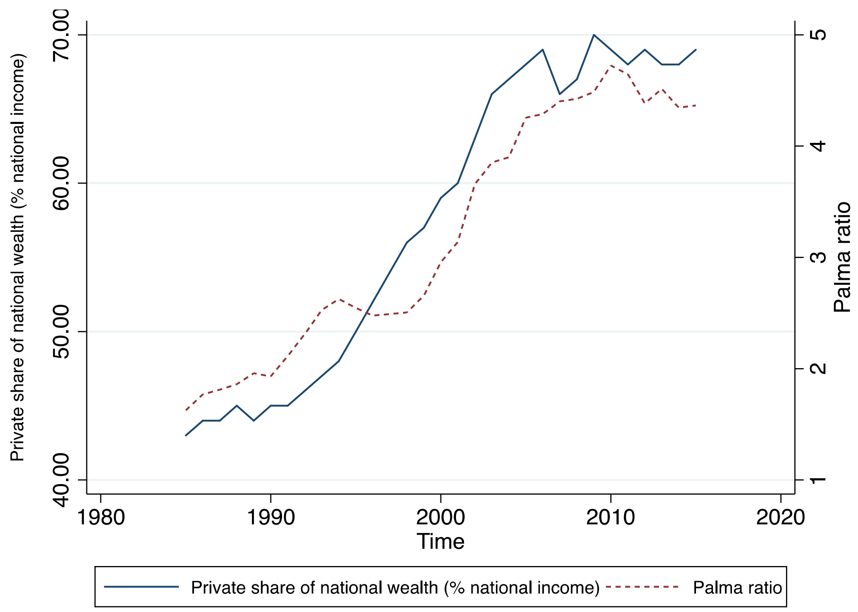
Privatization

In accordance with the empirical review, the distributional effect of privatization programs is ambiguous and dependent on various other structural conditions. At the same time, there is empirical support for hypothesizing that increased privatization can lead to increased income inequality if we assume that political institutions are not effectively consolidated, at least in the short term. In order to test the distributional effect of the considerable privatization process in China over the last decades, an explanatory variable will be constructed based on estimates of the share of private property in national wealth. The data is sourced from Piketty et al. (2017) and is calculated using both official and non-official estimates. The process is further found to have a stochastic mean trend (Appendix E.12) and will be stationarized accordingly:

$$Privatization = \Delta_1 \ln\left(\frac{Private\ share\ of\ national\ wealth}{National\ income}\right) \quad (7.12)$$

From figure 27 below, we can observe that the share of private property relative to that of public property has increased markedly from around 46% in 1985 to 69% by 2015. From 1985 to 1991 the private wealth share remained relatively stable, followed by a significant growth up until the global financial crisis, from where the public share of wealth surprisingly strengthened. In breaking down the process of privatizing the national wealth, we find that the private share of the housing stock was at 98% in 2015 compared to around 53% in 1985, with a clear structural break in the early 90s. Even though Chinese equity remain predominantly public properties, the private share of domestic corporate equity has followed a similar growth trajectory from 3% to around 34% in the same period, with the structural break occurring a few years later. Interestingly, the trend for the share of private property in other domestic capital and net financial assets gives a diverging pattern with a slower and steadier growth over the whole period from 42% in 1985 to around 52% in 2015 (Piketty et al., 2017).

Figure 27: Share of private property in total national wealth



Financial deepening

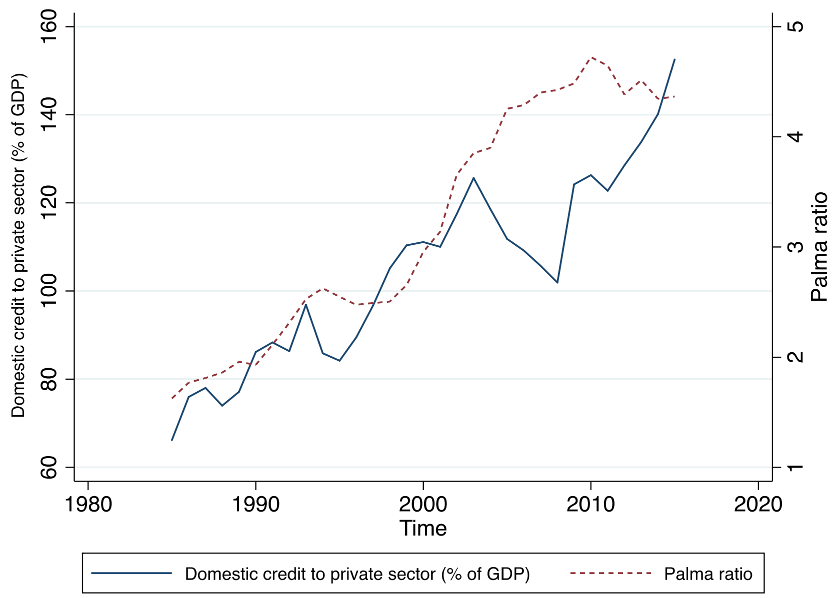
Following the empirical review of the research by Dabla-Norris et al. (2015) and others, we hypothesize that improved provision of financial services has a significant distributional effect on income. Despite the lack of empirical consensus in regard to impact specificity, relevant literature supports the notion of a distributional impact of financial deepening. In order to test for this effect, I will regress income inequality against the domestic financial market development proxied by the ratio of private credit to GDP in accordance with measurement specification employed by Dabla-Norris et al. (2015).

In this, I will measure the domestic credit to the private sector as a percentage of GDP sourced from the World Bank database (2019j). A measure that refers to the financial resources provided by financial corporations to the private sector. Following the ADF-test results (Appendix E.13), the process has been stationarized accordingly and will be as formulated:

$$Financial\ deepening\ = \Delta_1 ln\ (\frac{Domestic\ credit\ to\ private\ sector}{GDP} * 100) \tag{7.13}$$

From figure 28 below, we can see that the depth of financial intermediation has increased markedly over the period, domestic credit to the private sector rose from 66% of GDP in 1985 to more than 152% by 2015. From the graph we can observe two distinct shocks in the mid-90s and the late 00s. Breaks that coincide with periods of particularly strong growth in GDP, which naturally effects the process given the described measurement technique. Albeit some methodological contention, both provision, access and inclusion of financial services has undoubtably improved considerable over the last decades. Especially in terms of access to internet- and mobile-based services in most recent years (World Bank and the People's Bank of China, 2018). While nearly half the population saves at financial institution, only 17% employ accounts for receiving wages and 10% borrow from financial institutions. Although China still lags major advanced economies in several dimensions of financial inclusion, the last 15 years has seen the introduction of a myriad of policy reforms to narrow the inclusion gap. Comprehensive efforts that has bolstered financial inclusion significantly, demonstrated by the objective of the China Banking Regulatory Commission to ensure coverage of basic financial services in all villages by 2019 (Jain-Chandra et al., 2018).

Figure 28: Domestic credit to private sector (% of GDP)



7.2 Preliminary regression specifications

From the variable- identification and constructions presented above, I have established the preliminary regression model specifications based on relevant economic theory and existing empirical work, which is summarized in table 3. These specifications will function as the base models for the regression analysis, before the necessary adjustments identified by diagnostics.

Table 3: Preliminary regression model specification

Compiled openness indicator	$\Delta_1 \ln(palma)_t = \beta_0 + \beta_1\Delta_1 \ln(gdppc)_t + \beta_2\Delta_1 \ln(gdppc)^2{}_t + \beta_3\Delta_1 \ln(sec)_t + \beta_4\Delta_1 \ln(sec)^2{}_t + \beta_5\Delta_1 \ln(tert)_t + \beta_6\Delta_1 \ln(tert)^2{}_t + \beta_7\Delta_1 urban_t + \beta_8\Delta_1 urban_t^2 + \beta_9\Delta_1 \ln(tech)_t + \beta_{10}\Delta_1 \ln(open)_t + \beta_{11}\Delta_1 \ln(redist)_t + \beta_{12}\Delta_1 \ln(edu)_t + \beta_{13}\Delta_1 \ln(edu)_t^2 + \beta_{14}\Delta_1 \ln(aging)_t + \beta_{15}\Delta_1 \ln(privat)_t + \beta_{16}\Delta_1 \ln(findeep)_t + \mu_t$
Decomposed openness indicator	$\Delta_1 \ln(palma)_t = \beta_0 + \beta_1\Delta_1 \ln(gdppc)_t + \beta_2\Delta_1 \ln(gdppc)^2{}_t + \beta_3\Delta_1 \ln(sec)_t + \beta_4\Delta_1 \ln(sec)^2{}_t + \beta_5\Delta_1 \ln(tert)_t + \beta_6\Delta_1 \ln(tert)^2{}_t + \beta_7\Delta_1 urban_t + \beta_8\Delta_1 urban_t^2 + \beta_9\Delta_1 \ln(tech)_t + \beta_{10}\Delta_1 \ln(trade)_t + \beta_{11}\Delta_1 \ln(finint)_t + \beta_{12}\Delta_1 \ln(redist)_t + \beta_{13}\Delta_1 \ln(edu)_t + \beta_{14}\Delta_1 \ln(edu)_t^2 + \beta_{15}\Delta_1 \ln(aging)_t + \beta_{16}\Delta_1 \ln(privat)_t + \beta_{17}\Delta_1 \ln(findeep)_t + \mu_t$

In accordance with this regression model specification, we are facing two opposing objectives. Firstly, the model should be realistic and complete as possible, therefore we want to include all relevant regressors. On the other hand, a larger set of regressors we increase the complexity of the model. Additionally, by including statistically irrelevant regressors, we reduce the precision of the coefficient estimates and predicted values. Accordingly, the large set of regressors presented in the preliminary specification could challenge the balance between simplicity and fit, also known as parsimony.

In order to address these problems, I will additionally construct two stepwise regression models based on variable selection strategies to select subsets of significant regressors for the final models. Herein, there is several selection procedures which can be employed, including forward selection (step-up), backward selection (step-down) and stepwise selection which is a combination of the two techniques. The former method starts with no candidates and selects the variable with the highest coefficient of determination (R^2) at each step until it no longer increases the significance (NCSS, 2007). Given the dataset employed for the empirical analysis for this dissertation and the theoretically prediction of conditional causality for some of the variables, this forwards selection (step-up) strategy will be the preferred mode employed for the relevant stepwise regression procedure.

7.3 Limitations of variable measurement techniques

In this section, I will account for the relevant weaknesses in the measurement techniques applied in the variable construction described above. By doing so, I hope to account for some of the ambiguity related to the ability and precision in capturing the actual development of the process it is intended to measure. Potential limitations and weaknesses of the empirical analysis and the methodological approach will be discussed further in section 8.4.2.

Palma ratio

As discussed in Chapter 2, the principal methodological limitation of the Palma ratio as a measure of income inequality is the omittance of distributional changes to middle-income earners. More specifically, between the 10th and the 60th percentile of the income distribution. Contrary to the proposed oversensitivity of the Gini coefficient to changes for middle-income earners, the Palma ration does not account for changes to this segment of the distribution. In accordance with this limitation, the empirical analysis will only account for determinants of distributional changes to the 40% lowest and the 10% highest income earners over the period.

Technological progress

The measurement methodology applied to quantify technological development in China is a conventional approach, but still a very ambiguous indicator of technological progress both conceptually and empirically. According to the OECD manual on productivity measurement (2001), technological change does not necessarily translate into growth in total factor productivity. Additionally, TFP growth is not necessarily derive from technological change. The first principal measurement error can be explained by the distinction between embodied and disembodied technological changes, and the related difference in diffusion. While the former of which is dependent on markets transaction, this is not necessarily the case for the latter. The second weakness derives from the presence of various non-technology factors in the TFP residual, including adjustment costs, changes in efficiency and economies of scale.

Educational attainment

The primary weakness of employing tertiary education enrolment ratio as a measure for educational attainment is that the indicator does not directly reflect increased educational attainment for primary and secondary levels of education. Furthermore, the enrolment ratio that is applied in the model is based on annual school surveys that does not necessarily reflect the actual attendance of any given year, given that dropout rates are not accounted for.

Population aging

The old-age dependency ratio that is applied to quantify the process of population aging in China is based on the World Banks estimations of five-year period data and cohort units of five-year age groups from United Nations Populations Division's World Population Prospect. In accordance with this original data structure, annual observations are produced through interpolations that may not correspond to the actual age compositions of a given year.

Financial deepening

Domestic credit to the private sector as a percentage of GDP has been commonly applied as an indicator of the depth of financial intermediation in China for different empirical purposes (e.g. Liang, 2005; Lu and Yao, 2004; Dabla-Norris et al., 2015). A methodological argument for this approach would be that total credit as a percentage of GDP would overestimate the financial depth because of policy-directed lending and non-performing loans in the Chinese banking sector. On the other hand, by limiting the provision of credit to the private sector, there is a risk of underestimating the depth of financial intermediation. The principal reason for this is that other ownership structures besides state-owned enterprises is excluded from the measure. This includes join-venture enterprises (JVEs) which has been a common requirement for foreign companies to establish in China, but also township and village enterprises (TVEs) which accounted for nearly a third of the Chinese economy in 2007 (Zhang et al., 2007).

8. Empirical analysis

In this section, I will present the regression results from the empirical analysis on structural determinants of the development in income inequality in China between 1985 and 2015. The chapter consist of four subsections. This includes an elaboration of the regression procedure and rationale, relevant diagnostics and transformations of the preliminary modelling and the presentation of the final regression results for all model specifications. Lastly, I will summarize and discuss the results from the analysis in light of theoretical predictions, but also shed more light on some of the key limitations of the analysis and methodological approach.

8.1 Modelling procedure and rationale

In accordance with the preliminary regression modelling specification given in the previous chapter, I will test 4 regression models based on two different variable selection strategies and two distinct model specifications. This will include two models based on the all-possible regression approach and two stepwise procedures, specifically two forward (step-up) selection processes. A distinction is further made between two model specifications, whereas the first will include a compiled openness indicator in accordance with Milanovic's conceptual framework. The second specification will test for changes to trade dependence and financial integration discretely, to control for diverging effects between the two openness indicators.

The reasoning behind the segregated variable selection approach is two-fold, whereas the first facet relates to parsimony, the variable selection problem and overfitting. A complication that is underlined by the conceptual complexity in determining drivers of change to national income inequality at an aggregate level and the small sample size. Especially considering the broad-based variable selection approach adopted for this thesis, which is based on a comprehensive theoretical and empirical review with a great variety of research sources. Secondly, as highlighted in the theoretical review, some of the dynamics represented by the predictor variables could potentially be interrelated - in that the effect of some of the variables on inequality could be seen conditional or dependent on another variable. Such causal heterogeneity deriving from ambiguous causal constellations cannot be easily accounted for in meaningful way. However, by a structured process of elimination, I will attempt to mitigate some of the ambiguity related to the interpretation of the results, following the potential conditional relationships or multiple causal pathways. A process that is likely to have implications for the final results, an issue that will be discussed further in chapter 8.4.

8.2 Diagnostics and necessary transformations

1st Assumption – Linear in parameters

To check for the central mathematical assumption of linearity in parameters, the effect of the predictor variable on the response variable should first be assessed theoretically to account for the predicted nature of the relationship, but also be controlled technically for non-linearity. The theoretical assessment follows the predicted effect of the theoretical and empirical review, from which we have established that economic growth, urbanization, educational attainment and transfer of labor from one sector to another are suggested to have a parabolic relationship with income inequality and will be tested accordingly. Theory also suggest that the relationship between financial deepening and income inequality might be curvilinear, but relevant empirical findings suggest that this premise was ambiguous and inconclusive at best.

To detect potential non-linearities technically, I have performed a graphical diagnostic through an augmented component residual plot with a locally weighted scatterplot smoothing (lowess curve) given in Appendix F. As we can observe from the from the deviations of the lowess curve to the regression lines in the ACPR-plots, there is technical support for the theoretically predicted parabolic relationship with economic growth, industrialization, servicization and educational attainment. For the process of urbanization, we can only observe minor discrepancies between the lowess curve and the regression line for a linear functional form. However, given the theoretical notion, we cannot assume a linear relationship between urbanization and income inequality over time, and a squared term will therefore be included. We can further observe that the augmented partial residual plots for technological progress, redistributive policies and privatization is approximating linearity in parameters, which satisfies the necessary assumption. For the compiled openness indicator, trade dependence, financial integration, population aging and financial deepening there is clear indications of nonlinearity. To confirm the validity of these observations, we can further look at the standardized residual plot against each of the relevant predictor variables given in Appendix G. This alternative technique supports the findings from the initial ACPR-plot, indicating that the non-linear relationship for the above-mentioned variables. Even though there is a risk of magnification of errors following the small sample size, the theoretical and empirical ambiguity related to the predicted relationship leads me to address these findings accordingly. In order to attend to the issue of nonlinearity, I will include a squared term for each of the relevant predictors, which accounts for potential quadratic relationships with the regressand.

2nd Assumption – No perfect collinearity

In order to control for multicollinearity among the regressors and satisfy the 2nd assumption of no perfect collinearity, I have analyzed the correlation between the explanatory variables through a correlation matrix and a variance inflation factor (VIF) test. As given from the correlation matrix in Appendix H, the necessary assumption of no perfect collinearity is satisfied as every correlation coefficient gives a value lower than 1 or higher than -1. However, even though the minimum assumption is satisfied, high degree of multicollinearity reduces the efficiency of the models. This could lead to inflated coefficient of determination, elevated standard errors and unreliable coefficient estimates as the effect of the correlated variables becomes difficult to distinguish. Following the rule of thumb by Hinkle et al. (2003), coefficients with values exceeding 0.7 or -0.7 is regarded as high correlation, while Mehmetoglu and Jacobsen (2016) suggests that correlations above 0.8 could be problematic.

Based on this premise, we find that the structural collinearity between some of the variables that are predicted to have a parabolic relationship and the related squared terms is high. This elevated correlation is an expected and accepted byproduct, as the specification leads to a better prediction model in accordance with the assumption of linearity. By differencing the variables, we have also reduced this structural multicollinearity markedly. However, even though the quadratic dependency does not necessarily pose a serious concern for the models, it reduces the precision of estimating the separate effects of the variables and polynomials. We can further observe that the dataset does not entail a high degree of data multicollinearity, but several variables are moderately correlated in accordance with theoretical predictions. This can be shown by the correlation between GDP per capita and the share of employment in secondary and tertiary industries, at 0.49 and 0.55 respectively. Even though this correlation does not exceed the above-mentioned thresholds, this could potentially affect the efficiency of the models, which favors the mitigative stepwise regression procedure for model 3 and 4. To support these evaluations, we turn to the variance inflated factors tests given in Appendix I. The tolerance level for the VIF-test has been subject to debate, but the conventional rule of thumb suggests that VIF>10 could be problematic (Hair et al., 1995). The results from these tests confirm the quadratic dependencies identified in the correlation matrix and underlines the potential consequences of inflated standard errors for model 1 and 2, with a mean VIF of 155 and 198. Even though the overall fit of the regression is not likely to be affected, the confidence intervals of the coefficients will be wide and the t-statistics for the all-possible regression models could be deflated, which again could make it difficult to reject the null.

3rd Assumption – Zero conditional mean

As described in Chapter 6, the assumption of zero conditional mean is satisfied if the regressors included in the model are strictly exogenous and uncorrelated with the error term for each period. In other words, that the error term has an expected value of zero for any combination of the independent variables. There are several ways in which this assumption can be violated, including misspecification of the functional form by either not including a predictor variable in the correct way or by including the regressors incorrectly. To test for potential functional form misspecifications, I have performed a Ramsey's regression specification error test (RESET). The assumption would also fail if an important factor that is correlating with both the dependent and one or more of the explanatory variables is omitted from the model. This type of potential omitted variable bias will be addressed qualitatively.

Functional form misspecification

In accordance with the test result from the RESET test given in Table 4 below, we fail to reject the null hypothesis for each of the models saying that the models are correctly specified. This indicates that the functional form is correctly specified.

Table 4: RESET-test for non-linearity

	(1)	(2)	(3)	(4)
F	(3, 7) = 0.13	(3, 5) = 0.02	(3, 23) = 0.77	(3, 23) = 0.43
Prob > F	0.9367	0.9942	0.5225	0.7330

*Note: Significance at the *p < 0.1; **p < 0.05; and ***p < 0.01 level.*

Omitted variable bias

In consideration of the complex and holistic nature in the phenomena of income inequality, it is likely that there are relevant factors which are not included in the final regression models. However, to induce an omitted variable bias, the factor must be both a determinant of the dependent variable and correlated with one of the included predictor variables. In this, it is appropriate to address the potential effect of changes to skill premium and spatial disparity, which is factors that has been included in similar research previously. These factors have purposely been excluded, as they arguably reflect facets of inequality and represent exogenous transmission channels for the effect structural determinants such as for example education attainment, which violates the assumption of zero conditional mean. Beyond these factors, I argue the that comprehensive theoretical- and empirical review conducted for this thesis adequately accounts for theoretical predictions and empirical evidence related to the relevant research question, which has sufficiently mitigated the risk of potential omitted variables bias.

4th Assumption – Homoskedasticity

In order to control for heterogeneity of variance in the residuals, I have performed a conventional Breusch-Pagan test in addition to a graphical analysis to supplement the test diagnostics. The results from the Breusch-Pagan test is presented in Table 5 below.

Table 5: Breusch-Pagan test for heteroskedasticity

	(1)	(2)	(3)	(4)
chi2(1)	0.01	0.01	0.31	0.68
Prob > chi2	0.9346	0.9193	0.5754	0.4096

*Note: Significance at the *p < 0.1; **p < 0.05; and ***p < 0.01 level.*

From the test results given in Table 5, we accept the null hypothesis of homoscedasticity for all of the given regression models presented above, and thereby conclude that the assumption of homogenous variance of the residuals is satisfied. To support this conclusion, a graphical plot of the residuals versus fitted (predicted) value for each model is presented in Appendix J. In accordance with the statistical non-graphical test results, we cannot observe any clear pattern to the rvf-plot for either of the models that would indicate heteroscedastic residuals. Based on these findings, we conclude that the assumption of homoscedasticity is satisfied.

5th Assumption – No autocorrelation

The diagnostics procedure employed for detecting potential presence of autocorrelation consist of the conventional Durbin-Watson test in addition to supplementary graphical diagnostics conducted by analyzing the relevant correlograms of the lagged residuals. The Durbin-Watson test results for first-order positive (d) and negative (4-d) for each model are presented in Table 6 below, whereas the upper and lower critical values (d_L and d_U) from Savin and White (1977) are listed in the lower bracket following a 5% significance level.

Table 6: Durbin-Watson test for autocorrelation

	(1)	(2)	(3)	(4)
Durbin-Watson d-statistic	(20, 30) = 2.228575	(22, 30) = 2.912568	(4, 30) = 2.325405	(4, 30) = 2.351361
4-d	= 1.771425	= 1.087432	= 1.674595	= 1.648639
d_L	*0.195*	*0.156*	*1.214*	*1.214*
d_U	*3.368*	*3.564*	*1.650*	*1.650*

Note: 5% significance points of dL and dU

In accordance with the results from Table 6, we find that $d_L < d < d_U$ and $d_L < (4 - d) < d_U$ for model 1 and 2. This means that both tests remain inconclusive, and the presence of either positive and negative first-order autocorrelation cannot be determined. For model 3 and 4 on the other hand, d is higher than the upper critical value, which means that we reject the alternative hypothesis and conclude that errors are not positively first order autocorrelated. For model 3, we can further find that $(4 - d) > d_U$, which means that there is not statistical evidence for negatively autocorrelated error terms in the model. Whereas for model 4, we are unable to determine whether there is a presence of negative autocorrelation because the test statics for $(4 - d)$ lies within the zone of indecision between d_U and d_L.

Looking further at the estimated correlogram for the residuals in Appendix K, we can observe that there is no distinct pattern in the plot for either of the final models. Still, we find a statistically significant evidence against pure randomness for lag one of model 2 residuals, as the estimated correlation lies beyond Bartlett's formula for MA(q) 95% confidence bands. In this, the probability of obtaining a single significant observation increases with the number of coefficients plotted, especially with a small sample size and a higher risk of sampling errors. However, even though this is an individually significant observation that is barely beyond the confidence band with no noticeable pattern, it is still suggestive of negative autocorrelation that cannot be rejected by the formal Durbin-Watson test. Consequently, the test for first-order negative autocorrelation in model 2 remains inconclusive. Thus, we cannot rule out the possibility that the efficiency of model 2 is reduced by inflated variance of the residuals and estimated coefficients, which again potentially could lead to inflated F- and t-statistics values. For remaining models on the other hand, we find no statistically significant evidences for negative autocorrelation in the correlogram. Supplemented by the results from the formal Durbin-Watson test, we can firmly conclude that the residuals for model 3 and 4 are not autocorrelated and we find no statistical evidence for first-order autocorrelation in model 1.

6th Assumption – Normality

To test for normality in each regression model, I have performed a Skewness/Kurtosis test in addition to a supplementary graphical test by investigating a histogram plot of the residuals. The former consists of a skewness measure of asymmetry in the probability distribution, and a kurtosis measure that indicates the height and sharpness of distribution peak relative to a standard bell curve. The results of the statistical normality test is given in Table 7 below, whereas Pr(Skewness) and Pr(Kurtosis) gives the probability of skewness and kurtosis.

Table 7: Skewness/Kurtosis test for normality

Variable	Obs	Pr(Skewness)	Pr(Kurtosis)	---joint--- adj chi2(2)	---joint--- Prob>chi2
resid_mod1	30	0.9984	0.6460	0.21	0.8999
resid_mod2	30	0.9153	0.9377	0.02	0.9913
resid_mod3	30	0.5015	0.6789	0.65	0.7221
resid_mod4	30	0.4177	0.8501	0.73	0.6953

*Note: Significance at the *p < 0.1; **p < 0.05; and ***p < 0.01 level.*

From the results presented in Table 7 above, the null hypothesis stating that the residuals follow a normal distribution cannot be rejected and consequently the assumption is satisfied. To support this conclusion, a histogram plot of the predicted residuals for each model is given in Appendix L. From the graphical analysis, we can observe that residuals for model 1 and 2 are approximating a bell-shape distribution, despite of a moderately sharp and narrow peak for model 1, and a marginal skewness in model 2. For model 3 and 4, we find more asymmetry in the distribution, which is an expected observation given the selection procedure and the number of predictors included in these models. However, despite the lack of a distinct peak in the histogram for model 2 and the noticeable skewness in distribution for model 3, these asymmetries are subjective and not statistically significant. It is also important to note that the assumption is satisfied as long as the residuals are approximating a normal distribution and the probability of underestimating and overestimating a given value is approximately equal. Based on this premise and the relevant findings described above, there is not enough statistical evidence to reject the null hypothesis and I therefore conclude that the assumption is satisfied.

8.3 Regression estimation results

In table 8 below, the regression results for the four above-mentioned models are presented. Model 1 and 2 follows an all-possible regression, whereas model 1 includes a compiled openness indicator and model 2 segregates the effect of trade openness and financial integration. Model 3 and 4 follow a stepwise (step-up) regression, with the corresponding modelling specifications as those given for model 1 and 3. Following the table of the results, the estimated beta coefficients of each explanatory variable is given with standard errors listed in parentheses. The F-test results and adjusted coefficient of determination for each model is given in the bracket below. Statistical significance from the tests is indicated by number of stars (*) in accordance with standard levels of significance at 0.01, 0.05 and 0.10.

Table 8: Regression estimation results

	Dependent variable: Palma ratio			
	(1)	(2)	(3)	(4)
Economic growth	1.000	1.200	-	-
$\Delta_1 \ln(gdppc)_t$	(1.787)	(1.395)		
Economic growth^2	-2.342	-3.763	-	-
$\Delta_1 \ln(gdppc)^2{}_t$	(5.232)	(4.155)		
Industrialization	-1.884*	-1.965**	-	-
$\Delta_1 \ln(sec)_t$	(0.963)	(0.826)		
Industrialization^2	16.101	11.990	-	-
$\Delta_1 \ln(sec)^2$	(18.415)	(16.637)		
Servicization	0.771	-0.473	-	-
$\Delta_1 \ln(tert)_t$	(3.107)	(2.966)		
Servicization^2	-13.324	0.620	-	-
$\Delta_1 \ln(tert)^2{}_t$	(41.789)	(41.811)		
Urbanization	0.885	1.447	-	-
$\Delta_1 urban_t$	(1.056)	(1.041)		
Urbanization^2	-0.421	-0.688	-	-
$\Delta_1 urban_t^2$	(0.493)	(0.489)		
Technological progress	0.978	1.365	-	-
$\Delta_1 \ln(tfp)_t$	(0.841)	(0.863)		
Openness	0.371	-	0.245**	-
$\Delta_1 \ln(open)_t$	(0.232)		(0.103)	
Openness^2	-2.227	-	-1.292	-
$\Delta_1 \ln(open)^2{}_t$	(1.380)		(0.761)	
Trade openness	-	0.360**	-	0.209***
$\Delta_1 \ln(trade)_t$		(0.128)		(0.061)
Trade openness^2	-	-1.705	-	0.377
$\Delta_1 \ln(trade)^2{}_t$		(1.203)		(0.437)
Financial integration	-	0.010	-	-
$\Delta_1 \ln(finint)_t$		(0.143)		
Financial integration^2	-	-0.293	-	-
$\Delta_1 \ln(finint)^2{}_t$		(0.403)		
Absolute redistribution	-0.013	0.049	-0.132***	-0.131***
$\Delta_1 \ln(redist)_t$	(0.110)	(0.105)	(0.043)	(0.039)
Educational attainment	0.278	-0.075	-	-
$\Delta_1 \ln(edu)_t$	(0.437)	(0.423)		
Educational attainment^2	-1.365	0.113	-	-
$\Delta_1 \ln(edu)_t^2$	(1.771)	(1.481)		
Population aging	-6.522	-6.472	-	-
$\Delta_1 \ln(aging)_t$	(8.348)	(8.602)		
Population aging^2	120.759	116.154	-	-
$\Delta_1 \ln(aging)^2{}_t$	(156.782)	(146.726)		
Privatization	-0.188	-0.124	-	-
$\Delta_1 \ln(privat)_t$	(0.793)	(0.759)		
Financial deepening	0.086	-0.148	-	-
$\Delta_1 \ln(findeep)_t$	(0.265)	(0.292)		
Financial deepening^2	2.691	7.309**	-	-
$\Delta_1 \ln(findeep)^2{}_t$	(2.501)	(2.815)		
#. of Observations	30	30	30	30
Prob>F	0.2499	0.0987*	0.0018***	0.0001***
Adjusted R-squared	0.2561	0.5089	0.3680	0.4823

*Note: Standard errors in parentheses, significance at *p < 0.1; **p < 0.05; and ***p < 0.01.*

8.3.1 Model 1 – All-possible regression compiled openness indicator

In accordance with the results presented in Table 8 above, we find that the F-statistic is smaller than the critical F value for all common levels of significance as the probability value (p-value) is larger than all common levels of α. This means that we fail to reject the joint null hypothesis that all model parameters are equal to zero ($\beta_1 = \beta_2 = \cdots = \beta_{19} = 0$), even if one of the explanatory variables is individually significant and has a partial effect on the dependent variable. In other words, the fit of regression model 1 and consequently the regression results are found to be insignificant, and this suggests that the overall model has no statistically significant explanatory power in describing the variation in income inequality. Following the non-rejection of the null hypothesis, it is worth emphasizing that an F-test is relatively sensitive to non-normality, and this could have an effect on the test result (Box, 1953). Even though we did not find any significant kurtosis or skewness in the residuals, the distribution of the errors terms for model 1 is comparatively heavy tailed. This could potentially lead to deflated P-values and a higher probability of a type 1[11] error in the interpretation of the results.

8.3.2 Model 2 – All-possible regression decomposed openness indicator

Correspondingly to the presentation of the test results for regression model 1 presented above, we start by addressing the relevant F-test for model 2 to test the global significance of the model and how it compares to an intercept-only model without any predictor variables. For this test, we find that the p-value for model 2 is jointly significant at a 10% significance level ($\alpha = 0.10$), as $p < 0.10$, which means that we mistakenly reject H_0 10% of the time. In this, the guiding level of significance should be determined based on important factors including the sample size and the expected loss from both type 1 and type 2[12] errors (Leamer, 1978; Skipper at al., 1967). Given the small sample size (N=30) and the notion that level of significance should be a decreasing function of the sample size, there is compelling arguments for opting for lower level of confidence than the conventional 95% ($\alpha = 0.05$). However, given the purpose and limitations of this analysis, the consequences of a type 2 error would be regarded as far less consequential than that of a type 1 error. Based on this evaluation, I have opted for a conventional level of significance at 5%. This consequently leads to a non-rejection of the null hypothesis for the F-test of the second all-possible regression model as well. Accordingly, we are unable to find sufficient statistical evidence to suggest that the explanatory variables in model 2 has a joint significant influence on the endogenous variable.

[11] Type 1 error gives the rejection of a true null hypothesis
[12] Type 2 error gives the non-rejection of a false null hypothesis

8.3.3 Model 3 – Stepwise regression compiled openness indicator

In accordance with the variable selection procedure described in chapter 7.2, the final regression modelling for model 3 is determined by a process of regressing predictors discretely with their related polynomials, and then nominating them by the coefficient of determination (R^2). The selection process is concluded when none of the remaining variables are significant. Following this screening, the first candidate variable to be included in the model is absolute redistribution, with an adjusted R-squared of 0.2788. Thereafter, the compiled openness indicator is included with an increase in the adjusted coefficient of multiple determination to 0.3680. The screening is then finalized, as none of the outstanding predictors are found to be significant. Resultantly, the adjusted coefficient of determination suggests that model 3 can account for 36,8% of the total variation in the income inequality measure by the Palma ratio in China over the relevant period from 1985 to 2015. From this model specification and regression, we find that the F-test for model 3 gives a globally significant model at all common levels of significance (1%, 5% and 10%). This means that we reject H_0, accept the alternative hypothesis and conclude that model 3 fits the data better than an intercept-only model.

Based on these results, we turn to the relevant test on individual regression coefficients (t-test) to check for the individual significance of the predictor variables. From this t-test we find that absolute redistribution has a significant effect on the Palma ratio at all common levels of significance. As model 3 is specified as a log-log model in conjunction with first differencing, the coefficient estimate of the regressors represents the percentage change in the Palma ration from one year to another. Accordingly, we find that a 1% increase in the difference between the market and net Gini reduces income inequality by a Palma ratio by 0,132 percentage points. This is a highly interesting finding, which indicates that social policy through taxation and transfers has had a significant negative impact on the level of income dispersion in China in the post-reform era. Secondly, we find that compiled openness indicator is significant at a 95% confidence levels. Given the previously described significance level setting, we find statistically significant evidence suggesting that the process of globalization in terms of trade and financial integration accounts for parts of the upward portion of the rise in income inequality. More specifically, the effect of a 1% increase in the non-weighted average between trade dependence and total external assets and liabilities outstanding as a share of GDP is suggested to give a 0.245% increase in the Palma ratio. At the same time, we do not find any statistical evidence to suggest that the relationship between income inequality and openness in terms of trade and financial integration follows a parabolic relationship in the period.

8.3.4 Model 4 – Stepwise regression decomposed openness indicator

The variable selection procedure for model 4 follows the same nomination strategy as described for model 3. Following this screening process, we find that trade dependence and the related polynomial with an adjusted coefficient of determination of 0.287 is the first candidate variable to be included. Subsequently, absolute distribution is added to the model with an increase in the adjusted R^2 to 0.4823. This is the final candidate variable to be included in the model, as none of the remaining variables are found to be statistically significant. In accordance with these findings, we find that trade dependence and absolute redistribution is suggested to account for 48,2% of the variation in the estimated Palma ratio for the period that is being analyzed. This observation further indicates that model 4 explains the variability of the response data around its mean better than model 3, which again suggest that trade dependence separately accounts for more of the variation in the income dispersion than the compiled openness indicator. A finding that gives a preference for a model specification with a decomposed indicator for openness. The related F-test for model 4 further tell us that trade dependence and absolute redistribution are jointly significant in explaining the variation in income dispersion at all common levels of significance as the p-value of F (0.0001) < 1%. Even though the p-value of model 4 provides stronger evidence for a rejection of H_0 than that of model 3, application of this parameter is limited to binary decision-making of significance. Withal, the regression results and related diagnostics indicates an improved goodness of fit.

From the individual hypothesis tests given by the relevant t-tests, we find that absolute redistribution has had statistically significant effect on the disparity between the top 10% and bottom 40% income earners in China in the period at all common confidence levels (90%, 95% and 99%). Comparatively to the individual regression coefficient test in model 3, the t-test indicate that 1% increase in the difference between the Gini coefficient before and after taxation and transfer reduces the Palma ratio by 0,131 percentage points. The t-test for the predictor variable of trade dependence is correspondingly found to have a significant effect at all conventional levels of significance as estimated p-value $< \alpha = 0.01$. Accordingly, we reject the null hypothesis and conclude that openness to trade has a significant linear relationship with the Palma ratio from 1985 to 2015. In this, the regression results suggest that a 1% increase in the share of total imports and exports over GDP increases income dispersion between p0p10 and p60p100 by 0,209 percentage points. At the same time, we do not find any statistical evidence to suggest that the relationship between the Palma ratio and trade dependence has been of a parabolic nature in the relevant period.

8.4 Discussion and interpretation

In the following section, I will summarize and discuss the key findings from the empirical analysis. A discussion that will include interpretations in relation to the theoretical predictions and material observations from the descriptive analysis given in Chapter 3 and 7. Lastly, I will account for potential limitations and weaknesses in the methodological approach and dataset.

In accordance with the empirical analysis and regression results presented in the previous section, we fail to find any statistical evidence to suggest that model 1 and 2 has any significant explanatory power in describing the variation of the Palma ratio. A finding that consequently leads us to disregard the relevant estimation results of the model specifications. For model 3 and 4 on the other hand, we established a global significance which leads us to reject the null hypothesis and validate an interpretation of the individual regression coefficient estimates. At the same time, we give preference to the specification of model 4, as it is found to provide a greater fit to the observations than model 3. This again suggest that the predictor variables for trade dependence and financial integration should be analyzed discretely, and not conjointly.

From the relevant individual hypothesis tests, we have found statistical evidence to suggest that redistributive policies and openness to trade has had a significant impact on the development of income inequality in China from 1985 to 2015. This is a noteworthy finding considering the political intention of the Communist Party expressed by Deng Xiaoping in his famous dictum at the offset of the economic reforms. The consequences of the market-oriented reforms and process of 'opening up' the economy to the global market certainly led to some people getting rich first, as the Palma ratio increased by around 2,4 times from 1978 up until 2010. Coincidingly, the relative dependence of foreign trade increase by around 4 times, which suggest that the process of trade liberalization should account for around 1/3 of the rise in income disparity between the tails of the distribution according to the regression estimations. At the same time, the political pledge of gradually achieving common prosperity seem to have started to come into fruition, as the Palma ratio dropped by around 7,4% from 2010 to 2015. This recent decline needs to be seen as a function of the substantial decline in trade dependence and the marked efficiency improvement in redistributive policies - if we assume the regression estimation results to hold true. Nevertheless, we find evidence to suggest that the political agenda in pursuing a "harmonious society" through a wide-range of social welfare transfers, targeted taxation and other social policies, as described in Chapter 3 and 7, has had a significant impact in reducing the level of disparity between top and bottom income earners.

The Kuznets curve hypothesis

In light of the theoretical prediction from the renowned Kuznets curve hypothesis, we would except income inequality in post-reform China to follow an inverted U-curve relationship with economic growth. As illustrated in Chapter 3, we identified a corresponding pattern in the development of income dispersion to that of Simon Kuznets observations in Germany, United Kingdom and United States in the first half of the 20th century. Herein, the level of within-nation income inequality increased in the early phases of economic development, before the degree of income disparity leveled off and started to decline as the economic growth proceeded. Albeit these broad symmetries, we do not find any statistical evidence to suggest that economic growth has had any significant effect on the change in income disparity between the top 10% and bottom 40% income earners in China from 1985 to 2015. Despite the lack of any statistical support for the relationship proposed by Simon Kuznets, this does not conclusively refute his hypothesis, as the premise describes a tendency rather than a condition.

Looking further at the key mechanisms from the proposed dynamics of Kuznets theorem, we would expect the nation-wide process of industrialization, servicization and urbanization to interdependently give rise to income inequality as sectorial and geographic migration progressively increases. Followingly, the theoretical prediction suggests that once the high-productivity sectors become dominant and the urban areas arise as the center of economic activity the national income dispersion will start to decline. This as a consequence of democratization, greater demand for social transfers and reduced educational premium following educational attainment to the masses. As given by the data description in Chapter 7, these dynamics correspond to the development observed in China between 1985 and 2015. Around the change of the decade from 00s to 10s, we find that tertiary industries overtook primary industries as the dominant sector in terms of employment, and the process of urbanization in China reached a juncture as the share of urban population surpassed 50%. These circumstances coincide with a marked increase in tertiary educational attainment and an elevated difference between the market and net Gini coefficients, but most importantly with a turning point in the degree of disparity in income distribution as the Palma began to decrease. Regardless of the noteworthy consonance between these observations and the theoretically predicted dynamics, we are still not able to find any statistical evidence to support Kuznets hypothesis beyond the effect of social transfers in the period. Consequently, we are unable to accept Kuznets hypothesis for the determinants of variation in inequality in post-reform China.

Milanovic's hypothesis of Kuznets waves

According to Milanovic's hypothesis of Kuznets waves, we would expect the level of national income inequality to fluctuate in long-term cyclical motions that is being driven by an interplay between economic, social and political factors. Given that the thesis studies the development of inequality over a limited period of 30 years, we cannot make any assessment as to the validity of this proposed motion in the case of China. The facets to this hypothesis that is of interested to the research purpose of this thesis is the suggested drivers of this cyclical development in inequality, specifically related to modern societies with rising mean income. Herein, we would expect the upward portion of a cycle to be driven by technological revolutions and structural transitions under the condition of globalization, whereas policy would be considered exogenous to openness and economic preconditions. These so-called 'TOP elements' are denoted as mutually dependent and cannot be disentangled in any meaningful way, as the removal of an element is suggested to discourage the greater portion of the effect. This condition complicates the interpretation of the results given the methodological approach of the analysis. If we assume that this premise holds true, this would imply that the explanatory power of our model in explaining these causal mechanisms is curtailed, as we are unable to account for the majority of these effects.

Given the limitations of the methodological approach, we can address the fundamental logic of these elements and interpret the results in light of this condition. Herein, we have previously established that technological revolutions are denoted as a trigger for structural transformations such as the process of industrialization and servicization. The effect of the technological progress on inequality would derive from technological rents on the capital income side, which our model is unable to account for. On the labor side, we would expect an increased skill premium from the mass sectorial migration, which we do not find any statistical evidence to support. By testing for a direct effect of technological progress through growth in total factor productivity, we are still not able to identify any significant effect of technological change on income inequality in the period. On the other hand, the empirical analysis finds evidence to support the premise of increased inequality under the condition of globalization, which would imply that political factors and economic preconditions has been a significant factor. Accordingly, we are unable to conclusively accept Milanovic's hypothesis in terms of drivers for the upward portion of a cycle. At the same time, if the premise of his hypothesis holds true, then our results could lend support to his notion, but that would also imply that our model proves inadequate in accounting for the majority of the proposed effect.

In terms of the forces suggested to offset the rising level of within-nation income inequality in Milanovic's hypothesis, we would expect the downward portion of a cycle to be driven by both malign and benign forces. The former of which includes wars through destruction and higher taxation in addition to civil conflict through state breakdown. Following our empirical analysis, we are unable to account for these factors. However, beyond the Sino-Vietnamese conflicts in the immediate years after the economic reforms, no apparent historical events in the period is likely to have induced an effect of the described magnitude.

Looking further at the benign economic and demographic forces, there is a greater consonance to Kuznets original hypothesis, by a negative effect of widespread education and social pressure through politics. In this, the empirical analysis cannot find any statistical evidence to suggest that the former has had a significant on reducing inequality, despite the extraordinary achievements in educational attainment. For the latter, we find that increased efficiency in redistributive policies has had a significant negative impact on inequality for the tails of the distribution. However, whether this efficiency improvement derives from social pressure cannot be determined based on our analysis. An aspect that further connects to the proposed effect of population aging, which is expected to reduce inequality through increased demand for social protection. Here again, we are unable to find any significant direct effect from the process of an aging populai, and possible effects of population aging on redistributive policy efficiency cannot be determined from our analysis. The effect of low-skill-biased technological change will not be addressed further, as the notion is rather unsubstantiated. Resultantly, we cannot accept the Milanovic's hypothesis of determinants for the downward portion of a cycle to any further degree than what has been concluded for Kuznets hypothesis.

8.4.2 Limitations of analysis and methodological approach

One of the primary weaknesses of the empirical analysis is the limited number of observations for each regressors, and thus the small sample size of the dataset. On a general note, Roscoe (1975) suggests that a minimum sample size of 30 observations for each variable is appropriate for most research purposes and necessary for each category of samples that are decomposed into subsamples. This follows the central limit theorem in that sample means follows a normal distribution (Pinder, 2017). Following this premise, the number of observations in the sample would satisfy the rule of thumb. However, even though the small sample size does not necessarily make the dataset ineligible for research purposes, it will naturally affect the power of the statistical tests, lead to a magnification of error and undermined the validity of the study. Consequently, the results of the empirical analysis should be interpreted with great caution.

Beyond the weakness of the sample size, there are also certain conceptual limitations in the methodological approach applied for the empirical analysis that should be addressed. By employing a multiple regression analysis, we can merely determine relationships between variables by correlation coefficients, which does not strictly prove causation. Accordingly, Shalev (2007) argues that multiple regression is an unconvincing instrument if the purpose of the research is to conclusively determine causal mechanisms. An important facet to his criticism relates to possible causal configurations that produce the phenomenon we are interested in studying through multiple, additive or conditional pathways. The issue of causal heterogeneity is highly relevant for the empirical analysis of this thesis, given the theoretical prediction of interrelated and codependent dynamics. A way to mitigate this issue technically would be to introduce an interactive model. However, given the ambiguity in specifying these dynamics and interpreting the results in a meaningful way, this is deemed an unfavored option. Still, by segregating these effects, there is a marked risk of diluting the real effect of the relevant conditional processes. The discrete specification would also imply that we are inadequately capturing the proposed dynamics of the relevant predictors according to theory. At the same time, given the dataset and the purpose of this research, we have already established that the cost of type 2 errors is perceived to be lower than for type 1 errors. Based on this evaluation, we accept the methodological limitations with caution rather than attempt to construct ambiguous interactive predictors that cannot be interpreted in a meaningful way.

9. Conclusion

As given by the research purpose for the thesis, this paper has attempted to explain how aggregate disparity in the income distribution has evolved in China for the period between 1985 to 2015, but also to shed light on some of the most significant drivers of this evolution.

In accordance with the descriptive analysis of the development and composition of aggregate income inequality, it seems as if the political intention given by Deng Xiaoping in his renowned dictum has begun to come to fruition. From estimates by previous empirical work, there is a firm consensus of a marked increase in income inequality between 1978 and 2010, with a stagnation and moderate decline from 2010 to 2015. Based on data from Piketty et al. (2017), we found an increase of 21 Gini points from 1978 to 2010, equivalent to an increase of 60%. From 2010 to 2015, the Gini coefficient decreased by around 2%, compared to a drop of 4 % in official estimates. In terms of disparity between the tails of the distribution, we find an increase in the Palma ratio of nearly 140% from 1978 to 2010, with a comparable decline of 7% up until 2015. This aligns with the development in spatial disparity, whereas the urban-rural earning dispersion and contribution to overall inequality peaked in the late 00s and since declined. A corresponding pattern was found in intergroup regional- and educational disparity, while the contribution of inter-sectorial inequality has been declining ever since the mid-90s.

In terms of determinants for this development, the empirical analysis finds statistical evidence to suggest that increased trade dependence has had a positive impact on disparity between top and bottom income earners. Additionally, that increased efficiency of redistributive policies has had a significant negative impact on income inequality. If we assume these results to hold true, this would imply that the economic benefits from integrating China into the world market has not been equally distributed. Moreover, that the political agenda in pursuing a 'harmonious society' through targeted taxation, transfers and other social policies has reduce the elevated level of inequality. Nevertheless, there is not sufficient evidence to support Kuznets hypothesis of an inverted U-curve relationship between inequality and economic growth, sectorial migration, urbanization or educational attainment. Based on the same premise, we are unable to accept Milanovic's predicted effect of technological revolutions and population aging. Yet, Milanovic suggest that determinants of inequality entail dependency and causal heterogeneity that this analysis is unable to account for - which could lead to diluted results. The small sample size further induces a nonnegligible magnification of error - reducing the power of the tests. On the basis thereof, more data and dynamic models is needed to validate the hypotheses.

10. References

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11. Appendix

A. Pre-tax national income share to decile 5-9 in post-reform China

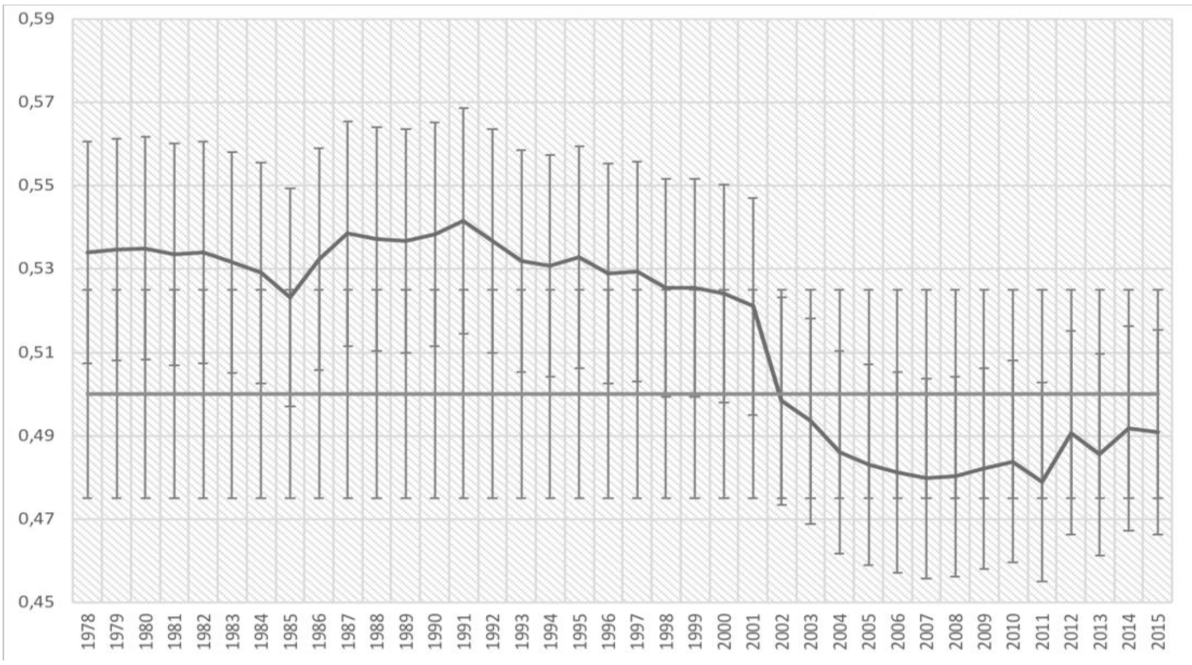
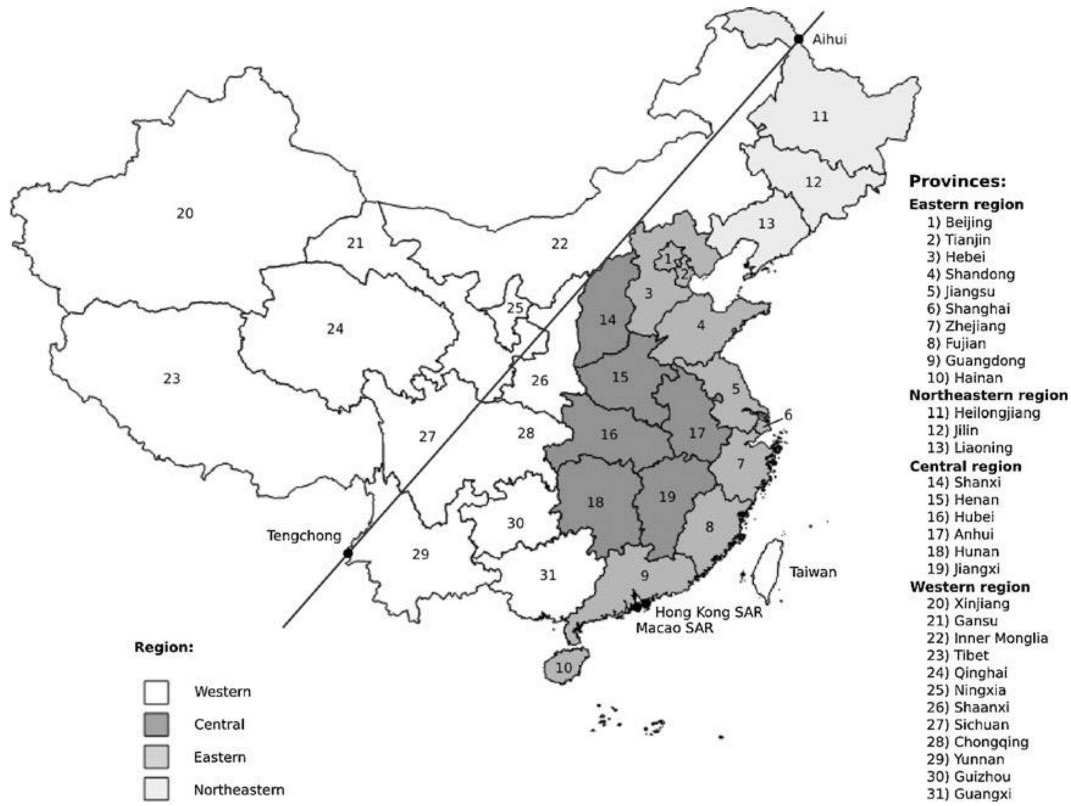


Illustration by author based on data from Piketty, Thomas; Yang, Li and Zucman, Gabriel (2016).

B. Regions (Eastern, Central, Western)



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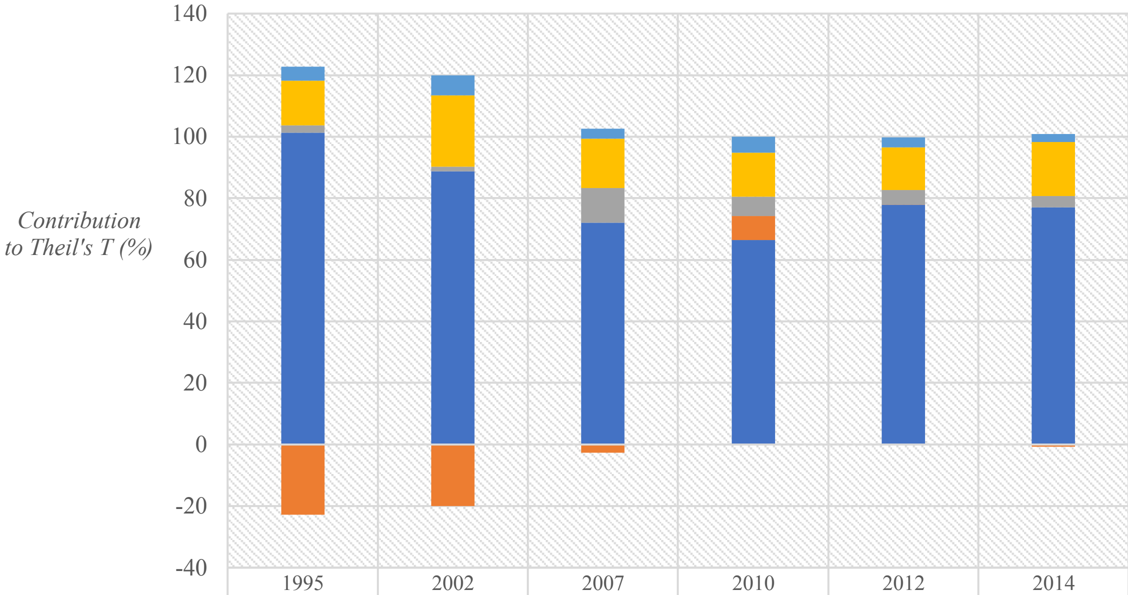
C. Theil Estimation Results based on China Family Panel Study

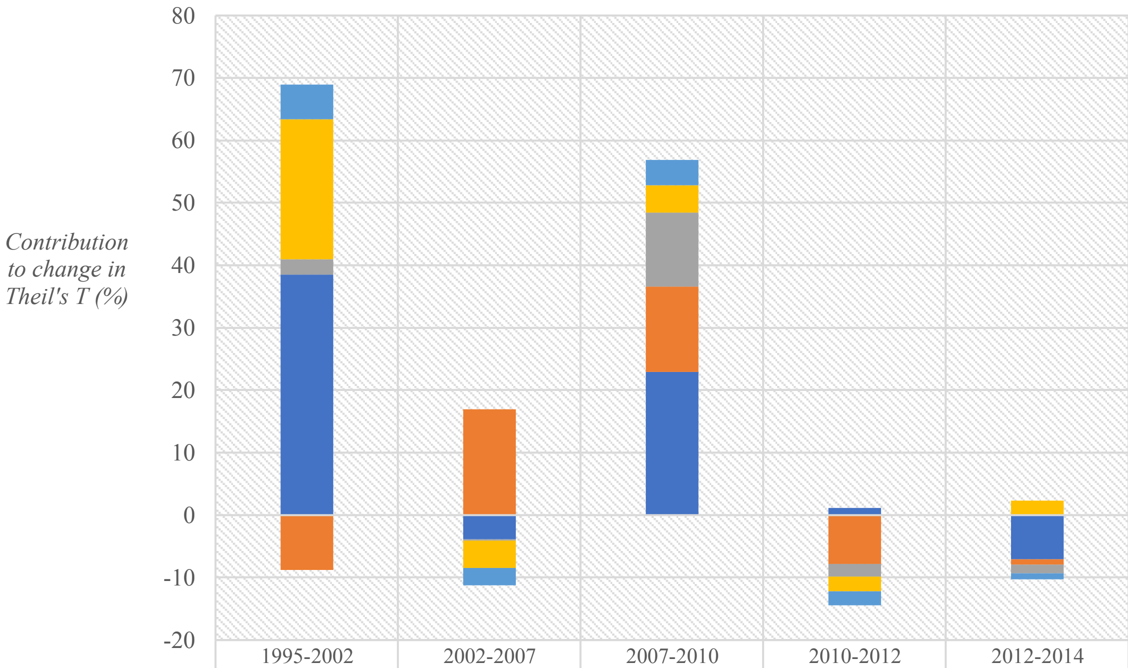
Educational attainment	2010		2012		2014		2016	
	Theil's T index	Share%	Theil's T index	Share%	Theil's T index	Share%	Theil's T index	Share%
Less than primary school	0,07015	0,15024	0,07464	0,14995	0,05184	0,13271	0,07439	0,157289
Primary school	0,06011	0,12873	0,06807	0,13675	0,04568	0,11695	0,07399	0,156440
Junior high school	0,07337	0,15713	0,08649	0,17376	0,05436	0,13914	0,07743	0,163723
Senior high school	0,07079	0,15161	0,06500	0,13058	0,04455	0,11403	0,06135	0,129709
3-year college	0,07153	0,15319	0,09579	0,19243	0,05250	0,13440	0,07959	0,168270
4-year college	0,00011	0,00023	0,00009	0,00017	0,00006	0,00015	0,00009	0,000194
Master's degree	0,00013	0,00028	0,00018	0,00036	0,00020	0,00051	0,00007	0,000148
Doctoral degree	0,00002	0,00004	0,00000	0,00000	0,00000	0,00001	0,00009	0,000182
Within	0.46692	0.83315	0.49777	0.87029	0.39065	0.87185	0.47296	0.87720
Between	0.09351	0.16685	0.07419	0.12971	0.05742	0.12815	0.06621	0.12280
Total	0.56043	100	0.57196	100	0.44807	100	0.53917	100

D.1 Contribution to overall income inequality by source (%)



	1995	2002	2007	2010	2012	2014
Other income	4.61	6.5	3.25	5.17	3.44	2.63
Transfer income	14.38	23.34	16.06	14.33	13.7	17.43
Property income	2.44	1.43	11.26	6.24	4.84	3.77
Operational income	-22.77	-20.02	-2.56	7.82	0.05	-0.81
Wage income	101.35	88.75	71.99	66.45	77.86	76.99

D.2 Contribution to change in overall income inequality by source (%)



	1995-2002	2002-2007	2007-2010	2010-2012	2012-2014
Other income	5.6	-2.7	4.1	-2.2	-1
Transfer income	22.4	-4.4	4.4	-2.4	2.3
Property income	2.44	-0.2	11.8	-2	-1.4
Operational income	-8.8	17	13.7	-7.8	-0.8
Wage income	38.5	-3.9	22.9	1.2	-7.1

E. Results of Augmented Dickey-Fuller tests

E.1 Results of Augmented Dickey-Fuller test for Palma ration

Augmented Dickey-Fuller test for unit root		Number of obs = 29		
		----------------Interpolated Dickey-Fuller----------------		
	Test Statistic	1% Critical Value	5% Critical Value	10% Critical Value
Z(t)	-1.178	-4.343	-3.584	-3.230

MacKinnon approximate p-value for Z(t) = 0.9150

log_palma	Coef.	Std. Err.	t	P > t	[95% Conf. Interval]	
L1.	-.1384715	.1175853	-1.18	0.250	-.3806429	.1036998
LD.	.3706619	.2110293	1.76	0.091	-.063961	.8052849
_trend	.0044302	.0048449	0.91	0.369	-.0055481	.0144086
_cons	.1023822	.0567997	1.80	0.084	-.014599	.2193633

ADF test accepts the null hypothesis of a unit root at all common significance levels. One lag included based on Schwarz's Bayesian Information Criterion (SBIC), experiments with more lags in the augmented regression yield same conclusion. A trend component is also included based on the observed upward trend in the process.

E.2 Results of Augmented Dickey-Fuller tests for GDP per capita

Augmented Dickey-Fuller test for unit root		Number of obs = 27		
		----------------Interpolated Dickey-Fuller----------------		
	Test Statistic Value	1% Critical Value	5% Critical Value	10% Critical Value
Z(t)	-2.189	-4.362	-3.592	-3.235

MacKinnon approximate p-value for Z(t) = 0.4962

log_gdp_pc	Coef.	Std. Err.	t	P > t	[95% Conf. Interval]	
L1.	-.1904934	.0870349	-2.19	0.040	-.3714924	-.0094945
LD.	.9312941	.1933281	4.82	0.000	.5292462	1.333342
L2D.	-.3690704	.2502945	-1.47	0.155	-.8895863	.1514454
L3D.	.2729692	.2104549	1.30	0.209	-.1646958	.7106342
_trend	.0254189	.0120666	2.11	0.047	.000325	.0505127
_cons	1.318473	.5708831	2.31	0.031	.131257	2.50569

ADF test accepts the null hypothesis of a unit root at all common significance levels. Three lags included based on Schwarz's Bayesian Information Criterion (SBIC), experiments with fewer or more lags in the augmented regression yield same conclusion. Trend component included based on the observed upward trend in the process.

E.3 Results of Augmented Dickey-Fuller tests for Secondary industry employment

Augmented Dickey-Fuller test for unit root Number of obs = 28

	Test Statistic Value	----------------Interpolated Dickey-Fuller---------------- 1% Critical Value	5% Critical Value	10% Critical Value
Z(t)	-2.833	-4.352	-3.588	-3.233

MacKinnon approximate p-value for Z(t) = 0.1849

log_secondary	Coef.	Std. Err.	t	P > t	[95% Conf. Interval]	
L1.	-.1835173	.064767	-2.83	0.009	-.3174981	-.0495364
LD.	.6707621	.1839185	3.65	0.001	.2902977	1.051227
L2D.	.1270994	.2021016	0.63	0.536	-.2909797	.5451785
_trend	.0022648	.0008715	2.60	0.016	.000462	.0040677
_cons	.5480163	.1931982	2.84	0.009	.1483553	.9476772

ADF test accepts the null hypothesis of a unit root at all common significance levels. Two lags included based on Schwarz's Bayesian Information Criterion (SBIC), experiments with fewer or more lags in the augmented regression yield same conclusion. Trend component included based on the observed upward trend in the process.

E.4 Results of Augmented Dickey-Fuller tests for Tertiary industry employment

Augmented Dickey-Fuller test for unit root Number of obs = 26

	Test Statistic Value	----------------Interpolated Dickey-Fuller---------------- 1% Critical Value	5% Critical Value	10% Critical Value
Z(t)	-2.042	-4.371	-3.596	-3.238

MacKinnon approximate p-value for Z(t) = 0.5785

log_tertiary	Coef.	Std. Err.	t	P > t	[95% Conf. Interval]	
L1.	-.1936435	.0948439	-2.04	0.055	-.3921541	.0048672
LD.	.6030622	.1911316	3.16	0.005	.2030193	1.003105
L2D.	.3549538	.1961068	1.81	0.086	-.0555025	.7654101
L3D.	-.4347519	.2309144	-1.88	0.075	-.9180612	.0485574
L4D.	.0960856	.2346152	0.41	0.687	-.3949696	.5871408
_trend	.0053227	.0029081	1.83	0.083	-.000764	.0114094
_cons	.5642315	.2594202	2.17	0.042	.0212587	1.107204

ADF test accepts the null hypothesis of a unit root at all common significance levels. Four lags included based on Schwarz's Bayesian Information Criterion (SBIC), experiments with fewer or more lags in the augmented regression yield same conclusion. Trend component included based on the observed upward trend in the process.

E.5 Results of Augmented Dickey-Fuller tests for Technological progress

Augmented Dickey-Fuller test for unit root		Number of obs = 27		
		----------------Interpolated Dickey-Fuller----------------		
	Test Statistic Value	1% Critical Value	5% Critical Value	10% Critical Value
Z(t)	-2.437	-4.362	-3.592	-3.235

MacKinnon approximate p-value for Z(t) = 0.3603

log_tfp	Coef.	Std. Err.	t	P > t	[95% Conf. Interval]	
L1.	-.1925666	.0790287	-2.44	0.024	-.3569157	-.0282175
LD.	.8409379	.1957581	4.30	0.000	.4338367	1.248039
L2D.	-.4048545	.2294959	-1.76	0.092	-.8821173	.0724083
L3D.	.22353	.1948681	1.15	0.264	-.1817203	.6287803
_trend	.0039742	.0015758	2.52	0.020	.0006972	.0072513
_cons	-.111958	.0480796	-2.33	0.030	-.2119449	-.0119711

ADF test accepts the null hypothesis of a unit root at all common significance levels. Three lags included based on Schwarz's Bayesian Information Criterion (SBIC), experiments with fewer or more lags in the augmented regression yield same conclusion. Trend component included based on the observed upward trend in the process.

E.6 Results of Augmented Dickey-Fuller tests for Compiled openness indicator

Augmented Dickey-Fuller test for unit root		Number of obs = 29		
		----------------Interpolated Dickey-Fuller----------------		
	Test Statistic Value	1% Critical Value	5% Critical Value	10% Critical Value
Z(t)	-1.042	-4.343	-3.584	-3.230

MacKinnon approximate p-value for Z(t) = 0.9382

log_openness	Coef.	Std. Err.	t	P > t	[95% Conf. Interval]	
L1.	-.1144671	.1098921	-1.04	0.308	-.3407942	.1118599
LD.	.2248018	.2091073	1.08	0.293	-.2058627	.6554662
_trend	.0005501	.0046991	0.12	0.908	-.0091279	.0102282
_cons	.4308631	.3313112	1.30	0.205	-.251485	1.113211

ADF test accepts the null hypothesis of a unit root at all common significance levels. One lag included based on Schwarz's Bayesian Information Criterion (SBIC), experiments with fewer or more lags in the augmented regression yield same conclusion. Trend component included based on the observed upward trend in the process.

E.7 Results of Augmented Dickey-Fuller tests for Trade openness

Augmented Dickey-Fuller test for unit root Number of obs = 28

	Test Statistic Value	1% Critical Value	5% Critical Value	10% Critical Value
		----------------Interpolated Dickey-Fuller----------------		
Z(t)	-1.301	-4.351	-3.588	-3.233

MacKinnon approximate p-value for Z(t) = 0.8876

log_trade	Coef.	Std. Err.	t	P > t	[95% Conf. Interval]	
L1.	-.1750928	.1345508	-1.30	0.206	-.4534322	.1032466
LD.	.341055	.2027082	1.68	0.106	-.0782788	.7603888
L2D.	.0746314	.2174411	0.34	0.735	-.3751797	.5244425
_trend	.0011438	.0039436	0.29	0.774	-.0070141	.0093017
_cons	.6325888	.4520954	1.40	0.175	-.3026417	1.567819

ADF test accepts the null hypothesis of a unit root at all common significance levels. Two lags included based on Schwarz's Bayesian Information Criterion (SBIC), experiments with fewer or more lags in the augmented regression yield same conclusion. Trend component included based on the observed upward trend in the process.

E.8 Results of Augmented Dickey-Fuller tests for Financial integration

Augmented Dickey-Fuller test for unit root Number of obs = 29

	Test Statistic Value	1% Critical Value	5% Critical Value	10% Critical Value
		----------------Interpolated Dickey-Fuller----------------		
Z(t)	-1.774	-4.343	-3.584	-3.230

MacKinnon approximate p-value for Z(t) = 0.7171

log_fin_~n	Coef.	Std. Err.	t	P > t	[95% Conf. Interval]	
L1.	-.3047669	.1717885	-1.77	0.088	-.6585719	.0490381
LD.	-.0786853	.2036303	-0.39	0.702	-.4980697	.3406991
_trend	.0124278	.0109015	1.14	0.265	-.0100242	.0348798
_cons	.9370083	.4375818	2.14	0.042	.0357916	1.838225

ADF test accepts the null hypothesis of a unit root at all common significance levels. One lag included based on Schwarz's Bayesian Information Criterion (SBIC), experiments with more lags in the augmented regression yield same conclusion. Trend component included based on the observed upward trend in the process.

E.9 Results of Augmented Dickey-Fuller tests for Redistributive policies

Augmented Dickey-Fuller test for unit root		Number of obs = 27		
		----------------Interpolated Dickey-Fuller----------------		
	Test Statistic Value	1% Critical Value	5% Critical Value	10% Critical Value
Z(t)	-0.962	-4.362	-3.592	-3.235

MacKinnon approximate p-value for Z(t) = 0.9490

log_abs_~n	Coef.	Std. Err.	t	P > t	[95% Conf. Interval]	
L1.	-.1126663	.117128	-0.96	0.347	-.3562474	.1309148
LD.	.3245038	.216138	1.50	0.148	-.1249796	.7739873
L2D.	.0195257	.2412453	0.08	0.936	-.4821715	.5212228
L3D.	-.1343248	.2395515	-0.56	0.581	-.6324995	.3638499
_trend	.0083438	.0052293	1.60	0.126	-.0025311	.0192188
_cons	-.0255327	.1177619	-0.22	0.830	-.2704319	.2193665

ADF test accepts the null hypothesis of a unit root at all common significance levels. Three lags included based on Schwarz's Bayesian Information Criterion (SBIC), experiments with fewer or more lags in the augmented regression yield same conclusion. Trend component included based on the observed upward trend in the process.

E.10 Results of Augmented Dickey-Fuller tests for Educational attainment

Augmented Dickey-Fuller test for unit root		Number of obs = 28		
		----------------Interpolated Dickey-Fuller----------------		
	Test Statistic Value	1% Critical Value	5% Critical Value	10% Critical Value
Z(t)	-2.978	-4.352	-3.588	-3.233

MacKinnon approximate p-value for Z(t) = 0.1383

log_edu_~y	Coef.	Std. Err.	t	P > t	[95% Conf. Interval]	
L1.	-.2244315	.0753633	-2.98	0.007	-.3803323	-.0685307
LD.	.5881169	.1953619	3.01	0.006	.1839801	.9922537
L2D.	.0694803	.2185286	0.32	0.753	-.3825805	.521541
_trend	.0252554	.0083486	3.03	0.006	.0079849	.0425258
_cons	.1130489	.0376287	3.00	0.006	.0352079	.1908898

ADF test accepts the null hypothesis of a unit root at all common significance levels. Two lags included based on Schwarz's Bayesian Information Criterion (SBIC), experiments with fewer or more lags in the augmented regression yield same conclusion. Trend component included based on the observed upward trend in the process.

E.11 Results of Augmented Dickey-Fuller tests for Population aging

Augmented Dickey-Fuller test for unit root	Number of obs = 27			
		----------------Interpolated Dickey-Fuller----------------		
	Test Statistic Value	1% Critical Value	5% Critical Value	10% Critical Value
Z(t)	1.209	-4.362	-3.592	-3.235

MacKinnon approximate p-value for Z(t) = 1.0000

log_age_~p	Coef.	Std. Err.	t	P > t	[95% Conf. Interval]	
L1.	.0623157	.0515322	1.21	0.240	-.0448513	.1694827
LD.	1.564032	.2239817	6.98	0.000	1.098237	2.029828
L2D.	-.4221131	.4069136	-1.04	0.311	-1.268336	.4241101
L3D.	-.3103115	.3015797	-1.03	0.315	-.937481	.3168579
_trend	-.0007774	.0007073	-1.10	0.284	-.0022482	.0006935
_cons	-.1282011	.1057308	-1.21	0.239	-.3480803	.0916782

ADF test accepts the null hypothesis of a unit root at all common significance levels. Three lags included based on Schwarz's Bayesian Information Criterion (SBIC), experiments with fewer or more lags in the augmented regression yield same conclusion. Trend component included based on the observed upward trend in the process.

E.12 Results of Augmented Dickey-Fuller tests for Privatization

Augmented Dickey-Fuller test for unit root	Number of obs = 29			
		----------------Interpolated Dickey-Fuller----------------		
	Test Statistic Value	1% Critical Value	5% Critical Value	10% Critical Value
Z(t)	-0.652	-4.343	-3.584	-3.230

MacKinnon approximate p-value for Z(t) = 0.9761

log_privat	Coef.	Std. Err.	t	P > t	[95% Conf. Interval]	
L1.	-.061068	.0936273	-0.65	0.520	-.253897	.131761
LD.	.2056004	.2148479	0.96	0.348	-.236887	.6480879
_trend	.000796	.0020079	0.40	0.695	-.0033394	.0049314
_cons	.2462769	.3460483	0.71	0.483	-.4664229	.9589766

ADF test accepts the null hypothesis of a unit root at all common significance levels. One lag included based on Schwarz's Bayesian Information Criterion (SBIC), experiments with more lags in the augmented regression yield same conclusion. Trend component included based on the observed upward trend in the process.

E.13 Results of Augmented Dickey-Fuller tests for Financial deepening

Augmented Dickey-Fuller test for unit root		Number of obs = 29		
		----------------Interpolated Dickey-Fuller----------------		
	Test Statistic Value	1% Critical Value	5% Critical Value	10% Critical Value
Z(t)	-2.713	-4.343	-3.584	-3.230

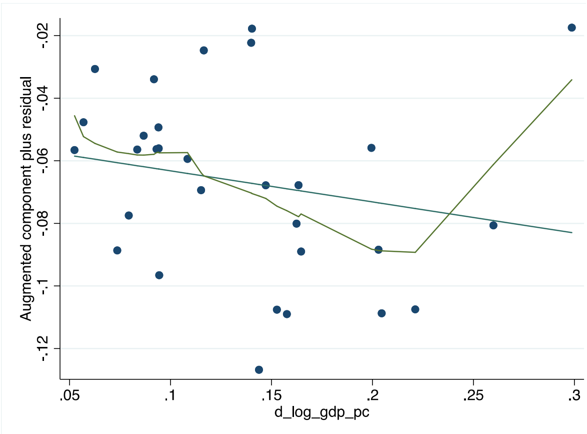
MacKinnon approximate p-value for Z(t) = 0.2305

log_fin_~g	Coef.	Std. Err.	t	P > t	[95% Conf. Interval]	
L1.	-.4912913	.1810549	-2.71	0.012	-.8641809	-.1184017
LD.	.2049901	.1876611	1.09	0.285	-.1815053	.5914854
_trend	.0106267	.0039654	2.68	0.013	.0024598	.0187936
_cons	2.123345	.777018	2.73	0.011	.5230466	3.723644

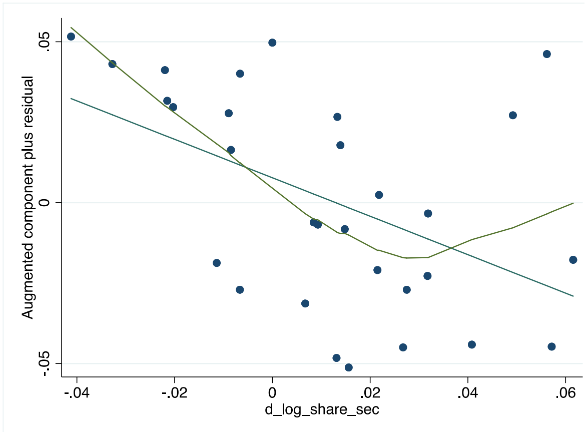
ADF test accepts the null hypothesis of a unit root at all common significance levels. One lag included based on Schwarz's Bayesian Information Criterion (SBIC), experiments with more lags in the augmented regression yield same conclusion. Trend component included based on the observed upward trend in the process.

F. Augmented component-plus-residual plot with lowess smoothing bandwidth of 0.8

F.1 Economic growth
(GDP per capita)

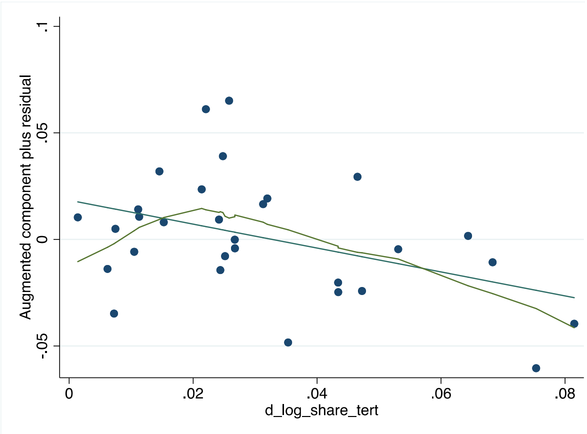


F.2 Industrialization
(Share of employment in secondary industries)



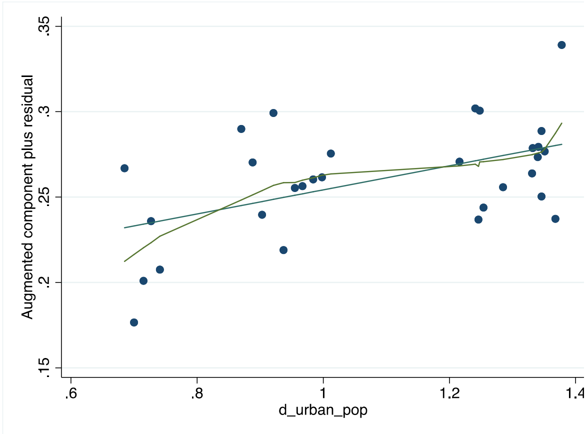
F.3 Servicization

(Share of employment in tertiary industries)



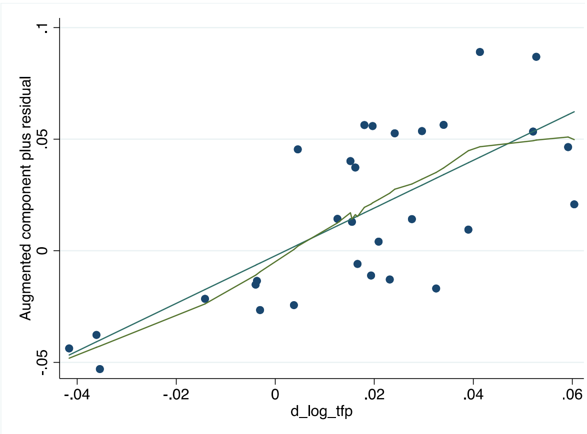
F.4 Urbanization

(Share of urban population)



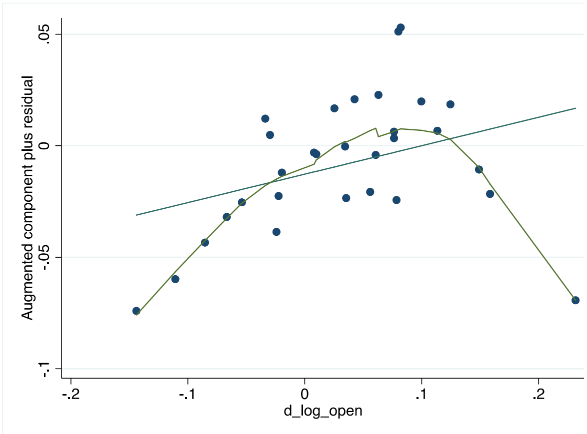
F.5 Technological progress

(Total factor productivity)



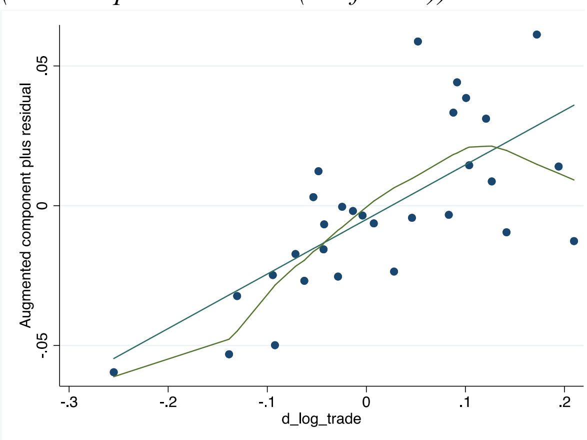
F.6 Openness

(Compiled openness indicator)



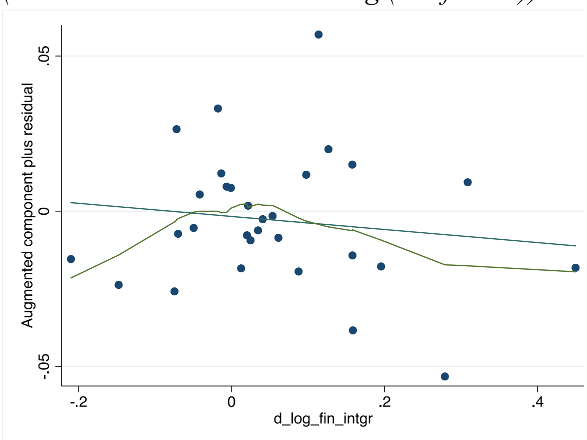
F.7 Trade openness

(Trade dependence ratio (% of GDP))

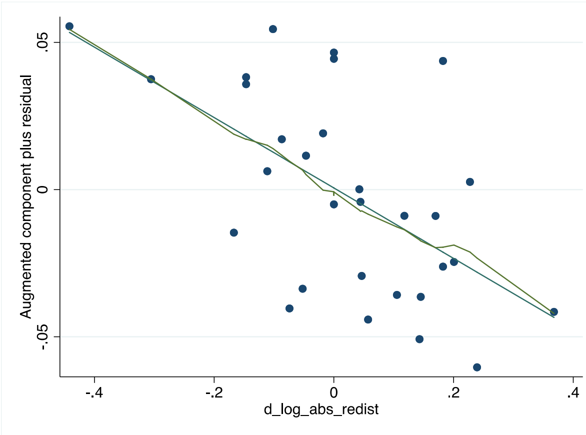


F.8 Financial integration

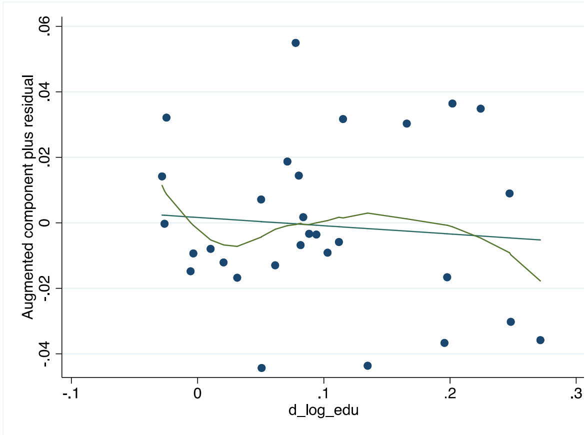
(Total external A/L. outstanding (% of GDP))



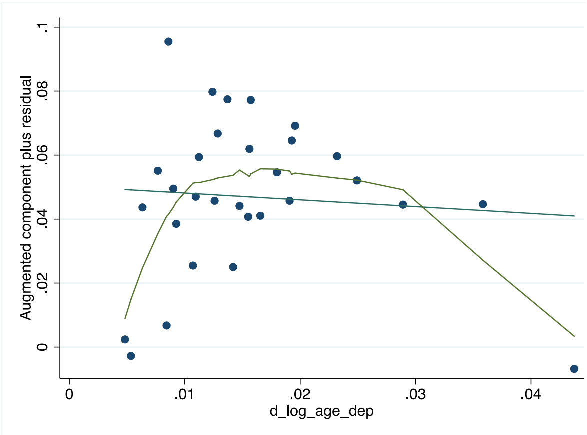
F.9 Absolute redistribution
(Difference between net and market Gini)



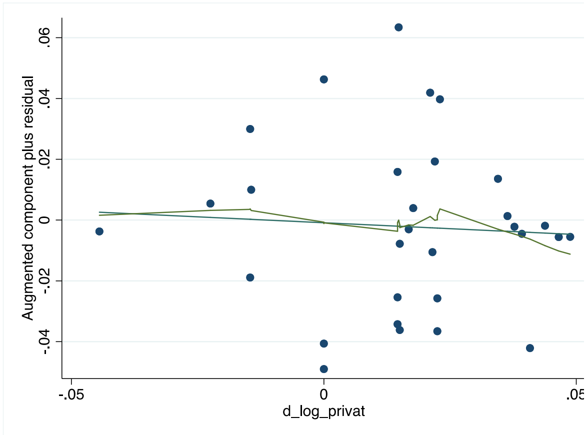
F.10 Educational attainment
(School enrollment, tertiary (% gross)



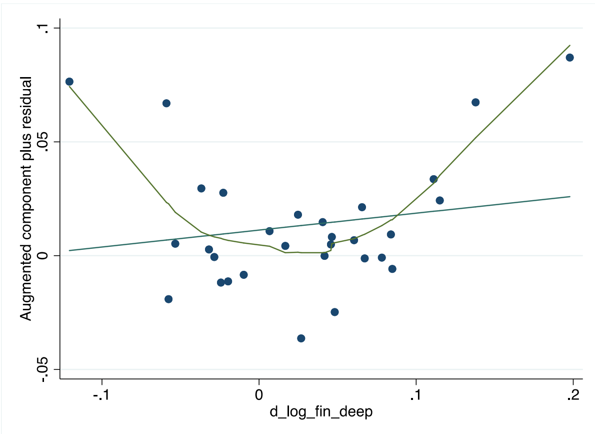
F.11 Population aging
(Old-age dependency ratio)



F.12 Privatization
(Private share of national wealth (% of NI))

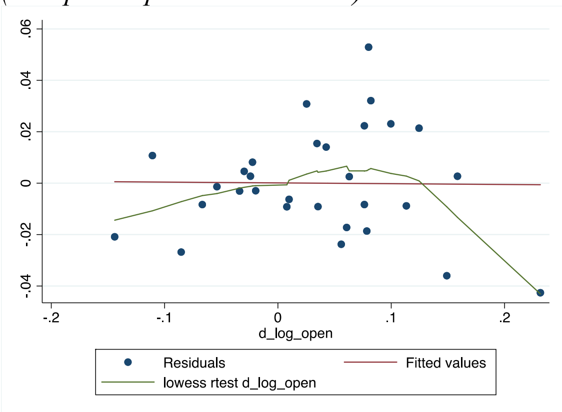


F.13 Financial deepening
(Domestic credit to private sector (% of GDP))

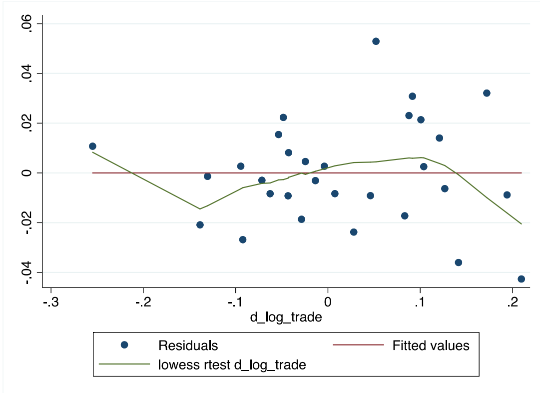


G. Standardized residual plot against relevant predictor variables

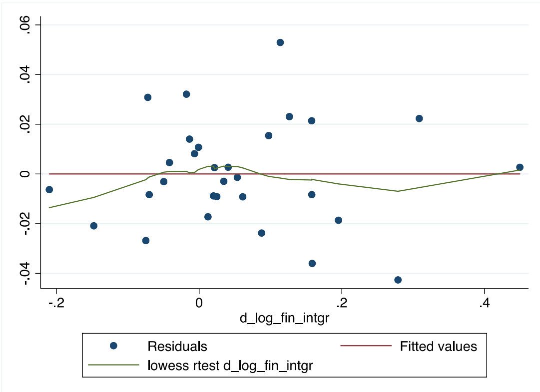
G.1 Openness
(Compiled openness indicator)



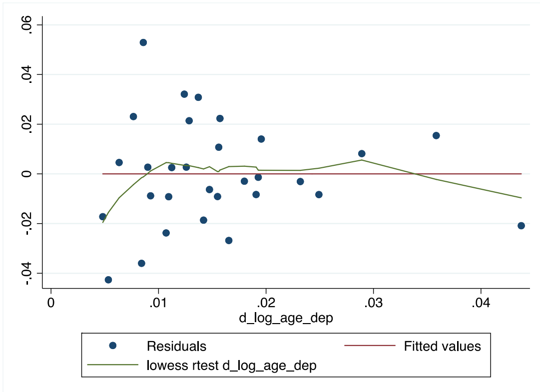
G.2 Trade openness
(Trade dependence ratio (% of GDP))



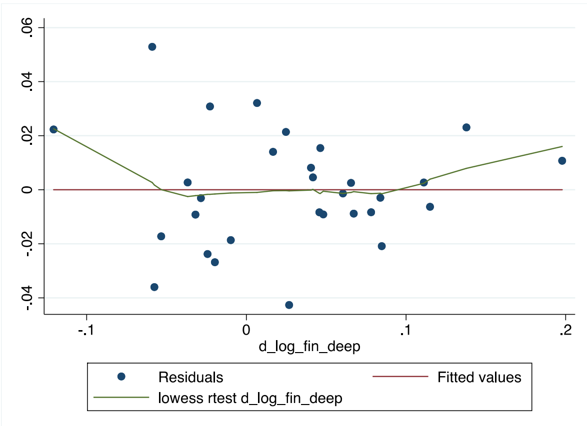
G.3 Financial integration
(Total external A/L. outstanding (% of GDP))



G.4 Population aging
(Old-age dependency ratio)



G.5 Financial deepening
(Domestic credit to private sector (% of GDP))



H. Correlation matrix

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)
(1)	1.00																				
(2)	0.98	1.00																			
(3)	0.49	0.40	1.00																		
(4)	0.16	0.08	0.63	1.00																	
(5)	0.55	0.60	0.08	-0.21	1.00																
(6)	0.59	0.68	0.04	-0.22	0.96	1.00															
(7)	-0.16	-0.20	0.25	0.33	-0.05	-0.12	1.00														
(8)	-0.16	-0.20	0.27	0.36	-0.08	-0.15	0.99	1.00													
(9)	0.56	0.48	0.63	0.52	0.37	0.30	0.40	0.41	1.00												
(10)	0.16	0.09	0.05	0.12	-0.08	-0.14	-0.20	-0.18	0.25	1.00											
(11)	-0.09	-0.11	0.02	-0.17	0.08	-0.04	0.09	0.11	0.18	0.07	1.00										
(12)	-0.05	-0.04	0.03	-0.02	-0.15	-0.11	-0.24	-0.22	-0.15	0.12	-0.10	1.00									
(13)	0.10	0.16	-0.09	-0.18	0.07	0.14	-0.40	-0.39	-0.22	0.08	-0.08	0.72	1.00								
(14)	0.02	-0.04	0.44	0.01	0.04	0.02	0.37	0.37	-0.01	-0.22	0.13	-0.04	-0.09	1.00							
(15)	-0.16	-0.08	-0.16	-0.06	0.32	0.32	0.27	0.25	0.13	-0.02	0.06	0.11	-0.09	-0.17	1.00						
(16)	-0.10	-0.03	-0.27	-0.11	0.30	0.31	0.15	0.14	0.09	0.02	-0.05	0.17	-0.02	-0.35	0.94	1.00					
(17)	-0.30	-0.21	-0.22	-0.30	0.30	0.27	0.33	0.29	-0.13	-0.50	-0.12	-0.36	-0.17	0.17	0.25	0.17	1.00				
(18)	-0.33	-0.25	-0.25	-0.26	0.28	0.23	0.28	0.25	-0.15	-0.44	-0.07	-0.33	-0.13	0.11	0.22	0.16	0.96	1.00			
(19)	-0.14	-0.08	-0.22	-0.31	0.18	0.11	-0.09	-0.11	-0.18	-0.02	0.34	0.00	0.03	-0.11	0.38	0.30	-0.11	-0.14	1.00		
(20)	-0.57	-0.52	-0.24	-0.17	-0.20	-0.24	-0.15	-0.15	-0.35	-0.20	0.41	-0.15	0.06	-0.02	0.02	-0.04	0.19	0.19	0.31	1.00	
(21)	-0.05	0.04	0.11	-0.02	0.11	0.10	-0.07	-0.06	-0.09	-0.38	0.50	0.08	0.22	0.03	0.08	0.02	-0.03	-0.04	0.37	0.60	1.00

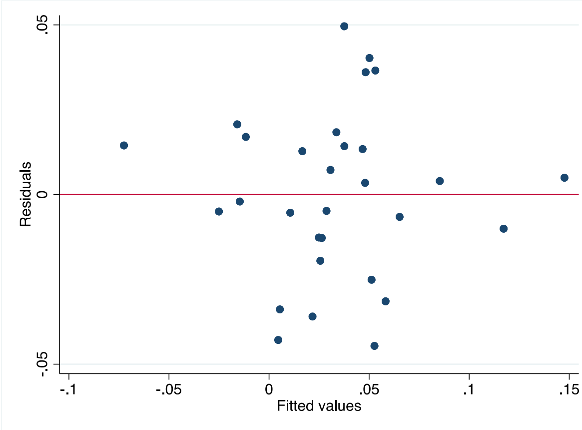
Note: (1) Economic Growth, (2) Economic growth^2, (3) Industrialization, (4) Industrialization^2, (5) Servicization, (6) Servicization^2, (7) Urbanization, (8) Urbanization^2, (9) Technological progress, (10) Trade openness, (11) Trade openness^2 (12) Financial integration, (13) Financial integration^2 (14) Absolute redistribution, (15) Educational attainment, (16) Educational attainmentt^2, (17) Population aging, (18) Population aging^2, (19) Privatization, (20) Financial deepening (21) Financial deepening^2

I. Variance Inflation Factor (VIF) test results

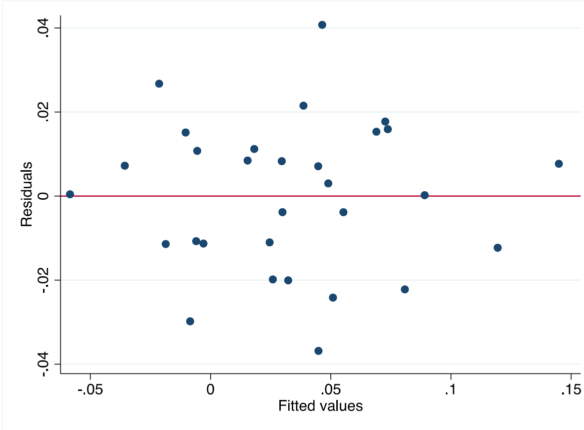
	VIF			
	(1)	(2)	(3)	(4)
Economic growth d1.log_gdp_pc	195.96	180.99	-	-
Economic growth^2 d1.log_gdp_pc_sq	183.83	174.27	-	-
Industrialization d1.log_share_secondary	10.92	12.18	-	-
Industrialization^2 d1.log_share_secondary_sq	6.26	7.74	-	-
Servicization d1.log_share_tertiary	72.36	99.87	-	-
Servicization^2 d1.log_share_tertiary_sq	89.01	7.74	-	-
Urbanization d1.urban_pop	1086.99	1599.45	-	-
Urbanization^2 d1.urban_pop_sq	1059.20	1575.24	-	-
Technological progress d1.log_tfp	8.01	12.78	-	-
Openness d1.log_open	6.26	-	1.44	-
Openness^2 d1.log_open_sq	3.86	-	1.38	-
Trade openness d1.log_trade	-	4.89	-	1.06
Trade openness^2 d1.log_trade^2	-	8.20	-	1.03
Financial integration d1.log_fin_intgr	-	9.57	-	-
Financial integration^2 d1.log_fin_intgr_sq	-	6.92	-	-
Absolute redistribution d1.log_abs_redist	5.82	8.02	1.06	1.07
Educational attainment d1.log_edu	24.24	34.30	-	-
Educational attainment^2 d1.log_edu _sq	24.21	25.68	-	-
Population aging d1.log_age_dep	88.85	142.90	-	-
Population aging^2 d1.log_age_dep^2	66.19	87.82	-	-
Privatization d1.log_privat	5.09	7.05	-	-
Financial deepening d1.log_fin_deep	5.39	9.93	-	-
Financial deepening^2 d1.log_fin_deep_sq	6.66	12.78	-	-
Mean VIF	155.22	197.88	1.29	1.05

J. Graphical test for heteroscedasticity of residuals: Residuals-versus-fitted plot

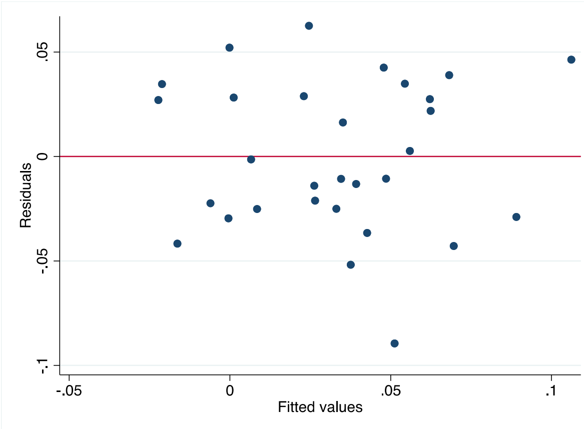
I.1 Model 1: All-possible regression compiled openness indicator



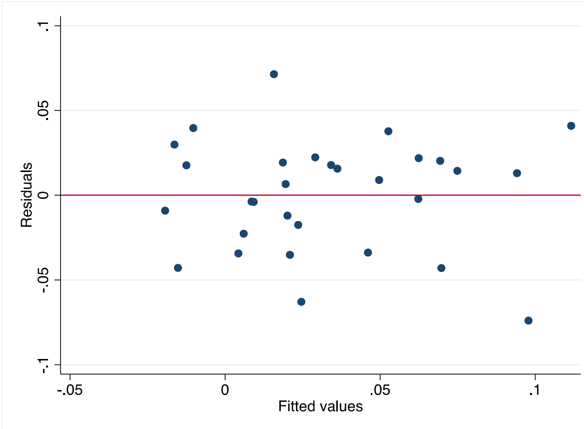
I.2 Model 2: All-possible regression decomposed openness indicator



I.3 Model 3: Stepwise regression compiled openness indicator

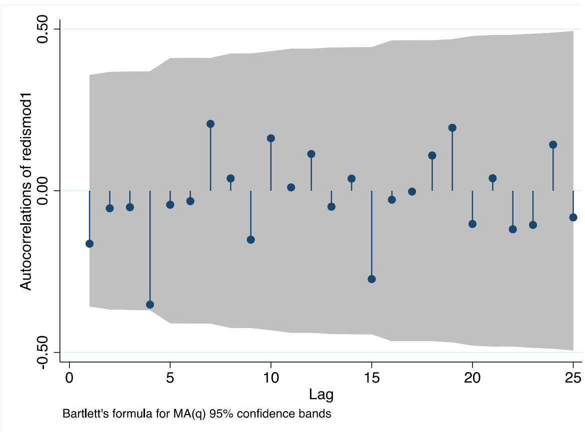


I.4 Model 4: Stepwise regression decomposed openness indicator

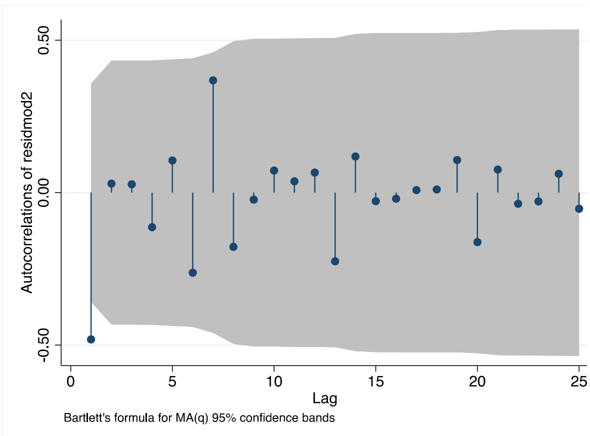


K. Graphical test for autocorrelation of residuals: Correlogram

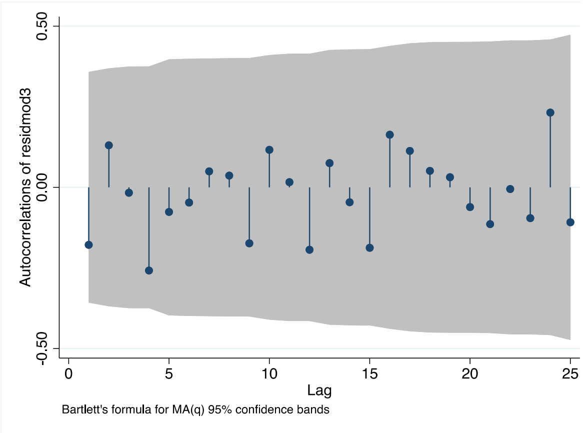
J.1 Model 1: All-possible regression compiled openness indicator



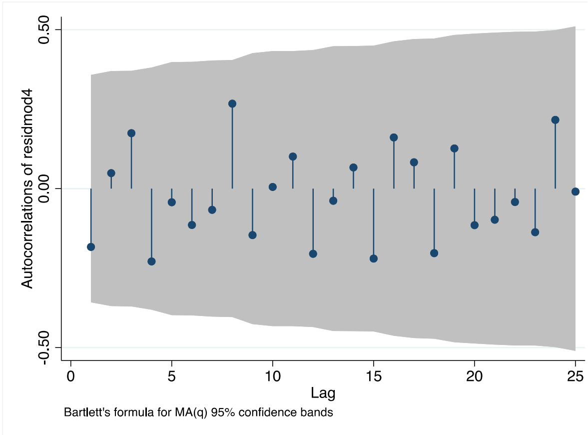
J.1 Model 2: All-possible regression decomposed openness indicator



J.3 Model 3: Stepwise regression compiled openness indicator

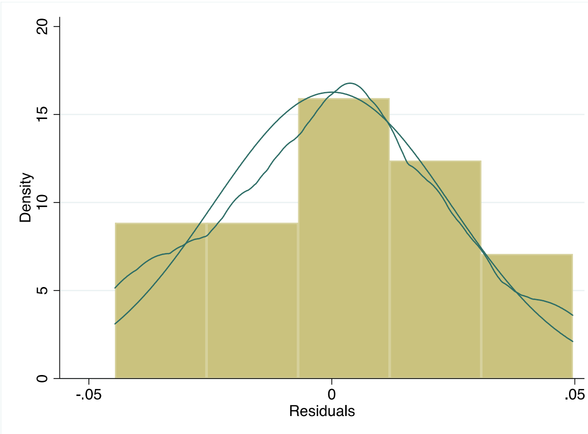


J.4 Model 4: Stepwise regression decomposed openness indicator

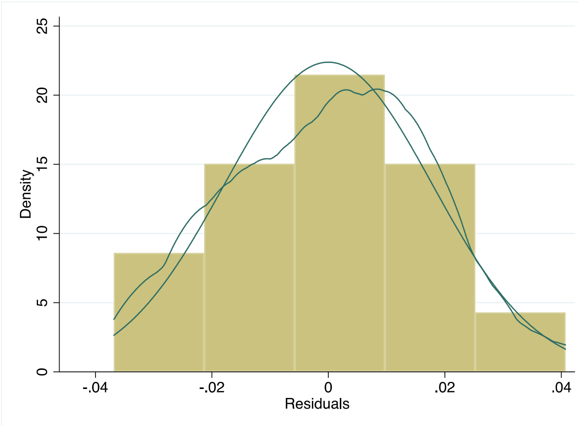


L. Graphical test for normality: Histogram plot of residuals

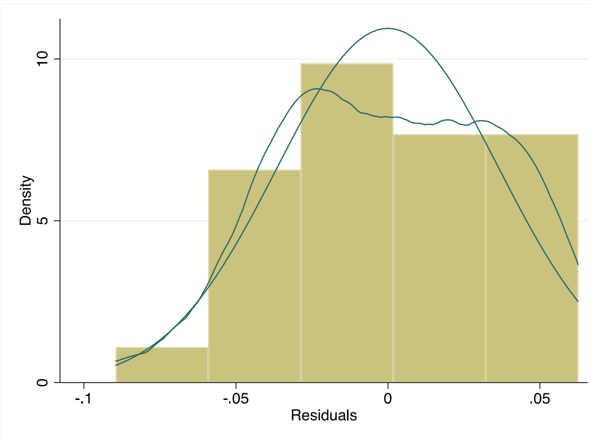
K.1 Model 1: All-possible regression compiled openness indicator



K.2 Model 2: All-possible regression decomposed openness indicator



K.3 Model 3: Stepwise regression compiled openness indicator



K.4 Model 4: Stepwise regression decomposed openness indicator