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Chen Gong
Maastricht University

Denisa M. Sologon
LISER and IZA

Zina Nimeh
Maastricht University

Cathal O'Donoghue
National University of Ireland and Maastricht University

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IZA – Institute of Labor Economics

Schaumburg-Lippe-Straße 5–9
53113 Bonn, Germany

Phone: +49-228-3894-0
Email: publications@iza.org

www.iza.org

ABSTRACT

Decomposition of the Changes in Household Disposable Income Distribution in China

Studies have shown that the previously growing inequality in China has stabilized and even declined since 2008 (Kanbur et al., 2021), nevertheless, the drivers of the latest transformation in income inequality remain to be unraveled. We address this research gap by examining the changes in the distribution of household disposable income and its drivers in China from 2010 to 2016. We apply the distributional decomposition method proposed by Bourguignon et al. (2008) and Sologon et al. (2021), and quantify the contribution of all factors into four general dimensions, (1) demographic composition, (2) labor market structure, (3) price and return, and (4) governmental transfers. This study considers not only the individual labor income as with existing literature, but also models other family incomes and social transfers to reflect the real economic conditions more accurately. The decomposition results show that all four factors contribute positively to the decline in income inequality during the period studied. The changes in urban labor market structure, specifically the general forms of employment, occupational and industrial structure, have been contributing as inequality augmenting factors.

JEL Classification: D63, D31, F63

Keywords: income distribution, decomposition, income inequality, microsimulation, overtime comparison, labor market structure, demographic structure

Corresponding author:
Chen Gong
Maastricht University
Boschstraat 24
6211 AX
Maastricht
The Netherlands

E-mail: chen.gong@maastrichtuniversity.nl

1 Introduction

China's evolution of inequality has been a focus of interest worldwide since its market-oriented reform in 1978. As inequality became an issue of concern leading to many negative social consequences (*Cheong and Wu*, 2015; *Zhang and Wan*, 2006), China began adopting different government interventions to address various aspects of inequality since the 2000s. Studies have shown that previously growing inequality has stabilized and even declined since 2008 (*Kanbur et al.*, 2021; *Wan et al.*, 2018). However, compared to the extensive literature on growing inequality and its determinants prior to 2010, much is still to be studied to disentangle the contributions to this latest income inequality transformation (*Wan et al.*, 2018). Only by understanding this process and its links to outcomes,will the development of policies to overcome the excessive inequality in the future, improve social cohesion, and build a harmonious society be possible. This paper aims to address this gap by decomposing the latest changes in household income distribution into its household and individual socio-economic determinants, and to quantify the contributions of policy and market factors to the changes in the income distribution observed over time.

The ongoing exploration of income inequality in China began with testing the well-known Kuznets hypothesis(*Chen and Fleisher*, 1996; *Kuznets*, 1955; *Tsui*, 1996) and later transitioned to the discussion of the determinants of inequality by applying various decomposition methods. The traditional inequality decomposition methods were introduced by *Shorrocks* (1982, 1984), *Bourguignon* (1979) and *Lerman and Yitzhaki* (1985), in which the contribution to overall inequality was decomposed by a small number of exclusionary components, such as sources of income or population subgroups. In the above mentioned framework, *Kanbur and Zhang* (1999) found that the between group (rural and urban) inequality, although decreasing, contributed to over 70 percent of total inequality in China from 1983 to 1995. By applying the same methodology, *Sicular et al.* (2007) reached a different conclusion, showing that the within-group inequality exceeded the leading position, contributing around 68 percent to the overall inequality in 2002. However, due to the methodological limitations, these studies only touched on overall spatial inequality and did not consider the underlying causes of the regional income difference, such as labor market structure and other household and individual socio-economic characteristics.

The development of regression-based decomposition methods allowed researchers to go beyond the contribution of a limited number of subgroups and to account for the effects of multiple determinants on inequality simultaneously. This approach was proposed by *Blinder* (1973) and *Oaxaca* (1973), which looks at the mean income difference. *Juhn et al.* (1993) extended the model to the full income distribution and allowed for decompositions showing differences between groups at all quantiles, providing more detailed information on the trend in income distribution. Other regression-based models, presented by *Fields and Yoo* (2000) and *Morduch and Sicular* (2002), despite the limitations in the regression functions, have also been used extensively to determine the drivers of income inequality in China. For example, (*Wan and Zhou*, 2005) apply the OB decomposition and find that location of residence is the most significant contributor to rural income inequality, followed by a growing importance of capital input. Using the *Juhn et al.* (1993) decomposition, *Han et al.* (2012) find that globalization has led to a rise in intra-regional wage inequality due to the faster growth in real wages at higher quantiles. While these studies have improved the understanding of economic inequality in China, they have not considered the dynamic relationship between these factors when examining their contributions to income changes.

Income inequality is a multidimensional process and shifts in income distribution may be caused by a variety of factors, including economic transitions, socio-economic measures, and demographic factors, which are not independent of each other (*Bourguignon et al.*, 2008; *Li*, 2016). Since reducing income inequality was recognized as one of the national development priorities in 2005, numerous policy reforms have been implemented, all aimed at inclusive growth but targeting different regions and socio-economic groups in China (*Li*, 2018).

Differences in policy changes and market responses lead to heterogeneous effects of influencing factors (e.g., labor market structure, sociodemographic endowments) on income changes at different income levels. Thus, if only average effects or the single source of income is considered, important and clear policy implications may remain hidden. Recent studies suggest that the previously widening income gap has stabilized since 2008, but whether it will maintain its downward trend remains controversial (*Kanbur et al.*, 2021; *Li*, 2018). Therefore, a more disaggregated and up-to-date study is needed to understand the drivers of the evolution of the income distribution in China.

Building on existing literature, we explore the drivers of changes in the household income distribution from 2010s, after the declining trend emerged according to existing literature (*Kanbur et al.*, 2021; *Li*, 2018; *Xie et al.*, 2015; *Zhang*, 2021). A more detailed and comprehensive decomposition of the drivers of inequality change is provided by examining the differences in the distribution of household disposable income between 2010 and 2016, which captures the pre- and post-phase of the 12th Five-year Plan [1]. The study further builds on the decomposition model proposed by *Sologon et al.* (2021), which is based on a parametric income-generation process that consists of a system of equations for multiple income sources for the household, including but not limited to parametric earning process for individual wage, household capital income and public transfers. The contribution of the factors to the differences in household disposable income inequality is assessed by taking the difference between the actual income distribution and a sequence of simulated counterfactual distributions of it. The contribution to the change in income distribution over time will be presented as groups of four general factors, (1) demographic composition, (2) labor market structure, (3) price and return, and (4) governmental transfer. This study considers not only the individual labor income as with existing literature, but also models other family incomes and social transfers to reflect the real economic conditions more accurately.

[1] The Five-Year Plans(Wunian Jihua) are the long-term strategic plans that are set forth by the Chinese government to guide both economic and social development. The Twelfth Five-Year Plan (2011-2015) was established with the goals of addressing rising inequality, promoting sustainable economic growth, and improving social safety nets (*the National People's Congress of the People's Republic of China*, 2011)

The paper is organized as follows: Section 2 provides information on the context of mainland China and the research's state of arts. Section 3 explains the choice of methodology and the empirical framework. Section 4 presents the data description and the decomposition outputs. Section 4 summarizes and concludes and discusses the results.

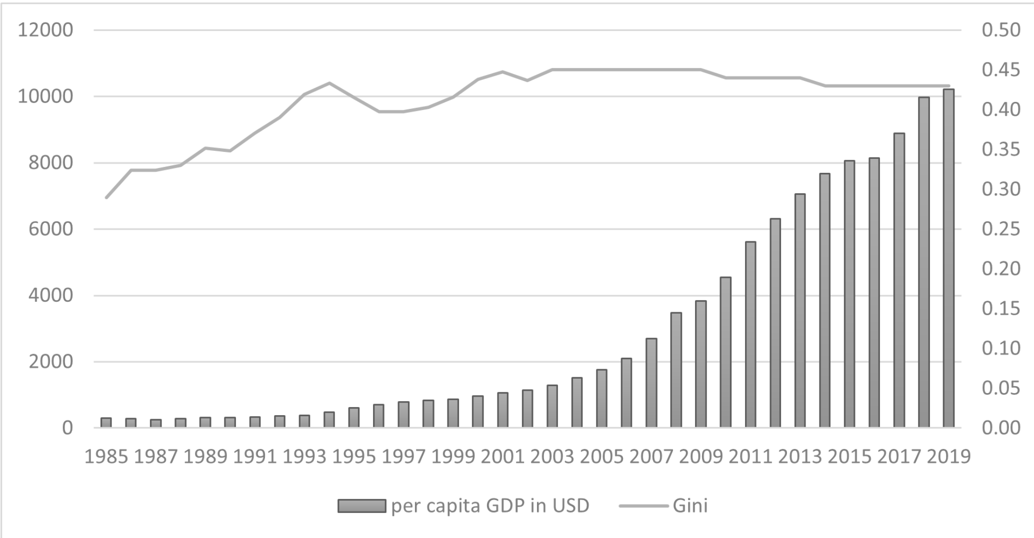
2 Background

Since the late 1970s, China has undergone a series of historic economic and institutional transitions that have placed the country among the fastest growing economies in the world (*Fan et al.*, 2013). However, economic prosperity has not been shared equally across the country. As can be seen in Figure 1, income inequality has been increasing since the 1980s, when market economic reforms were implemented. From 1980 to 2000, China's Gini coefficient doubled from 0.23 to 0.44, jumping from a level of inequality equivalent to that of Scandinavian countries to that of the United States in less than 20 years (*UNU-WIDER*, 2021).

Extensive studies have contributed to the understanding of the drivers of the changes in income inequality from different aspects and dimensions. Various research identified the urban-rural income gap as the major contributors to the national income gap over time (*Sicular et al.*, 2007; *Wan and Zhou*, 2005; *Xie and Zhou*, 2014). This can be attributed to the dualistic socio-economic system introduced during the period of the planned economy. Compared to inequality within the region, the urban-rural gap has contributed to over 60 percent of the national Gini (*Kanbur and Zhang*, 1999). The figure flattens slightly after 2000, largely due to the effects of labor migration and urbanization (*Sicular et al.*, 2007; *Zhuang and Li*, 2016).

Along the same vein, the household registration system (hukou) is another factor for increasing inequality brought about by the dualistic structure (*Li and Zhao*, 2017; *Zhu*, 2016). Although national average income increased significantly during the 2000s, those at the bottom of the income distribution, especially the rural population, did not benefit from the rapid economic growth as much as the urban residents (*Knight*, 2021). Studies have shown that rural laborers are more vulnerable to discrimination in urban labor markets from wage inequality and employer cuts in social insurance premiums (*Whalley and Zhang*, 2007). Having a rural hukou is also negatively associated with educational attainment, social capital, and access to social insurance, all of which contribute positively to income levels (*Golley and Kong*, 2016). *Ito* (2008) notes that even without restrictions on labor mobility, the schooling variable would still account for 25 percent of the rural-urban gap. Unequal educational attainment between rural and urban populations can be seen as the biggest challenge in reducing inequality.

Since the 1990s, Wage income has consistently accounted for more than 60 percent of urban households' disposable income (*Luo et al.*, 2017). Hence, examining the wage income inequality and its drivers have important implications for understanding the changes in overall income inequality in urban China. In addition to Hukou (*Zhang*, 2010; *Zhu*, 2016), studies found that gender (*Li* *and Li*, 2008; *Tang and Long*, 2013), education (*Chi et al.*, 2011; *Gustafsson and Wan*, 2020; *Luo*, 2018), industry and enterprise ownership (*Chen et al.*, 2010; *Chi et al.*, 2011) all have significant effects on wage disparities, but the extent to which these variables contribute to inequality varies across time. Prior to and shortly after the privatization of state-owned enterprises(SOEs) and the labor market reform in the 1980s, workers employed in SOEs and SOE-controlled industries enjoyed higher wage premiums due to monopolies (*Chen et al.*, 2010; *Chi et al.*, 2011). However, the economic structure in China has changed significantly since the 21st century. SOEs have become much less dominant and the rapidly growing private sectors has crowded out the quasi-rents previously shared by SOE employees (*Li*, 2018). Wage becoming a better reflection of the market demand for labor and productivity value of education and skills. Instead of enterprise ownership and age, education and occupation have become the main contributors to wage inequality (*Chen et al.*, 2010).



Sources: 1985-2001 from (*Ravallion and Chen*, 2009), 2002-2019 from WIID, World Income Inequality Database of UNU-WIDER. All estimates are based on the dataset released by National Bureau of Statistics of PRC. GDP per capita is generated from World Bank.

Figure 1: Per capita GDP and National Gini index

In the current wave of skill-biased technological development, the Chinese central government has been heavily investing in industrial upgrading and high-tech R&D, despite the different ownership of enterprises (*Liu*, 2016). Compared to the traditional labor-intensive manufacturing, the higher marginal utility in capital- and technology-intensive industries is transferred into more wage premium for the better educated employees in those sectors (*Blanchflower et al.*, 1996; *Castro Silva and Lima*, 2017). Studies have already shown that the return to college education was more prominent at upper income quantiles than at lower ones, and college education in general broadens income inequality (*Chi et al.*, 2011; *Luo*, 2018). However, the technological advancement also creates more job opportunities for the less educated, such as machine learning trainers, which to some extent, offer better returns than that of the traditional sectors. To date, to the best of our knowledge, the contribution of this structural change has not been discussed and quantified in the income inequality decomposition analysis.

Another important determinant of household income inequality is the mismatch between income sources other than labor income. More than 19.8 percent of workers aged 16 to 70 were self-employed in 2013, a substantial increase from 1.4 percent in 1988 (*Gustafsson and Wan*, 2020). Depending on the industry and region in which the business operates, differences in operating income can be substantial (*Bai and Chen*, 2013; *Xie*, 2012). In addition, the amount of return from capital assets such as real estate and finance increases sharply for top earners in urban areas. Based on national accounts and tax data, *Piketty et al.* (2019) show that China's national wealth-to-income ratio has risen from 350 percent in 1978 to 700 percent in 2015, approaching the level of the United States. While including wealth in inequality studies is challenging due to data limitations, it will be crucial to consider wealth-creating income, such as financial and property rental income in the analysis, because these incomes may magnify the income gap between the rich and poor.

In addition to labor income, household income includes investment income, property income, and, more importantly, public social transfers. Although generally aiming at reducing inequality, empirical analysis shows that government transfers in China, including public pensions and social safety nets, in fact induced income inequality (*Huang et al.*, 2003; *Li et al.*, 2020). *Huang et al.* (2003) examined income inequality from a compositional perspective and paid particular attention to the contribution of government transfer income to overall income inequality in mainland China from 1993 to 2001. It was shown that the income difference between urban and rural areas have increased after government transfers during the period studied. This could be because the social transfer is administered at the local level and the amount of the transfer is directly related to regional economic development. Since rural areas tend to be less developed, transfers for rural residents are lower than for their urban counterparts.

During the 12th Five-Year Plan (2011-2015), the establishment of a sound social security system covering urban and rural residents was identified for the first time as one of the national government's priorities (*the National People's Congress of the People's Republic of China*, 2011). The government has corrected and continued to implement many social protection programs for the poor, including rural, agricultural, and farmers' measures, especially rural pension programs and education subsidies. So far, it remains unclear how the latest transfer programs contribute to the overall change of income inequality. This study includes variables that measure the implementation of the updated social security policy to examine government transfer income along with the contribution of other household income components to changes in regional and household income inequality.

3 Methodology and Data

3.1 Methodology background

Most existing studies on the determination of income inequality have used the OB decomposition method first proposed by *Blinder* (1973) and *Oaxaca* (1973). It is found that the difference between the means of two distributions could be explained by the different characteristics (the "endowment effect") and the returns to these characteristics (the "price effect"). To distinguish between these two effects, a counterfactual mean is constructed that can resemble the characteristics of one distribution and the returns of the other. Although the method mentioned is informative, its ability to examine differences between distributions is limited. Moreover, the contributions of determinants to changes in individual and family income over time are multifaceted, whereas the OB decomposition can examine only a small number of components and cannot account for the interactions among their effects. Given the complicated determinants of income distribution, such as demographic factors, labor market response, various sources of income, and social policies, a multidimensional framework would be needed to quantify distributions.

In an effort to go beyond the mean and systematically examine the entire income distribution, we adopt the decomposition method introduced by *Bourguignon et al.* (2008) and later adapted by *Sologon et al.* (2021). Based on the approach proposed by *Bourguignon et al.* (2008), *Sologon et al.* (2021) refined the model by adding a labor supply response module and a direct examination of the impact of the tax-benefit system on the income distribution. Due to data limitations, we are not able to tease out the specific contribution of the tax system to income inequality in China. However, the framework still allows us to identify the explicit impact of governmental transfers on income changes.

We first use the generic household income generation model (IGM) to estimate the econometric (parametric) structure of the labor market response and the various household income distributions as functions of individual and household characteristics. By sequentially "swapping" the characteristics in two different time periods, different counterfactual income distributions can be constructed. By comparing these counterfactual distributions, which correspond to the demographic, labor market, and social policy conditions of the alternative time period, we can quantify the impact of changes in these components on the overall household disposable income distribution. In this study, the overall change in income inequality will be decomposed into changes in four dimensions (1) demographic composition, (2) labor market structure, (3) price and return, and (4) governmental transfer. The demographic composition dimension reflects the contribution of changes in the distribution of demographic characteristics to changes in income distribution. It includes, but is not limited to, the distribution of gender, age, education, hukou, residence, and household composition. The labor market structure quantifies the contribution of changes in employment status (employed, unemployed, self-employed), occupational choice, and industry distribution to changes in the distribution of income. Price and return effects refer to the income functions of demographic and labor market factors. At this level, labor, agricultural, capital, and other incomes are modeled as returns to individuals, household characteristics, and labor market structure. Last but not least, the governmental transfer dimension focuses on the joint effect of public pensions and social safety nets on changes in income distribution. In the following section, we present in detail the methodology adopted for this paper.

3.2 General formulation of the decomposition method

In this paper, we want to compare changes in income distribution over two different periods and how socio-demographic characteristics of individuals and households contribute to such changes. Based on *Sologon et al.* (2021), the parametric model has been adapted to the dataset and variables of interest in this paper.

$$y_h = \frac{1}{n_h}\left(y_h^L + y_h^F + y_h^C + y_h^O + y_h^B - y_h^H\right) \tag{1}$$

As in the above expression, household per capita income y_h^L is defined as the combination of all labor income y_h^L, farming income y_h^F, capital investment earning y_h^C, other lump sum income y_h^O the governmental welfare transfers y_h^B, and subtracting the housing cost y_h^H, a combination of rent and mortgage, then divided by the family size n_h. Each source of income and expenditure will be modeled separately, defined by individual-level or household-level characteristics, depending on the level of the income source.

3.2.1 Labor income

Because labor income is an important component of household income and a reflection of income inequality, education, and other types of endowment inequality, this paper focuses specifically on the decomposition and parametric representation of labor income, as described further below.

Labor income is usually monitored at the individual level as the sum of different activities, such as from wage work or self-employment. Since being in wage work or self-employment in any sector of occupation can be understood as a consequence of individual characteristics such as age, education level, gender, and household registration status (hukou), a series of choice model equations will first be introduced to capture the probability of being in any type of job in a certain occupation and in a certain industry.

The binary choice of being in work or not is expressed as a logistic model, with a latent variable represents the utility for the choice, assuming $I_{hi}^{LS*} = x_{hi}\beta^{LS} + \varepsilon^{LS}$, where x_{hi} is the characteristics of the individual I is household h, ε^{LS} is the unobserved utility determinants that follows a logistics distribution.

$$I_{hi}^{LS} = \begin{cases} 1, & \text{if } I_{hi}^{LS*} > 0 \\ 0, & \text{if } I_{hi}^{LS*} \leq 0 \end{cases} \tag{2}$$

As in equation 2, I_{hi} takes the value 1 if the individual mentioned takes participation in any wage work or self-employment, and 0 if not. For simplicity, this paper treats wage work and self-employment as mutually exclusive choices. However, it should be noted that depending on the month of work, farmers who work as migrant workers during agricultural lean season can be treated as employed or self-employed in this context. The income used in the regression is annual income. As described:

$$y_h^L = I_{hi}^{LS}\left(I_{hi}^{\text{wage}}\, y_{hi}^{\text{wage}} + I_{hi}^{\text{sel}}\, y_{hi}^{\text{sel}}\right), \quad \text{in which } I_{hi}^{\text{sel}} = 1 - I_{hi}^{\text{wage}} \tag{3}$$

For the earnings obtained from self-employed family members, the extended Mincer model will be applied:

$$\ln\left(y_{hi}^{sel}\right) = x_{hi}\rho^{sel} + \omega^{sel} \tag{4}$$

where ω^{sel} represents the unobserved heterogeneity of individual self-employed earnings, which is a zero-mean term with homoscedastic variance.

In addition, for those with wage jobs, both occupation and employed sector will be monitored by a multinomial logistic model to generate the parameters for the counterfactuals.

Similar to the binary choice model, the multinominal logistic model will employ a latent variable representing the utility of occupational choice, $U_{hi}^{j,occ*} = x_{hi}\beta^{j,occ} + \delta_{hi}^{j,occ}$,with j being the occupation choice and $\delta_{hi}^{j,occ}$ as a iid follows a type I extreme value distribution.

$$P\left(I_{hi}^{j,occ} = j \mid x_{hi}\right) = P\left(U_{hi}^{j,occ*} > U_{hi}^{k,occ^*}, \forall j \neq k\right) \tag{5}$$

As in the equation, individual is expected to choose occupation j when the utility of choosing j is higher than all the other occupational choices, represented by U_{hi}^{k,occ^*}, k corresponds to the alternative occupations. The occupations are classified according to ISCO-08[2] major group categorization, which includes nine one-digit categories. The same model is used to differentiate the industries of employment, with three categories being primary, secondary and third.

After the composition of the choice models, the final step is drawing the parametric distribution between annual and personal characteristics for the employed.

Although the Mincer earnings function is the well-known and most-used model to estimate income determinants, it is also widely agreed that to further add some form of accuracy in estimating return to certain endowments and counting for uncertainty would be more ideal in labor income analysis

[2]More information can be found via: https://www.ilo.org/public/english/bureau/stat/isco/isco08/.

(*Heckman et al.*, 2003). On the other hand, the *Singh and Maddala* (2008) model has more relaxed assumptions to accommodate for heterogeneity in income, and can capture the shape and scale of the income distribution more precisely, thus Singh-Maddala distribution will be applied to represent wage income distribution as below:

$$F_X = \pi\left(y_{hi}^{\text{wage}}\right) = SM\left(y_{hi}^{\text{wage}}; a(\pi), b(\pi), q(\pi)\right) = 1 - \left[1 + \left(\frac{y_{hi}^{\text{wage}}}{b(\pi)}\right)^{a(\pi)}\right]^{-q(\pi)} \tag{6}$$

In which the wage distribution is conditional on the vector of personal characteristics π, that is shaped by three parameters, $a(\pi)$, $b(\pi)$ and $q(\pi)$ to outline the tails ($a(\pi)$, $q(\pi)$), and the scale $b(\pi)$. π includes occupation, industry that one is employed in and all the variables in x_{hi}.

3.2.2 Other income sources and expenditure

For household income received from sources other than labor income, a log-linear model will be used to demonstrate the relationship between the amount received and household or individual characteristics. To prepare the decomposition, binary logistic choice regressions will be generated for each source of income to capture the probability of receiving income from that source. Same procedure will be applied to model the relationship between housing cost and the household characteristics.

$$I_{hi}^{K,O,B,H} = 1\left[x_{hi}\alpha^{K,O,B,H} + \vartheta^{K,O,B,H} > 0\right] \tag{7}$$

$$\ln\left(y_{hi}^{K,O,B,H}\right) = x_{hi}\gamma^{K,O,B,H} + \sigma^{K,O,B,H} \tag{8}$$

where x_{hi} is the characteristics of the individual i is household h, K, O, B, H represents the income sources of capital investment, other income, government benefits, and housing expenses respectively.

The detail list of amounts received and spent from different sources and is presented in the next section.

3.3 Empirical demonstration of the decomposition process

To simplify the decomposition process and catch the most fundamental contributors to the household disposable income difference, all related factors are quantified and grouped into four broad categories for the parametric swap before the further exploration of the variables of interest. This paper will quantify the contribution of the difference is thus quantified into (1) demographic composition, (2) labor market structure, (3) price and return, (4) governmental transfer to the total household disposable income difference (*Foerster and Tóth*, 2015; *Sologon et al.*, 2021).

The effect of demographic composition will be modelled through a reweighting technique that modifies the distribution of household characteristics X_h that are generated based on personal ones from year t^1 to t^2, and conversely (*DiNardo et al.*, 1995). The variables that are included in X_h are age, gender, education, marriage status, hukou status, working status of the household head and the age range, residential location (urban or rural) and the total number of children of the family.

Change in labor market structure includes switching the parameters and the residuals that are generated for work binary choice, occupational and industry structure that was introduced in equation 2 and 5. For the labor price and return function, the decomposition will be done through the parameters and residuals that were established in equation 4 and 6, the capital investment and other lump sum income, minus the housing expenses related parts in equation 7 and 8. The last broad aspect of contribution, governmental transfer, will be evaluated via switching the α^B, ϑ^B, γ^B, σ^B for the two years.

3.4 Data

3.4.1 Data source

This paper uses data from two waves of the China Household Panel Studies (CFPS), 2010 and 2016, for the study. The CFPS is a panel dataset that has been built since 2010 and is followed up every two years. The 2010 baseline survey covers 42,590 individuals from 14,960 households nationwide, a sample of households representing 95 percent of the Chinese population. The 2016 survey has information from 45,319 individuals in 14,763 households. Compared to other large surveys in mainland China, CFPS contains more information on the individual, household, and community levels, focusing not only on the economy, but also on social, health, and immigration topics. The limitation of the dataset is that all the income reported are net income, with taxes deducted. So the redistributive effect of taxation is scattered in the effects of different income sources.

In addition, the two surveys were chosen to consonant with the beginning and end of the 12th Five-Year Plan for National Economic and Social Development of the People's Republic of China (the 12th Five-Year Plan), which can be described as one of the most important transition period for industrial upgrading and the development of comprehensive social security programs. By comparing the differences in household disposable income and their contributing factors in these two waves, the extent of the system's impact on citizens' daily lives can also be reflected to some extent.

3.4.2 Descriptive findings

With reference to Table 1, it can be seen that most of the changes in the Chinese socio-demographic features occurred in terms of educational structure and economic related factors from 2010 to 2016. From the first two rows, we can see that the share of citizens with higher education degree increased from by 4 percentage points(p.p) in five years while the share of secondary level education earners increased by 1.7 p.p. Since education level is considered an important driver of income differences, we further disaggregated the differences between rural and urban areas with a special focus on the age and gender subgroups. As presented in Table A3, the younger generation (25-34 age group) is in general getting higher education, with the population who completed tertiary education increased from 17.3 percent in 2010 to 26.4 percent in 2016. However, this number is still notably lower than that of the OECD countries, where 42 percent of people in the same age group received tertiary degree according to the data from 2015 (*OECD*, 2016). Moreover, although the differences are converging, the education gap between rural and urban areas is still evident at a later stage. To some extent, this can be attributed to the heterogeneity of the industrial structure between rural and urban areas and the differences in their demand for talent with different levels of education. And how regional labor market differences and education affect income distribution respectively will be discussed in the next chapter.

In terms of the demographic structure, the proportion of the working-age population has declined by 3.7 p.p, while the number of people over 65 years old has increased by 3.4 pp, indicating a deepening aging trend. At the same time, low fertility rates persist, with children under the age of 16 accounting for only 18.9 percent of the total population, which is considered a severely low sub-fertility rate. In response to the aging population, the national government has relaxed the One-child policy since 2011, allowing and encouraging the one-child generation to have two and more children. However, after the implementation of the Two-child policy, the percentage of children under four does not seem to have increased much in 2016.

Another point worth mentioning is that the population who de facto living in urban areas has increased by nearly 10 percent, while the population holding urban hukou has not. Since China's social security system is locally administered based on the hukou registration, those who live outside their registered areas are likely to face difficulties in receiving social security benefits. As a result, the rural population may be further disadvantaged.

In addition, the proportion of the population working in the non-agricultural sector increased by 11.2 p.p from 2010 to 2016, while the agricultural population, mainly farmers, decreased by 1.8 p.p. Furthermore, among the total working population, the number of active workers in the service sector increased by 3.8 p.p, while the number of workers in the agricultural sector decreased by 5.8 pp, possibly as a result of urbanization and structural changes in the economy. Regarding the occupational structure, it is clear that the number of workers in both high- and low-skilled occupations was expanding, while the number of workers in traditional, labor-intensive occupations, such as machine operators and crafts, was decreasing. This is consistent with the pattern of employment polarization in the United States and the United Kingdom in the late 20th century (*Autor and Dorn*, 2009; *Goos and Manning*, 2007). However, in 2016, 38.9 percent of China's active labor force was still working in the agricultural sector. Most of them work in informal farm-household system that earn a lot less than their counterparts in formal urban sectors, which may have a negative effect on inequality alleviation.

Table 1: Population and labour market structures (shares of total population)

	2010	2016
Demographic		
Tertiary Education	0.082	0.122
Secondary Education	0.446	0.463
People 16-65	0.726	0.689
People > 65	0.088	0.122
Child 0-15	0.185	0.189
Child 0-3	0.043	0.046
Married	0.750	0.757
Urban Hukou	0.261	0.261
Urban residency	0.444	0.529
Male/Female ratio	1.016	1.004
Labour market		
In-work (Employed+Self-employed)	0.382	0.494
All-work (Family farming included)	0.688	0.782
Family farming	0.306	0.288
Work type		
Self-employed	0.102	0.117
Employed	0.442	0.494
Farming	0.456	0.389
Occupation		
Senior officials and Manager	0.022	0.057
Professionals	0.055	0.067
Technicians and Associate professionals	0.031	0.038
Clerks	0.024	0.032
Services and Sales workers	0.142	0.147
Skilled agricultural workers	0.465	0.397
Craft and related trades workers	0.151	0.126
Machine operators and Assemblers	0.088	0.075
Elementary and Unskilled occupations	0.021	0.060
Industry		
Agriculture	0.462	0.404
Industry	0.237	0.257
Services	0.301	0.339
Other market factors		
With capital income	0.088	0.130
With other income	0.471	0.232

Note: The estimates are weighted. The shares for education refer to age-group 25 to 65(incl.); married and gender ratios refers to population age above 16(incl.); in-work related variables refer to ages from 16 to 65(incl.); for employees, occupation, industry and sector, refer to those who are in work; For capital and other income, refer to the household.

Note: In-work, all-work and family farming rates refers to the percentage of the population that age between 16 to 65(incl.) who holds different types of work. The sum of "In-work" and "Family farming" equals to "All-work".The rates under "Work type" are calculated based on the working population that age between 16 to 65(incl.). The sum of all three types is equal to one.

Source: CFPS 2010 and 2016, based on author's calculation.

4 Result

4.1 Changes in disposable income distribution

Table 2 shows the summary statistics of the disposable income distribution related to 2010 and 2016. We can see that both the mean and median annual disposable income of households have increased significantly in these five years of the study, constituting an increase of 92 percent and 110 percent, respectively [3] Positively, the increase in the general income level did not lead to any widening of inequality. In line with the findings of *Kanbur et al.* (2021) and *Li* (2018), the inequality index presented in this study showed a flat and decreasing trend from 2010 to 2016 [4]. Among the inequality indices presented, Theil's L-index (GE(0)) reports the largest change from 0.491 to 0.419, which is some evidence that China's economic development was pro-poor during the period studied.

Table 2: Summary statistics of equivalized household disposable income (Annually, in 2016 value)

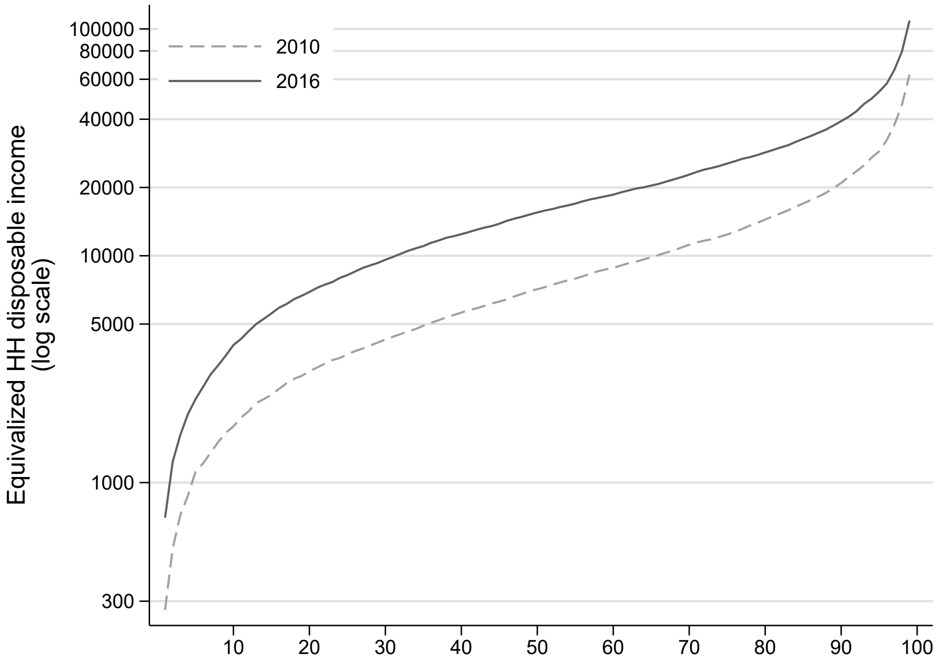
	Mean	Median	GE0	GE1	Gini
2010	11131	7539	0.491	0.495	0.498
2016	21378	15867	0.419	0.453	0.460

Note: Calculation of summary index does not consider zero household disposable income. Less than 1 percent of the sample has zero household disposable income.
Source: CFPS 2010 and 2016, author's calculations based on income adjusted for provincial price differences over year, in 2016 Chinese yuan.

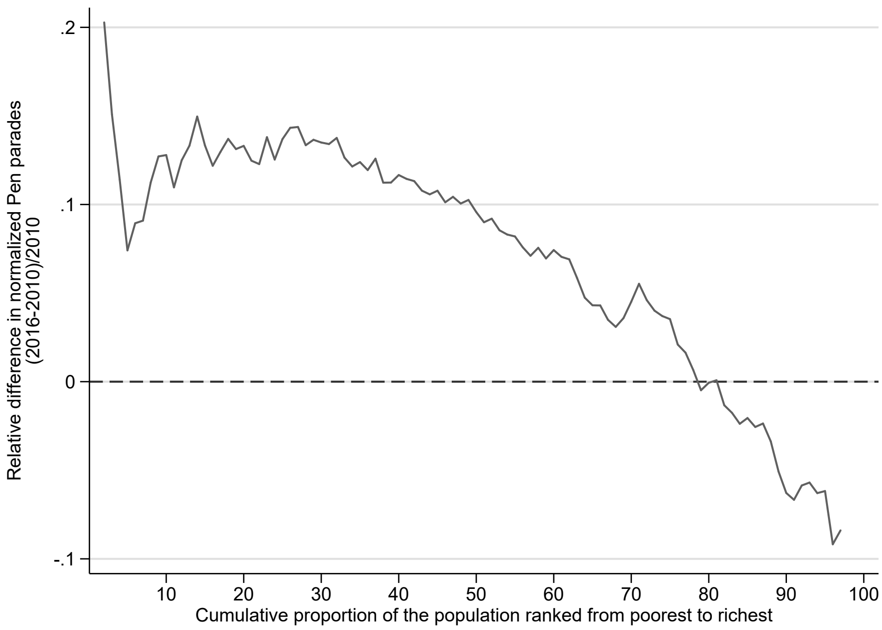
To support the above argument, we further explore the changes in the full disposable income distribution by presenting the relevant results from Pen's parades. Figure 2(a) shows the distributions of equivalized household disposable income for 2010 and 2016. We can see that all the quantiles experienced an income boost, while the 2016 distribution shows a more progressive profile compared to 2010, with a smaller income gap between the rich and poor. Figure 2(b) tells the same story, while further showing that the bottom 80 percent of earners receiving higher incomes relative to the average for that year. From the figure, the relative income growth is generally negatively correlated with income levels. In other words, China's economic development has been inclusive, with the bottom income earners enjoying more income growth comparatively. However, it is worth noting that inequality remains high in China, with a Gini coefficient of 0.46 in 2016. In both periods, the richest 5 percent to 10 percent have significantly higher incomes compared to the average.

[3] According to the Chinese National Bureau of Statistics, the national per capita disposable income was 23,821 yuan in 2016, an increase of 62.6 percent in real terms compared to 2010.

[4] In our study, the Gini coefficients for both years are slightly smaller than those from (*Kanbur et al.*, 2021). This could be due to the difference in the definitions of disposable income we used. In this article, we deducted the mortgage and housing rental costs from the total income, which *Kanbur et al.* (2021) did not.



(a) Equvalized HH income distribution(in 2016 nominal value)



(b) Growth Incidence Curve

Source: CFPS 2010 and 2016, author's calculation.

Figure 2: Changes in the distribution of equivalized household disposable income

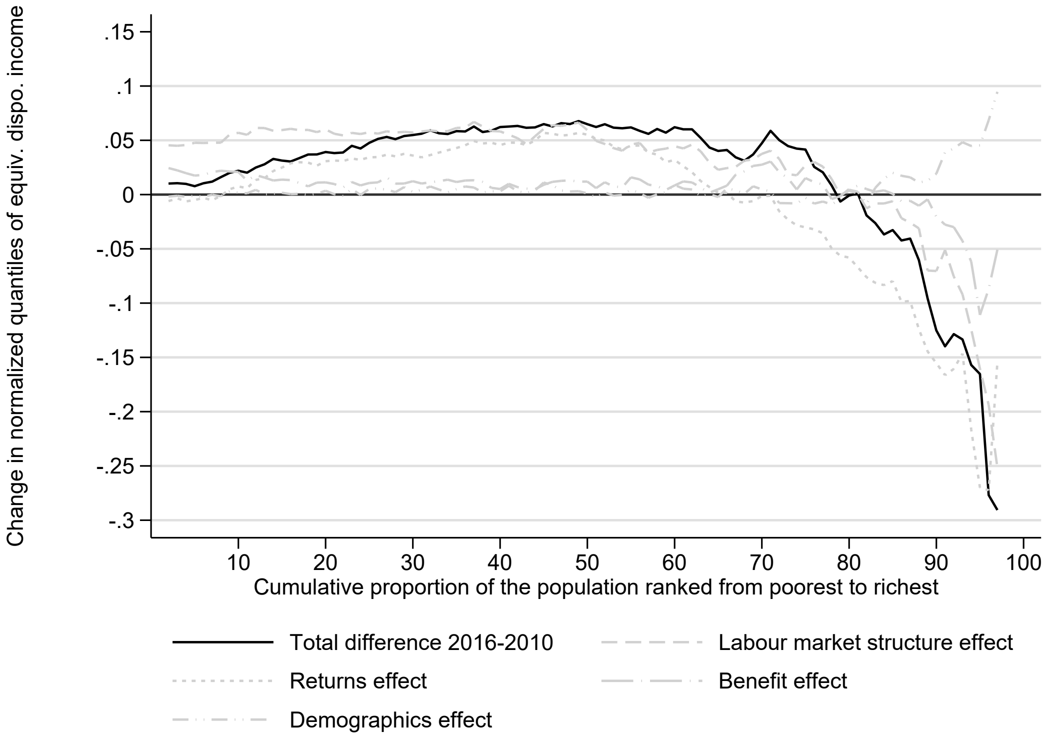
4.2 Determinants of changes in the income distribution between 2010 and 2016

This section presents the results of the counterfactual decomposition approach presented in Section 3. The drivers of changes in the income distribution are decomposed to better understand the causes of changes in income inequality.

Figure 3 shows the total differences between the household disposable income distribution in 2010 and 2016 in the form of the mean-normalized quantile function. As it can be seen in the Figure 3, the mean normalized quantile value is higher in 2016 than in 2010 until around the 80th percentile and turns negative for the top 20 percentiles. The result is consistent with the previous findings of the decreasing Gini coefficient and the relative difference in the normalized Pen's parade. What is more, the difference kept a steady increasing trend up to the 60th percentiles and turned downward afterwards. This suggests that the bottom 80th percentiles enjoys higher income growth relative to the mean over the period studied, with middle-income earners benefiting the most from all effects. To some extent, the Gini coefficient declined slightly from 2010 to 2016, which can be attributed to the expansion of the Chinese middle class and the convergence of the top earners towards the mean.

The labor market structure(LMS) transformation presented in Figure 4(a) includes the contributions of the job status factor (employed, unemployed, retired), the job type factor (employed or self-employed), the employment structure factor (occupation and industry category), and the income source factor. By applying the 2010 LMS to the 2016 data, the difference between the 2016 actual distribution and counterfactual distribution after the LMS transplant shows a similar pattern as the total difference shown in Figure 3. The positive effect for households with incomes below the 80th percentile suggests that the labor market structure has evolved inclusively from 2010 to 2016, with significant benefits for most people, especially low- and middle-income households. It is noteworthy that the labor market structure had a higher impact on the lowest 30 percent of earners than the total impact, implying that the transformation of LMS has benefited more on the low-income families. As it has shown in Table 1, more people have moved from primary sector, informal agriculture to industry and service sectors and entered relatively formal labor market. The transformation from informal to relatively formal work is especially beneficial for the low-income families whose income used to come exclusively from farming.

The returns effect quantifies the returns to the demographic and labor market factors. It includes the effects of income return to given occupations and industries on the individual level, and farming, capital and other incomes minus the mortgage and rental cost on the household level. Compared to the LMS, changes in prices and returns are concentrated in favorable impacts for a smaller number of households from around the 10th percentile to the 70th percentile. The negative differences for the poorest and richest households shown in Figure 4(b) suggests that the effect of price and return structure observed in 2016 is twofold. On the one hand, it drives the poorest 10 percent of households further away from the average income level, and on the other hand, it brings the richest households closer to the mean. The overall effect of price and returns on the alleviating income inequality is



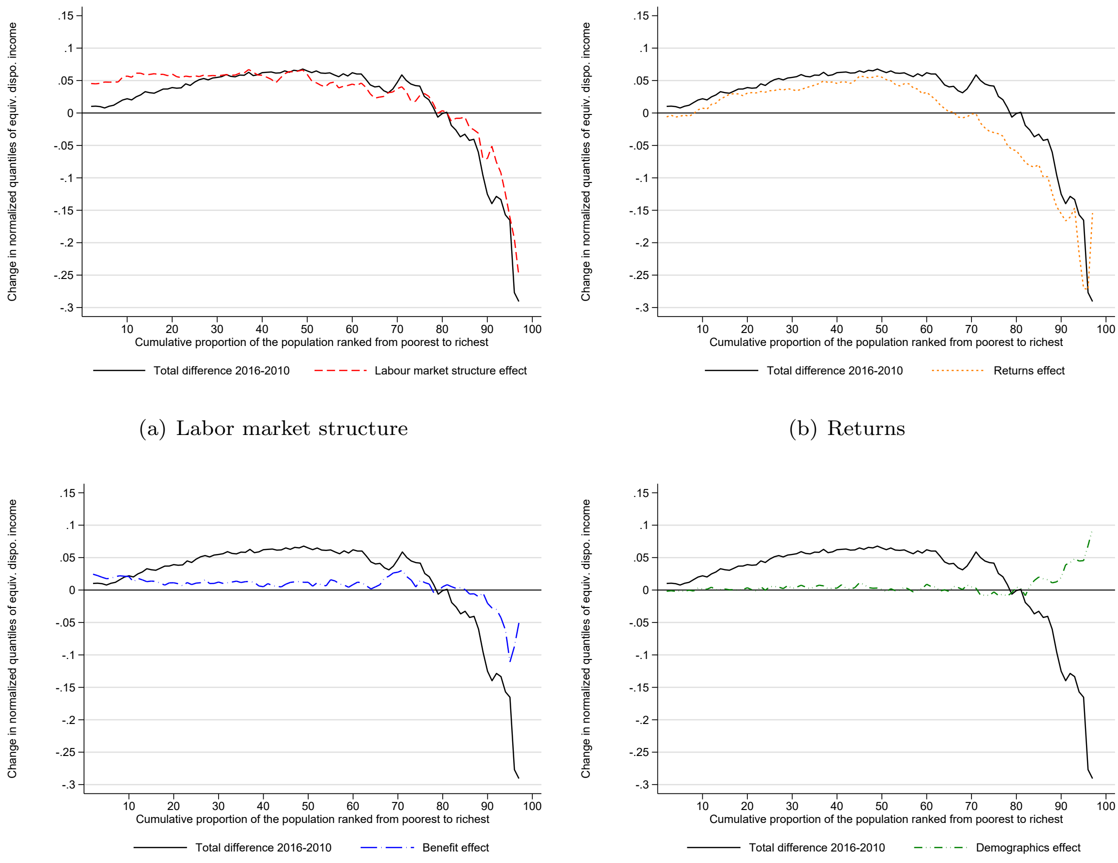
Source: CFPS 2010 and 2016, based on author's calculation.
Note: The mean-normalized quantile value is calculated as $\frac{Q2016}{Avg2016} - \frac{Q2010}{Avg2010}$.

Figure 3: Percentage changes in equivalized household disposable income

small, but positive.

The change in social protection transformation is an income booster for households up to around 83th percentile of the income distribution. This means that the reform in social security structure during the period studied has a positive effect on the majority of the households in China. However, the combined effects of public pension and social safety net did not provide sufficient redistributive functions. From Figure 4(c), the benefit effect fluctuates along the income distribution, while having a relatively higher rate around the 65th to 72th percentiles. This may be due to the fact that the amount of pension received depends on contributions made in previous employment, whereas members from low-income households have a greater chance of making limited social security contributions.

Demographic effects are generated using a nonparametric weighting technique that captures the fraction of changes in the distribution of income due to changes in the distribution of demographic characteristics. In our analysis, we considered the distribution of age, gender, education, Hukou, living region (urban or rural) and family composition. Figure 4(d) shows the difference between the



(a) Labor market structure

(b) Returns

(c) Social benefits

(d) Demographics

Source: CFPS 2010 and 2016, based on author's calculation.

Figure 4: Distributional differences across quantiles of equivalized household disposable income and counterfactuals after each transplant

actual income distribution in 2016 and the counterfactual income generated by applying the 2010 socio-demographic structure to the 2016 labor market structure, returns and social benefit scheme. Although the result in Table 1 shows that there is a large increase in the national educational attainment, the join contribution of the demographic factors to the change in income distribution is limited for the majority. Unlike the other effects, the demographic effect is positive for the top 20 percent of income earners. In the year studied, there is minimal variation in the demographic factors other than the rise in tertiary education and de-facto urban residency. Therefore, it is likely that the rises in the number of people with tertiary education and urban residency are associated with higher income, with the richest being the main beneficiaries. It should be noted, however, that the demographic effect captures only a portion of the overall education effect. This is because the demographic effect only considers the proportion of people with higher education and does not consider the returns to education.

4.3 Decomposing changes in inequality index

Here we move to examinate the contributions of the four factors to the changes in Gini indices from 2010 to 2016.

The first column of Table 3 shows the direct effects of the four factors to the changes in the Gini coefficients of the household disposable income. It is done by applying each of the four transformations of the corresponding factors in 2010 onto the original distribution in 2016 respectively and documenting the differences in the Gini coefficients between the actual distribution of 2016 and the counterfactuals. We can see that all four factors, the labor market structure, prices and returns, social benefit and demographics are contributing positively to the decrease in Gini over time. The labor market structure transformation appears as the largest equalizing effect, showing a direct effect of -0.047, followed by the return effect of -0.18. Compares to the -0.012 of policy (social benefit) effect, the labor market composition and its return are the main driving forces to the decrease in household disposable income inequality from 2010 to 2016. We can say that the economic transitions and labor market response have been inclusive and pro-poor during the 12th Five Year Plan period.

Table 4 offers a more detailed disaggregation of the contributions of the sub-factors of labor market structure(LMS) and Return to the changes in Gini coefficient over time. Interestingly, the effects of the sub-factors under LMS are heterogeneous. In-work estimates the effect of being in formal labor market, including self-employment and agricultural employment, excluding family farming work. Being in work is the largest equalizing effect within the LMS, showing a size of 3.2 p.p. With the descriptive results presented in Table 1, we know that there was an inflow of migrant workers from rural to urban area who switched from working as farmers to formally employed or self-employed individuals. Together, the present findings confirm that rural-to-urban labor migration has been effectively mitigating national income inequality (*Li and Sicular*, 2014). On the contrary, the changes in the labor market structure including the general forms of employment (employed or self-employed), occupational and industrial structures, demonstrate small yet inequality augmenting

Table 3: Decomposition of changes in equivalized income inequality

	Gini Disposable (1)	Gini Gross Income (2)	Net Redistr. (3)	Benefit Regressivity (4)	Avg. Benefit Rate (5)
2016	0.461	0.497	0.036	0.758	0.144
2016-2010	-0.036	-0.024	0.012	0.020	0.040
Contribution of direct effects (2016-2016*) to the total over year difference					
Labor market structure	-0.047	-0.052	-0.005	-0.031	-0.011
Returns	-0.018	-0.014	0.006	0.014	-0.066
Social benefit	-0.012	0.000	0.012	0.030	0.070
Demographics	-0.003	-0.006	-0.003	-0.024	-0.016
Interactions	0.080	0.075	-0.002	-0.026	0.051
Other population effect	-0.037	-0.027	0.004	0.057	0.012

Note 1: 2016* refers to the Gini coefficient generated from the counterfactual distribution after applying the transformation in respective factors of 2010.
Note 2: Gini coefficient of disposable income consider zero household disposable income, as a result, it is a slightly different than the Gini indices presented in Table 1.
Note 3: Disposable income refers to the adjusted household disposable income defined in equation 1. Gross income refers to the components without social benefit transfers.
Source: CFPS 2010 and 2016, based on author's calculation.

effect. However, the labor income effect under the return factor shows a relatively large equalizing effect of 1.3 p.p.

By comparing the difference and its decomposition between the Gini coefficients for gross income and the disposable income, we can explore to what extent the difference in net redistributive effects of the two periods can be attributed to governmental redistribution (social benefit) and gross incomes. As shown in the column 3 of Table 3, the social benefit effect contributes the most to the total difference in the net redistributive effect. Building a more integrated public pension and social safety net scheme is one of the governmental priorities during the period studies. The result shows that the change in redistribution system, particularly public pension and social safety net, has shown positive effect in reducing income gaps. The average benefit rate the benefit regressivity increased from 2010 to 2016, suggesting a more generous and equal social benefit system.

5 Conclusion and policy discussion

This paper explores the drivers of changes in the distribution of household disposable income in China from 2010 to 2016 and examines changes in the structure of labor market, the economic returns to labor and capital investment, socio-demographic factors, and the contribution of the government's social safety net and public pension redistribution programs. During the period of interest, China

Table 4: Decomposition of changes in equivalized income inequality: disaggregation of the transformations

	Gini Disposable	Gini Gross Income
2016	0.461	0.497
2016-2010	-0.036	-0.024
Contributions to changes (2016-2016*)		
Labour market Structure	-0.047	-0.052
Labour Market Structure Components		
In-work	-0.032	-0.037
Employed/Self-employed	0.001	0.002
Occupation/Industry/Sector	0.001	0.001
Has family-level income	-0.017	-0.017
Interactions	-0.000	-0.001
Returns	-0.018	-0.014
Returns Components		
Labour Income	-0.013	-0.006
Family-level income	-0.011	-0.014
Mortgage and rent	0.005	0.004
Interactions	0.001	0.001

Note 1: 2016* refers to the Gini coefficient generated from the counterfactual distribution after applying the transformation in respective factors of 2010.
Note 2: Gini coefficient of disposable income consider zero household disposable income, as a result, it is a slightly different than the Gini indices presented in Table 1.
Source: CFPS 2010 and 2016, author's calculation.

recorded a 10.3 percent nominal GDP growth rate, making it the world's second largest economy for the first time (*Yao and Zhang*, 2011). At the same time, a series of tax and welfare reforms targeting inequality in the national economy were identified as priorities for the 12th National Five-Year Plan, which is expected to reverse growing inequality and promote inclusive development in China. To clarify whether China's economic development has been reoriented to be more inclusive, we must decompose the explicit role of economic structural upgrading and national redistribution programs in changes in income inequality.

Based on household disposable income generated from the CFPS datasets, the results show that China experienced a decline in inequality between 2010 and 2016. However, the level of inequality remains high in 2016, showing a Gini coefficient of 0.46. As the main source of income in both years, the reduction of inequality in labor income helps to mitigate the total inequality.

By applying the decomposition method developed by *Bourguignon et al.* (2008); *Sologon et al.* (2021), we are able to disentangle and quantify the different drivers of the changes in income distribution. Through comparing the actual income distribution with its counterfactuals, we conclude that the changes in the labor market structure (LMS) and return factors are the largest contributors to differences in income distribution and inequality over the analyzed period, both of which are inequality mitigating factors. According to the decomposition figures, changes in LMS and returns have mostly positive effect on middle-income households, while they have the least and negative effects on the poorest and richest households.

From the decomposition of the differences in Gini coefficients in section 4.3, we see that the changes in urban labor market structure, specifically the general forms of employment, occupational and industrial structure, have been contributing as inequality augmenting factors. This could mean that the industrial upgrading in China alters the urban labor market structure, which creates more opportunities for high-skilled labors while reserving jobs for the low- and unskilled individuals. On the other hand, the labor income component under the returns factor helps reduce the income inequality by 1.3 p.p. To some extent, it implies that although the urban labor market structure in China has been polarizing, the growth rate of wages for the middle- and low-income earners were still faster than the top ones, at least during the period studied. More research on the individual level needed to be done to confirm this finding. The "in-work" component, one of the largest equalizing factors of income distribution, can be understood as the continued positive effect of labor migration on national income equality. It is consistent with the reality we see that more migrant workers are working as flexible workers in service sector, where they can earn higher incomes compares to working on family farms. However, this also means that it is important to improve and build a more inclusive and portable social protection system, especially for labor migrants.

This leads us to the discussion on the effect of social transfers. Our study shows that the social benefit factor is positive in closing the household income gap, but in a limited manner. The change in public pension and social safety net transfers improved the income levels for most of the families from 2010 to 2016 but with a limited amount. The Chinese government has been doing more work on building a comprehensive social security system and fulfilling its role of income redistribution for the past decades (*Li and Sicular*, 2014). The results suggest that there is positive effect with the redistribution reform, yet there is more to be done.

To ensure that inequality can be further reduced, China needs to continue to promote industrial upgrading and rural-to-urban labor transition, while guaranteeing a minimum income for agricultural workers. From 2010 to 2016, changes in the public pension program have served as an income booster for low- and middle-income households. It is important to continue providing them with a higher minimum pension benefit.

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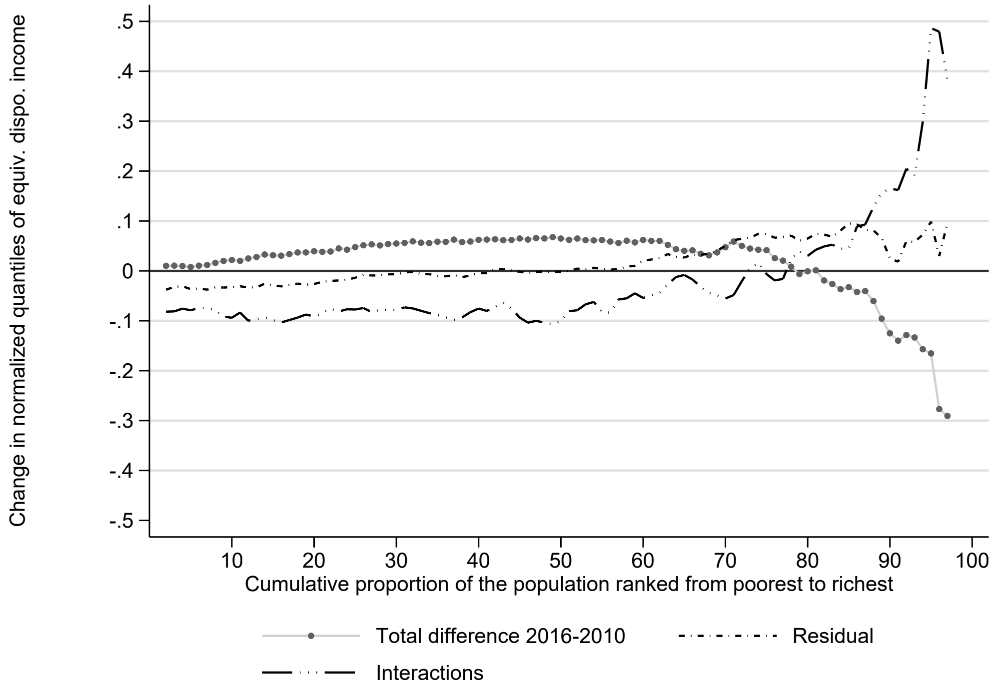
Appendix



Source: CFPS 2010 and 2016, author's calculation.

Figure A1: Decompostion of changes in the distribution of equivalized household disposable income (Other population effect)

Table A1: Definition of income components and summary modelling information

Variable	Definition	Level	Treatment	Factor	Model	Conditioning variables
y_h	total household disposable income	household	aggregate		–	–
y_h^L	gross labor income (tax deducted)	household	aggregate		–	–
I_{hi}^{emp}, y_{hi}^{emp}	employee income (tax deducted, receipt, amount)	individual	modelled	Returns	logit, Singh-Maddala	x_{hi}, occ_{hi}, ind_{hi}
I_{hi}^{se}, y_{hi}^{se}	self-employment income (tax deducted, receipt, amount)	individual	modelled	Returns	logit,log-linear	x_{hi}
I_h^F, y_h^F	household farming income (net income, receipt, amount)	household	modelled	Returns	logit,log-linear	x_h
I_h^C, y_h^C	capital income (property and investment, receipt, amount)	household	modelled	Returns	logit, log-linear	x_h
I_h^O, y_h^O	other incomes (receipt, amount)	household	modelled	Returns	logit, log-linear	x_h
y_h^H	housing expenditure	household	aggregate	Returns	–	–
I_h^{Rent}, y_h^{Rent}	Rent paid (Paid, amount)	household	modelled	Returns	logit, log-linear	x_h
I_h^{Mort}, y_h^{Mort}	Mortgage paid (Paid, amount)	household	modelled	Returns	logit, log-linear	x_h
y_h^B	public transfer (net amount)	household	aggregate	Benefit	–	–
I_{hi}^{Pen}, y_{hi}^{Pen}	public pension (receipt, amount)	individual	modelled	Benefit	logit, log-linear	x_{hi}
I_h^{Safe}, y_h^{Safe}	social safety net (receipt, amount)	household	modelled	Benefit	logit, log-linear	x_h

Note: Imputed consumption value included in household farming income.

Table A2: Demographic and labor market variables

Variable	Definition	Level	Treatment	Factor	Model	Conditioning variables
x_h	household-level demographic characteristics (number of children aged 0–3, 4–11, 12–15 or 0-15 collectively) and individual characteristics of the household head (marital status, gender, age and age squared, university education, secondary education,household registration, area of residence)	household	observed	Demo	–	–
x_{hi}	individual-level characteristics: gender, age and age squared, university education, marital status, number of children in the household (aged 0–3, 4–11 and 12–15, or 0-15), household registration, age*university, age squared*university, sex, sex*university, age*sex, area of residence	individual	observed	Demo	–	–
occ_{hi}	occupation(1-digit ISCO); for working individuals only	individual	modelled	LMS	multinomial logit	x_{hi}
ind_{hi}	industry sector (primary, secondary or tertiary); for working individuals only	individual	modelled	LMS	multinomial logit	x_{hi}
y_{hi}^{emp}	employed income; for employees only	individual	modelled	Returns	Singh-Maddala	x_{hi}, occ_{hi}, ind_{hi}
y_{hi}^{se}	self-employed income; for self-employed only	individual	modelled	Returns	log-linear	x_{hi}
$retired_{hi}$	retired	individual	modelled	LMS	logit	x_{hi}
$uenemployed_{hi}$	unemployed	individual	modelled	LMS	logit	x_{hi}

Table A3: Education attainment disaggregation

	2010				2016			
	Rural		Urban		Rural		Urban	
	No.	%	No.	%	No.	%	No.	%
Tertiary	336	2.25	1,851	14.79	570	4.74	2,044	18.38
Secondary	5,502	36.90	6,657	53.20	4,857	40.36	5,694	51.19
Primary	4,105	27.53	2,087	16.67	3,130	26.01	1,857	16.70
Semi/iliterate	4,969	33.32	1,920	15.34	3,476	28.89	1,528	13.74
Total	14,912	100	12,515	100.00	12,034	100	11,123	100
25-34 age group								
Tertiary	217	6.37	894	29.81	484	15.12	1,208	37.71
Secondary	1,733	50.91	1,658	55.29	1,758	54.95	1,546	48.27
Primary	894	26.26	347	11.57	698	21.81	351	10.97
Semi/iliterate	560	16.46	100	3.33	260	8.12	98	3.05
Total	3,405	100	2,999	100	3,199	100	3,202	100
Female								
Tertiary	123	1.71	835	13.18	256	4.36	958	17.10
Secondary	2,017	27.88	3,147	49.7	1,841	31.29	2,714	48.42
Primary	1,882	26.01	1,088	17.18	1,510	25.68	923	16.47
Semi/iliterate	3,214	44.41	1,263	19.94	2,275	38.67	1,010	18.01
Total	7,236	100	6,332	100	5,882	100	5,605	100
Male								
Tertiary	213	2.77	1,018	16.46	314	5.10	1,086	19.68
Secondary	3,485	45.4	3,514	56.83	3,019	49.08	2,981	54.02
Primary	2,223	28.96	999	16.15	1,620	26.33	934	16.93
Semi/iliterate	1,755	22.87	652	10.55	1,199	19.49	517	9.37
Total	7,676	100	6,183	100	6,152	100	5,518	100

Note: Other than the disaggregation for the 25-34 (incl.) age group, the total shares for education refer to age-group 25 to 65(excl.)
Source: CFPS 2010 and 2016, author's calculation.