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Measurement and Decomposition Analysis of Occupational Income Inequality in China

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Abstract: Using the China CFPS database, this paper measures the degree of intra-occupational inequality in China with the Pareto coefficient and uses the generalized entropy index to decompose the top income gap by region as well as by industry. The empirical results show that, firstly, the degree of income inequality between occupations in China has increased significantly in recent years. The provinces with a higher degree of income inequality between occupations are mostly located in the more economically developed regions in the central and eastern parts of the country, while the degree of inequality between occupations in the western part is lower. Secondly, the highest-income occupations are mainly in the manufacturing industry, with relatively high levels in the construction industry, the education sector, the wholesale and retail trade, and public administration and social organizations, while the levels in other occupations are relatively low. Lastly, the top income gap primarily originates from within industries. However, the contribution rate of the top income gap between industries is gradually increasing, while the contribution rate of the top income gap within industries is gradually decreasing.

Keywords: occupational income inequality; Pareto coefficient; generalized entropy index

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1. Introduction

It is well known that since the reform and opening up policy in the early 1980s, economic development in China has seen remarkable progress in all aspects; in particular, both people's incomes and lives have improved significantly. However, the year-on-year widening of the income gap remains a concern for society as a whole. Income inequality in China began to exceed that of developed countries such as Germany, the Republic of Korea, and the United Kingdom in 2001. Since then, the Gini coefficient has consistently been above the warning line at 0.40 and has continued to rise recently.

According to the "Distribution of Household Wealth and High Net Worth Household Wealth in China 2021" report, the average income of the top 5% affluent households, by total assets, is about RMB 272,000, while the average annual income of the top 1% affluent households is about RMB 494,000. For annual income, the average for the top 5% affluent households is about $452,000, and for the top 1% affluent households, it is about $1.151 million. Nationally, 48.7% of household income is derived from wage and salary income, followed by transfer income (25%) and income from business operations (16%). In the top 1% of households, the share of income from business operations in total income is the highest at 45.4%, followed by wage and salary income (20.2%) and transfer income (17.1%). In the top 5% of households, the share of wage and salary income in total income is similar to that of business income, at 34.3% and 33.5%, respectively. For ordinary households (those in the 40–60th percentile of assets), wage and salary income and transfer income account for 58.1% and 25.8% of total income, respectively, which are slightly higher than the national average, while income from business operations constitutes only 5.4% of total income. The Gini coefficient for Chinese residents at the beginning of the reform and opening up period was about 0.28, indicating that income disparity in China as a whole was relatively stable. However, by 2018, China's Gini coefficient had risen sharply to 0.474, and the income share of the top 10% of the population had surged from 26% in 1980 to 41.7% in 2008, making the issue of income inequality increasingly severe.

How to measure wealth inequality in China is of major concern. For example, refs. [1–3], among others, measured wealth inequality in China and the existing literature provides a theoretical and empirical foundation for research on income inequality. However, there are several shortcomings. Firstly, the measurement of income inequality predominantly relies on the Gini coefficient and other related inequality indices. Researchers often judge the degree of inequality based on changes in these indices. The literature primarily focuses on measuring China's overall wealth or income inequality, with a notable absence of studies on occupational income inequality. Secondly, since the 1980s, the rise in top incomes has been accompanied by an increase in the inequality of these incomes. The topic of high income inequality has been widely debated in academic circles. The study of high income inequality within occupations can significantly impact the formulation of income distribution policies. Recently, the new requirement put forth by the Chinese Government is to "raise stable employment to a strategic level for overall consideration". In conjunction with this, many analysts in recent years have conducted analyses on the prospects of different occupations to guide future research directions and employment planning for Chinese college graduates. This paper tries to provide a comprehensive analysis of high income inequality within occupations in China. Additionally, the analyses of occupation prospects conducted by many analysts in recent years have guided the future research and employment planning of Chinese college graduates. The scientific measurement of income inequality within occupations across 31 provinces and cities as well as autonomous regions (for brevity, 4 cities and 5 autonomous regions are still considered provinces) in this paper can provide certain employment references for job-seekers, thus aligning with China's policy direction of efficient and stable employment. Secondly, by extracting the top ten occupational incomes to measure the associated income inequality, this paper focuses on the highest levels of occupational income inequality, which broadens the scope of income inequality research and adds new perspectives to the measurement of income inequality.

The rest of the paper is organized as follows. Section 2 reviews the relevant literature and Section 3 describes the statistical tools used to measure occupational income inequality and to perform decomposition analysis. In Section 4, we detail the coefficient of internal inequality of the top ten occupations by wage income in 31 provinces in China using the Pareto distribution, and Section 5 measures the internal income inequality of the top ten occupations by income in each region of China and analyzes the decomposition. Finally, Section 6 concludes the paper.

2. Literature Review

2.1. Wealth Inequality Measurement in China

The two most important dimensions for depicting the rich–poor divide are income and wealth inequality. The former reflects the current state of the divide in terms of cash flow, while the latter represents the accumulation of the divide in terms of assets. The study of global income and wealth inequality originated in [4] for cross-country analysis, which compared income disparity data among some developed countries in the first half of the 20th century and introduced the renowned "inverted U-shape" hypothesis, which suggests that a country's income disparity first increases and then decreases with different stages of economic development. As country-specific data became available, economists turned their attention to global disparities in wealth and income distribution, examining the historical facts of inequality in one or more countries. For instance, ref. [5] utilized inheritance tax data, capital income data, and property household survey data from the United Kingdom to investigate wealth distribution inequality trends from 1922 to 1972. Similarly, ref. [6] estimated the long-term trends in the income share of high-income individuals in France and the United States throughout the 20th century.

With the progression of economic globalization and increasing concerns about social justice, long-term cross-country research on income and wealth distribution has garnered significant attention. Scholars have been combining various data sources such as tax records, household surveys, balance sheets, and rich lists from different countries. By employing the same or similar methodologies, they have constructed comparable indicators of income and wealth inequality, allowing for direct cross-country comparisons. A prime example of such a database is the World Inequality Database (WID), established in 2015, which now encompasses nearly 120 countries or territories worldwide, with data spanning up to 200 years. Table 1 presents the findings of calculations using the Chinese data from the WID, which shows that there are two distinct differences in the income distribution of Chinese residents compared to the global pattern. First, the average income of the low-income group in China (for instance, the bottom 50%) is higher than the global average for low-income groups. Second, the average income of the high-income group in China (comprising the top 10% and 1%) is lower than the average income of high-income groups globally.

Table 1. Mean income and wealth of different groups in the world and China in 2022 with unit RMB.

Position in Global Revenue Distribution	Average Pre-Tax Annual National Income per Capita	Average Value of Personal Net Worth	Position in China's Income Distribution	Average Annual Pre-Tax per Capita Income in China
Bottom 50%	1486.5	1470.4	Bottom 50%	12,048.9
Middle 40%	18,049.2	48,386.1	Middle 40%	95,491.8
Top 10%	100,829.3	201,748.6	Top 10%	385,704.9
Top 1%	383,724	1,056,727.1	Top 1%	1,399,003.6
Top 0.1%	1,557,726.6	5,658,806	Top 0.1%	6,995,018

Note: The results pertaining to global income distribution are derived from the World Inequality Database. All reported results are expressed in constant 2023 RMB prices, with conversions made using purchasing power parities (PPPs). Household income and wealth are assumed to be distributed equally among adult members of the household, irrespective of the presence of children.

With the successive implementation of large-scale household surveys and the adoption of new methodologies, a growing body of research has emerged, delving into the evolving dynamics of wealth inequality in China. Since the beginning of the 21st century, the wealth gap among Chinese residents has been widening, with the Gini coefficient of wealth increasing from 0.538 in 2002 to 0.739 in 2010, marking a rise of nearly 40% as in [1]. Part of the literature attempts to merge micro-survey data with rich list data to address the issue of underestimating wealth disparities. For instance, ref. [2] developed the generalized Pareto interpolation method, which was initially employed by [3] to measure the wealth inequality of Chinese residents. Utilizing CHIP data for 1995 and 2002, and CFPS data for 2010 and 2012, and analyzing these in conjunction with corresponding years' data from the Hurun Rich List, they found that the wealth share of the top 10% increased from 40% in 1995 to 67% in 2015. Meanwhile, the wealth share of the middle 40% class decreased from 43% to 26%, and the wealth share of the bottom 50% class remained below 7%.

2.2. Measurement of Income Disparity in China

Income, particularly wage income, serves as the primary source of household wealth accumulation. Consequently, income disparities are a significant driver of wealth inequality as addressed by [6,7], and [8], respectively. This process is further accelerated by variations in savings rates across different social classes as in [9]. On the other hand, wealth generates income through channels such as interest, dividends, and rents. The distribution of wealth influences the distribution of income to a certain degree as in [10]. Wealth appreciation among wealthy households is likely to be much higher than that of the average wage earner as in [11]. Moreover, wealth inequality contributes to broader inequality by limiting the accumulation of human capital among the poorer segments of society as elaborated by [12] and by affecting entrepreneurial opportunities discussed by [13], which in turn amplifies income inequality. Ref. [14] conducted a comparative study of the determinants of income inequality in China and the United States using comparable data. They found that China's income inequality is primarily driven by regional disparities and the urban–rural divide. In contrast, factors contributing to income inequality in the United States include family structure and race. Using various survey data, ref. [14] empirically demonstrated that China's income inequality has been at a high level since 2005, with the Gini coefficient ranging from 0.53 to 0.55.

There are two main opposing views in the research on China. One view is that the gap between the rich and the poor in China, including both the wealth gap and the income gap, is widening. For example, ref. [15], using CHIP data from 1995 and 2002, demonstrated that the distribution of wealth in China has become more unequal, and this trend is primarily due to the significant widening of the gap between urban and rural areas. Furthermore, ref. [16], also using CHIP data, found that from the mid-1990s onwards, shifts in property rights have led to greater wealth inequality between different occupational groups and between groups working in different types of work organizations. Also, ref. [17], using CHNS data, concluded that while income inequality has increased following economic reforms, wealth inequality has actually been decreasing in recent years, suggesting that the benefits of the economic reforms have been more widely shared. Moreover, ref. [18] utilized data from the China 2004–2015 Health and Nutrition Survey (CHNS), with the results showing that minimum wage increases can reduce household income inequality. Finally, ref. [19] used data from the China Health and Nutrition Survey (CHNS) with the findings indicating that the primary distribution system reforms significantly influenced wage inequality across all income strata. From 1989 to 1997, wage inequality was mainly driven by unexplained wage variances. However, between 1997 and 2006, reforms became a key factor exacerbating wage inequality, which was further accentuated by rising educational levels and shifts in employment sectors. After 2006, the reforms shifted towards promoting equity, helping to mitigate wage inequality.

In summary, the measurement of income inequality primarily depends on the Gini coefficient and other relevant inequality indices. The degree of inequality is then assessed by analyzing the changes in these inequality indices. Furthermore, the aforementioned literature concentrates on measuring overall wealth inequality or income inequality in China, and to date, there appears to be a lack of research on the measurement of intra-occupational inequality within the country.

3. Statistical Methodologies

3.1. Pareto Coefficient

It is well documented in the literature that income and wealth distribution are skewed to the right, exhibiting a thicker upper tail distribution, which means there is a substantial and slowly declining share of income or wealth at the top. In fact, this statistical characteristic fundamentally determines the state of wealth inequality and can illustrate the wealth distribution in most countries over the majority of time periods. The key feature of the distribution introduced by Pareto is the linear relationship between the logarithm of the proportion of individuals (p_w) with wealth greater than w and the logarithm of w itself. The Pareto distribution describes a distribution known as a decaying distribution, which, similar to the power function, displays "thick tails". This concept later came to be known as "Pareto's Law".

In modeling, the upper end of the income and wealth distribution is usually described by a Pareto I (or "power law") distribution. In the case of income or wealth, this distribution is expected to be only in the upper tail, i.e., above some minimum level of wealth $\overline{w}$. The Pareto distribution is the model that describes the top wealth distribution and is sometimes used to model the distribution of wealth in the Forbes list of the rich. The Pareto I distribution function is

$$F(w) = 1 - [\overline{w}/w]^{\alpha}, \quad w > \overline{w},$$

and its density is $f(w) = \alpha\overline{w}^{\alpha}w^{-1-\alpha}$, where α is a parameter that captures the "weights" of the upper tail of the distribution, and $\overline{w}$ is a parameter of the "localization" distribution (a threshold value). The proportion of the population with wealth greater than or equal to $\overline{w}$ is $p_w = 1 - F(w)$. The linearity of the Pareto chart follows the following equation:

$$\log(p_w) = \log(\overline{w}^{\alpha}) - \alpha\log(w).$$

Based on theoretical and empirical findings, in this paper, we measure maximum intra-occupational income inequality through the estimated Pareto parameters α and $\overline{w}$. Consider a set of observations of $\{x_i\}_{i=1}^{N}$, where N is the number of observations observed from a Pareto distribution with two parameters: the minimum and the Pareto parameter α. The maximum likelihood estimate for the minimum is $x_{\min} = \min\{x_i\}_{i=1}^{N}$ and the Pareto parameter is estimated by

$$\hat{\alpha}^{-1} = \frac{1}{N}\sum_{i=1}^{N}\ln(x_i/x_{min}).$$

The estimated parameter of the Pareto inverse is the average logarithmic distance from the observation to the minimum (the chosen threshold value). The estimated Pareto parameter is therefore a measure of income inequality. In this paper, the 70th percentile of income is chosen as the measure of x_{min}. Note that the reason of using the 70th percentile is given in Sections 4.2 and 4.3 later. This results in the calculation of the provincial Pareto coefficient

$$\hat{\alpha}_{p,j}^{-1} = \frac{1}{N_{p,j}}\sum_{i=1}^{N_{p,j}}\ln(x_{p,j,i}/x_{p,j,min}),$$

denoting the province-wide Pareto coefficient for province p in year j, which measures the maximum income inequality in a province in a given year, where $x_{p,j,min}$ denotes the maximum income threshold for the province as a whole in province p in year j, which is replaced in this paper by the 70th quartile income value, and $N_{p,j}$ denotes the number of observations in province p in year j that exceeded this threshold of $w_{p,j,min}$. Calculation of the Pareto coefficient for the top ten occupations in each province is given by

$$\hat{\alpha}_{p,j,k}^{-1} = \frac{1}{N_{p,j,k}}\sum_{i=1}^{N_{p,j,k}}\ln(x_{p,j,k,i}/x_{p,j,k,min}),$$

indicating the highest income inequality for occupation k in province p in year j, where $N_{p,j,k}$ is the number of observations of important occupations k in province p in year j, i.e., the number of people engaged in k occupations exceeding the threshold value of $x_{p,j,min}$, which is the minimum income value of occupation k in province k in year j. Here, we consider the occupation set $k \in K_{p,j}$, a collection of the 10 most important occupations in the top 30% of income distribution for province p in year j. The importance of occupations is measured by using the observed frequency of year j occupation wealth levels being above the threshold $x_{p,j,k,min}$. The more frequent, the more important the occupation is.

3.2. GE Index

To determine the contribution of income disparities among different population groups to regional inequality, first, we use the generalized entropy (GE) index as in [20,21] to measure the extent of inequality. The GE index is expressed as follows:

$$I(y) = \begin{cases} \sum_{i=1}^{n} f(y_i)[(y_i/\mu)^c - 1], & \text{if } c \neq 0,1 \\ \sum_{i=1}^{n} f(y_i)[(y_i/\mu)\log(y_i/\mu)], & \text{if } c = 1, \\ \sum_{i=1}^{n} f(y_i)[\log(y_i/\mu)], & \text{if } c = 0. \end{cases}$$

In the above formula, $I(y)$ is the overall level of inequality, y_i is the income of the i-th sample, and μ is the average income of all samples. As for parameter c, no matter what value is taken, the GE index can be added and decomposed. When $c = 1$, the GE index becomes the Theil index. Regardless of whether $c = 1$ or $c = 0$, the results of the two inequality indices are basically the same, so that for simplicity, we take $c = 0$; that is, GE(0).

On the basis of the measured GE index, we group the sample by urban and rural areas or regions, decompose the GE index into group inequalities and inter-group inequalities, and calculate the contribution of intra- and inter-group inequalities to total income inequality separately. According to [22,23], the decomposition of the GE index is shown as follows:

$$I(y) = \sum_{g=1}^{k} W_g I_g + I(\mu_1 e_1, \ldots, \mu_k e_k),$$

where

$$W_g = \begin{cases} f_g(\frac{\mu_g}{\mu})^c, & \text{if } c \neq 0,1 \\ f_g(\frac{\mu_g}{\mu}), & \text{if } c = 1 \\ f_g, & \text{if } c = 0. \end{cases}$$

In the above equation, k is the number of identified subgroups, I_g denotes the inequality (GE index value) of group g, μ_g is the per capita value of group g, e_g is a vector of length n_g, n_g is the number of people in group g, n is the total population, and $f_g = n_g/n$. Also, $W_g I_g$ denotes the degree of inequality within a group and $W_g I_g / I_{(y)} \times 100$ stands for the contribution of the inequality degree of group g to the overall inequality degree. Finally, $I(\mu_1 e_1, \ldots, \mu_k e_k)$ denotes the inter-group inequality component of the total inequality degree and $I(\mu_1 e_1, \ldots, \mu_k e_k)/I(y) \times 100$ represents the contribution of the inter-group inequality degree to the overall inequality degree.

4. Measurement of Occupational Income Inequality

4.1. Data

The income data are from the Chinese Household Tracking Survey, published by the National Centre for Social Research at Peking University. Conducted in 2010, the survey reflects changes in demographic characteristics, income and expenditure, agricultural production, economic activities, and non-economic benefits of Chinese households by tracking and collecting data at the individual, household, and community levels. The survey employs a stratified multistage sampling method, and the sample results are representative of about 95% of the Chinese population. This paper uses data from five periods of the annual adult pools in 2014, 2016, 2018, 2020, and 2022 with sample sizes: 7879, 4350, 8477, 7370, and 7727, respectively. The income data in this paper are derived from wages, bonuses, cash benefits, and in-kind subsidies of the "current most important job", after deducting taxes and contributions to five insurances and one pension. The classification of occupations is based on the Eriksson–Goldthorpe–Portocarero model occupational classification criteria used in the CFPS adult database. The sample selection is constrained by a current work status of being employed and an employment age of at least 25 years for the selected sample.

4.2. Analysis of Measurement Results

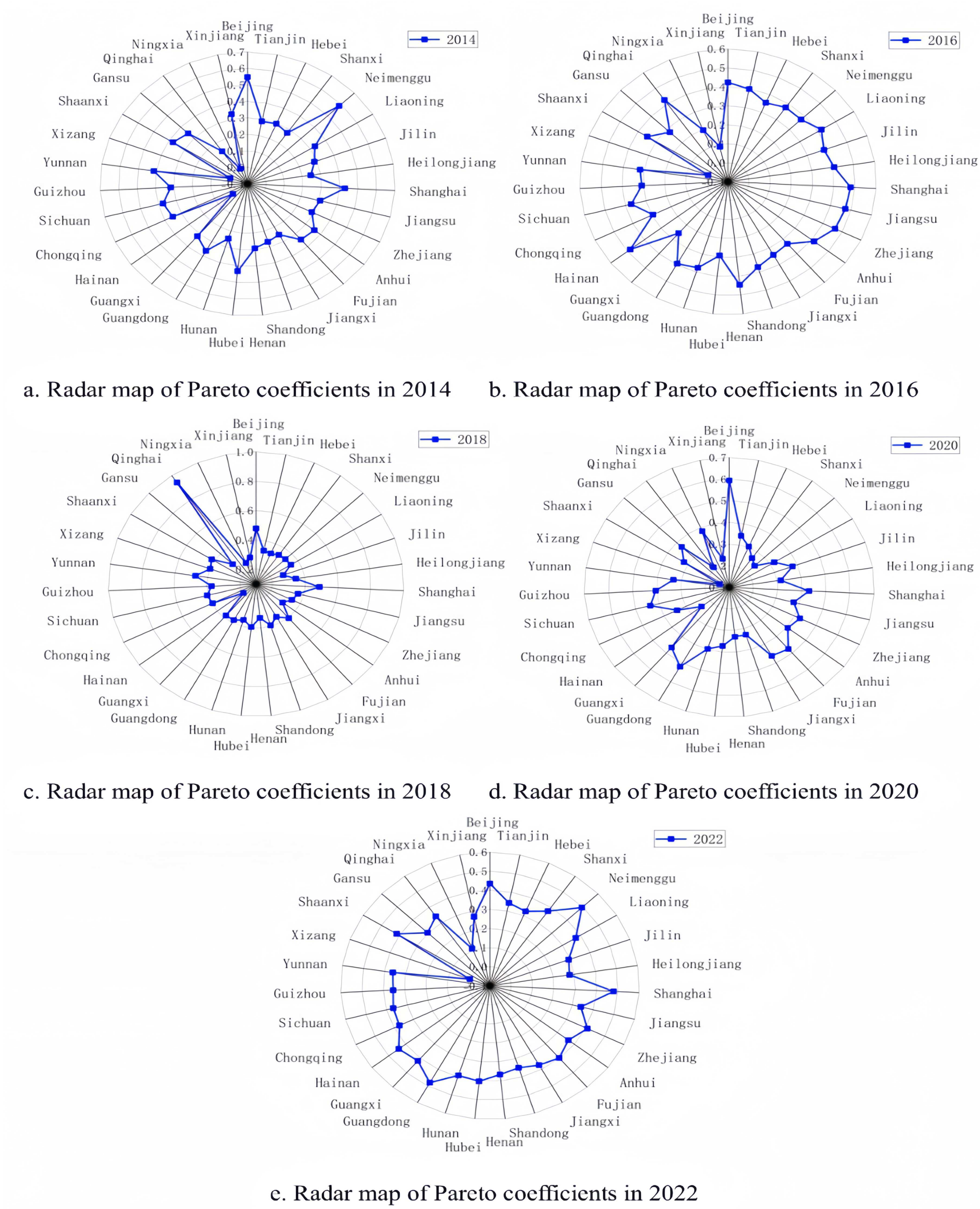
Using the Pareto coefficient formula, first, the Pareto coefficients are computed for the overall top incomes across China's 31 provinces for the years 2014, 2016, 2018, 2020, and 2022, respectively. Subsequently, the intra-occupational Pareto coefficients are measured for the top 10 income-earning occupations within each of China's 31 provinces. Table 2 presents the results of the Pareto coefficient measurements for the 70th percentile of top incomes throughout China for the years 2014, 2016, 2018, 2020, and 2022, respectively. Note that the literature commonly employs the 50th, 70th, and 90th percentiles; see, for example, the papers by [24,25] for details. However, the sample size for China's 90th percentile data is too small. Therefore, this paper opts to use the 70th percentile. To see how sensitive the choice of the threshold value is, a robustness test is conducted in Section 4.3 by using the 50th percentile data for 2022. The ranking results for each year are provided in parentheses.

The results in Table 2 show that in 2014, three provinces with a high Pareto coefficient (Inner Mongolia with a coefficient at 0.586, Beijing with a coefficient of 0.548, and Hubei with a coefficient of 0.432) were ranked as the top three regions in China with the highest income inequality. The Pareto coefficients for Hainan, Tibet, and Ningxia were all zero in that year because their samples either contained only one individual or those who exceeded the sample income happened to have equal incomes, except for the three regions mentioned above. The 28th highest Pareto coefficient was 0.141 for Qinghai. Inner Mongolia, which had the highest income and most inequality, had a Pareto coefficient nearly five times higher than that for Qinghai. In 2016, the regions with Pareto coefficients of 0.4 or higher included Hainan at 0.484, Shanghai at 0.480, Jiangsu at 0.472, Zhejiang at 0.463, Henan at 0.447, Qinghai at 0.425, Beijing at 0.423, Liaoning at 0.419, Anhui at 0.414, and Heilongjiang at 0.407, with the exception of Tibet, which had a Pareto coefficient of 0.000. The region with the highest income and most equality was Xinjiang, with a Pareto coefficient of only 0.088. In 2018, Qinghai jumped to first place with a coefficient of 0.943, while Shanghai was ranked second with 0.487, and Beijing was ranked in third place with 0.479. Hainan was the only province in China with a Pareto coefficient below 0.20 in 2018, with a value of only 0.198, making it the province with the most equal top incomes that year. In 2020, Beijing had the most unequal top incomes, with a Pareto coefficient of 0.595, which was also higher than the coefficient for Guangdong at 0.519. Tibet, with a Pareto coefficient of 0.143, far below that of other Chinese provinces, was the region with the most equal top incomes in 2020. In 2022, Inner Mongolia, Shanghai, and Guangdong were in the top three rankings for top income inequality that year, with coefficients of 0.495, 0.481, and 0.480, respectively, while Xinjiang, Ningxia, and Tibet were in the bottom three, with coefficients of 0.269, 0.111, and 0, respectively.

Table 2. Pareto coefficients for top income inequality in the 70th percentile of 31 provinces in China in 2014, 2016, 2018, 2020, and 2022, respectively.

Province	2014	2016	2018	2020	2022
Beijing	0.548 (2)	0.423 (7)	0.479 (3)	0.594 (1)	0.435 (5)
Tianjin	0.287 (22)	0.399 (11)	0.332 (23)	0.343 (17)	0.343 (23)
Hebei	0.297 (18)	0.353 (19)	0.327 (25)	0.305 (25)	0.324 (25)
Shanxi	0.277 (23)	0.377 (14)	0.342 (22)	0.265 (26)	0.376 (12)
Inner Mongolia	0.586 (1)	0.376 (15)	0.346 (19)	0.244 (28)	0.495 (1)
Liaoning	0.331 (14)	0.419 (8)	0.350 (18)	0.319 (23)	0.374 (14)
Jilin	0.287 (21)	0.383 (13)	0.276 (29)	0.379 (13)	0.293 (27)
Heilongjiang	0.247 (27)	0.407 (10)	0.345 (20)	0.315 (24)	0.278 (28)
Shanghai	0.429 (4)	0.480 (2)	0.487 (2)	0.431 (7)	0.481 (2)
Jiangsu	0.306 (17)	0.472 (3)	0.363 (15)	0.375 (14)	0.340 (24)
Zhejiang	0.289 (20)	0.463 (4)	0.344 (21)	0.425 (8)	0.408 (8)
Anhui	0.359 (9)	0.414 (9)	0.304 (26)	0.406 (9)	0.365 (18)
Fujian	0.345 (11)	0.331 (22)	0.406 (7)	0.475 (3)	0.398 (10)
Jiangxi	0.252 (25)	0.342 (21)	0.355 (17)	0.462 (5)	0.375 (13)
Shandong	0.268 (24)	0.372 (18)	0.394 (10)	0.329 (21)	0.350 (21)
Henan	0.292 (19)	0.447 (5)	0.332 (24)	0.330 (20)	0.367 (17)
Hubei	0.432 (3)	0.291 (26)	0.394 (11)	0.372 (15)	0.402 (9)
Hunan	0.247 (26)	0.376 (16)	0.356 (16)	0.398 (11)	0.392 (11)
Guangdong	0.365 (8)	0.394 (12)	0.380 (13)	0.519 (2)	0.480 (3)
Guangxi	0.318 (15)	0.257 (28)	0.382 (12)	0.466 (4)	0.418 (6)
Hainan	0.000 (29)	0.484 (1)	0.198 (31)	0.245 (27)	0.440 (4)
Chongqing	0.352 (10)	0.294 (25)	0.395 (9)	0.340 (18)	0.372 (15)
Sichuan	0.373 (7)	0.372 (17)	0.407 (6)	0.437 (6)	0.368 (16)
Guizhou	0.318 (16)	0.308 (24)	0.372 (14)	0.404 (10)	0.354 (20)
Yunnan	0.414 (5)	0.320 (23)	0.474 (4)	0.333 (19)	0.360 (19)
Tibet	0.000 (29)	0.000 (31)	0.398 (8)	0.143 (31)	0.000 (31)
Shaanxi	0.377 (6)	0.349 (20)	0.419 (5)	0.321 (22)	0.414 (7)
Gansu	0.345 (12)	0.278 (27)	0.296 (27)	0.371 (16)	0.303 (26)
Qinghai	0.141 (28)	0.425 (6)	0.946 (1)	0.213 (30)	0.343 (23)
Ningxia	0.000 (29)	0.196 (29)	0.256 (30)	0.383 (12)	0.111 (30)
Xinjiang	0.331 (13)	0.088 (30)	0.285 (28)	0.235 (29)	0.269 (29)

Based on the Pareto coefficients of the top ten occupations at the 70th percentile of income across the panel of China's 31 provinces, radar charts are shown in Figure 1 to depict the occupational income inequality in these regions for the years 2014, 2016, 2018, and 2020. Especially, the radar chart for the regions in 2014 in Figure 1a shows that most regions have Pareto coefficients close to 0.3, with a few, such as Beijing and Inner Mongolia, exceeding 0.5. Figure 1b represents the situation in 2016, where the regions generally have Pareto coefficients near 0.4, and none exceed 0.5, suggesting that top income inequality is less disparate across regions in 2016 compared to 2014. In Figure 1c, almost all of China's 31 provinces have Pareto coefficients around 0.4, with only Qinghai standing out. Figure 1d reveals that in 2020, most regions have Pareto coefficients ranging between 0.3 and 0.5, with Beijing exhibiting a more unequal distribution of top income and a more prominent figure among all regions. In Figure 1e, most provinces fall between 0.3 and 0.5, with Inner Mongolia, Shanghai, and Guangdong having the largest Pareto coefficients, implying that top incomes in these three regions are the most unequal, while Tibet, Ningxia, and Xinjiang are the regions with the smallest Pareto coefficients that year.



a. Radar map of Pareto coefficients in 2014
b. Radar map of Pareto coefficients in 2016
c. Radar map of Pareto coefficients in 2018
d. Radar map of Pareto coefficients in 2020
e. Radar map of Pareto coefficients in 2022

Figure 1. Pareto coefficients for 31 provinces in 2014, 2016, 2018, 2020, and 2022, respectively.

When comparing vertically, income inequality in 22 provinces increased to varying degrees in 2020 compared to 2018, with the exception of nine provinces: Inner Mongolia, Liaoning, Hubei, Hainan, Chongqing, Yunnan, Tibet, Shaanxi, and Xinjiang. According to the 2020 calculations, the provinces with the highest income inequality were Beijing, Guangdong, Fujian, Guangxi, Jiangxi, Sichuan, Shanghai, Zhejiang, Anhui, and Guizhou, all with Pareto coefficients of 0.4 or higher. The provinces with the largest increases in income inequality were Ningxia, Jiangxi, Hunan, Qinghai, Zhejiang, Guangxi, Guangdong, Fujian, Jilin, and Heilongjiang. The provinces with the lowest income inequality were Shanxi, Hainan, Inner Mongolia, Xinjiang, Qinghai, and Tibet, all with Pareto coefficients below 0.3. In 2022, compared to 2020, the Pareto coefficients increased significantly, with Inner Mongolia seeing the largest increase by 0.25083, followed by Hainan with an increase of 0.19534, Hebei with an increase of 0.01943, Qinghai with an increase of 0.12994, and Shanxi with an increase of 0.111.

Guangdong, with its unique geographical location, leading role in reform and opening up, and robust manufacturing and service sectors, has drawn substantial domestic and foreign investments, particularly in high-paying industries such as high-tech, finance, the internet, and e-commerce. These sectors not only offer salary levels significantly higher than traditional industries but also generate a substantial number of high-end jobs, allowing certain occupations to achieve exceptionally high income levels. In contrast, regions like Henan and Sichuan in central and western China often lack the backing of these high-paying industries due to their relatively weaker economic foundations and homogenous industrial structures. This results in a scarcity of high-paying jobs and a relatively small income disparity among occupations, with overall income levels also being on the lower side. Moreover, there are significant differences in the level of economic development among cities within Guangdong, such as the pronounced gap between first-tier cities like Shenzhen and Guangzhou and the eastern and northwestern regions of the province. This regional imbalance in economic development further intensifies occupational income inequality. As hubs of economic activity, first-tier cities are home to more high-end industries and talent, leading to a concentration of high-paying jobs. Conversely, in regions where the economy is less developed, employment opportunities are limited and predominantly in labor-intensive industries, with wages generally being lower. Additionally, disparities in educational resources and skill levels are crucial factors influencing occupational income inequality. Guangdong, especially its economically advanced cities, boasts superior educational resources and training systems, enabling it to produce more professionals to cater to the needs of high-paying industries. In contrast, central and western regions are hindered by the uneven distribution of educational resources and a relative shortage of highly skilled personnel, making it challenging for them to fulfill the demand for high-paying jobs, thereby limiting local residents' opportunities to enter such occupations.

Therefore, the greater inequality in top occupational incomes in Guangdong does not directly reflect the absolute superiority or inferiority of workers' treatment, but rather is a manifestation of the combined impact of various factors. These include the stage of regional economic development, disparities in industrial structure, the allocation of educational resources, and the dynamics of supply and demand in the labor market. This does not inherently imply that workers in less prosperous provinces are treated less favorably, but rather highlights significant variations in the distribution of occupational earnings and the structure of opportunities across different levels of economic development and industrial compositions. Addressing this issue necessitates collaborative efforts from both the national level and local governments to progressively reduce inter-regional and inter-occupational income disparities. This can be achieved through a range of measures, such as optimizing the industrial structure, fostering balanced regional development, and enhancing the quality of education and the level of skills training, in order to establish a fairer and more equitable pattern of income distribution.

4.3. Robustness Analysis

To check how the choice of the threshold value performs, the Pareto coefficients of inequality for the 50th percentile are calculated for 2022 and the results are displaced in Table 3. From Table 3 for 2022, it reveals that the ranking of regions based on the Pareto coefficient does not significantly change when compared to that for the 70th percentile. For instance, Beijing's Pareto coefficient is 0.435 at the 70th percentile, ranking 5th, and it increases to 0.635 at the 50th percentile, moving up to 4th in the ranking. Additionally, 13 regions, including Tianjin, Inner Mongolia, Liaoning, Shanghai, Jiangxi, Henan, Hunan, Guangdong, Tibet, Shaanxi, Ningxia, and Xinjiang, show a difference of three or fewer positions in their Pareto coefficient rankings between the 70th and 50th percentiles. Almost all regions exhibit acceptable differences in ranking. However, Hainan stands out with a larger gap with a rank of 4th in income inequality at the 70th percentile and a Pareto coefficient of 0.44; however, it drops to 27th with a coefficient of 0.385 when the 50th percentile is used. These analyses suggest that the calculations in this paper are relatively robust.

Table 3. Pareto coefficient of inequality for 70th and 50th percentile top incomes in 2022 with ranking in parentheses.

Province	70th Percentile	50th Percentile
Beijing	0.435 (5)	0.635 (4)
Tianjin	0.343 (23)	0.407 (25)
Hebei	0.324 (25)	0.465 (19)
Shanxi	0.376 (12)	0.455 (20)
Inner Mongolia	0.495 (1)	0.931 (1)
Liaoning	0.374 (14)	0.467 (17)
Jilin	0.293 (27)	0.45 (21)
Heilongjiang	0.278 (28)	0.465 (18)
Shanghai	0.481 (2)	0.658 (2)
Jiangsu	0.34 (24)	0.51 (10)
Zhejiang	0.408 (8)	0.468 (16)
Anhui	0.365 (18)	0.494 (11)
Fujian	0.398 (10)	0.44 (23)
Jiangxi	0.375 (13)	0.486 (13)
Shandong	0.35 (21)	0.404 (26)
Henan	0.367 (17)	0.471 (15)
Hubei	0.402 (9)	0.637 (3)
Hunan	0.392 (11)	0.49 (12)
Guangdong	0.48 (3)	0.555 (6)
Guangxi	0.418 (6)	0.478 (14)
Hainan	0.44 (4)	0.385 (27)
Chongqing	0.372 (15)	0.528 (8)
Sichuan	0.368 (16)	0.537 (7)
Guizhou	0.354 (20)	0.423 (24)
Yunnan	0.36 (19)	0.598 (5)

Table 3. *Cont.*

Province	70th Percentile	50th Percentile
Tibet	0 (31)	0.105 (31)
Shaanxi	0.414 (7)	0.513 (9)
Gansu	0.303 (26)	0.447 (22)
Qinghai	0.343 (23)	0.315 (29)
Ningxia	0.111 (30)	0.261 (30)
Xinjiang	0.269 (29)	0.363 (28)

4.4. Characterization of High-Income Occupations

Figure 2 depicts a word cloud map of all high-income occupations over the five-year period represented by the years 2014, 2016, 2018, 2020, respectively. In this map, the frequency of occurrence of each occupation is represented by the font size, with more frequent occupations appearing in larger fonts. Figure 3 shows the top 20 most frequently occurring occupational names in the high-income sample over the four-year period. Figure 4 plots the distribution of top earnings by industry for each of the four years, and the industry compilation in this paper draws on the CFPS occupational industry coding approach (Referencing the "China Family Panel Studies 2010 Occupation and Industry Coding").

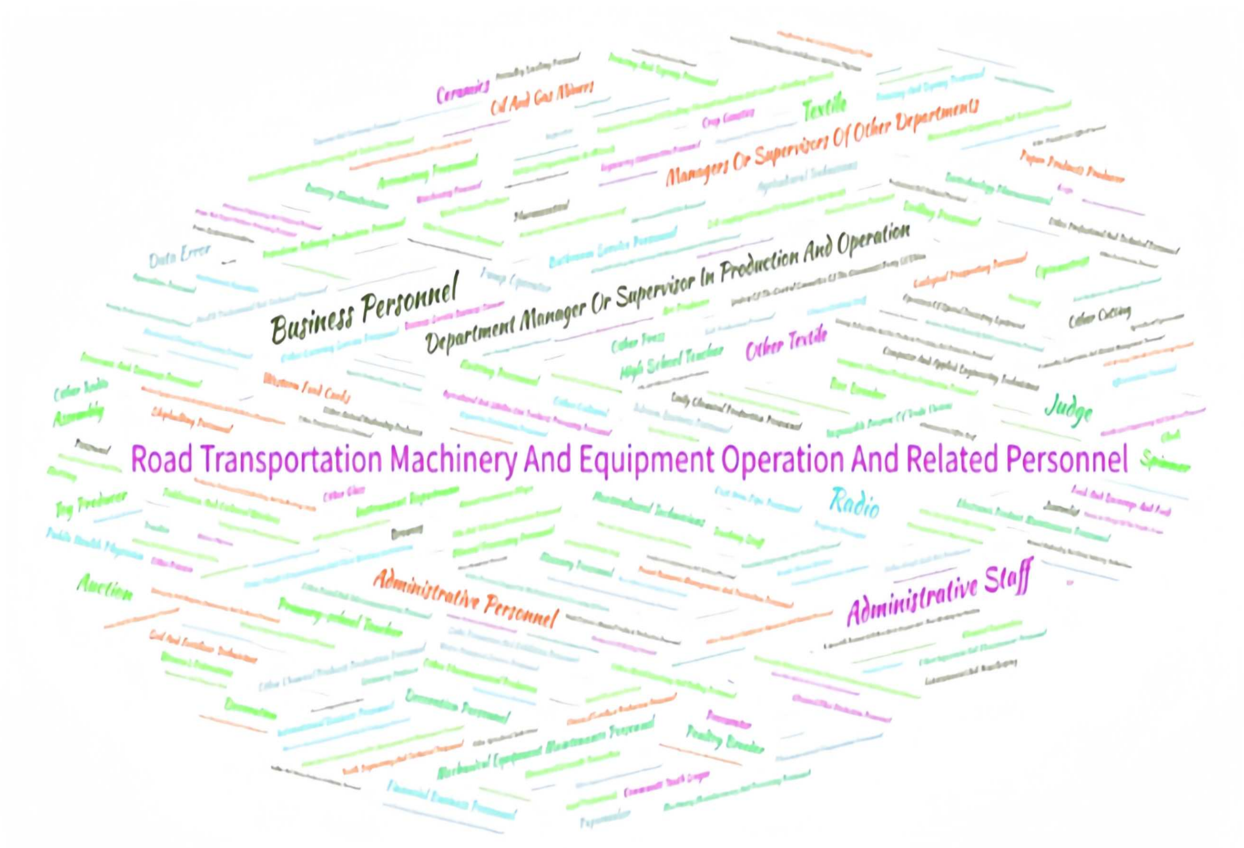


Figure 2. Word cloud of top earning occupational names for 2022.

It can be observed that individuals likely to earn higher incomes are public (road) transport machinery and equipment operators and related personnel, an occupation that accounted for 6.01% of the highest incomes across all samples over the four years. This is followed by salespersons and administrative clerks, with percentages of 5.46% and 5.01%, respectively. Additionally, there are two occupations with proportions between 4% and 5%: departmental managers or supervisors of production and operations, and administrative and operational personnel. It can be concluded that the distribution of the highest-income occupations in our country is relatively dispersed, although there is a concentration in a small number of occupations.

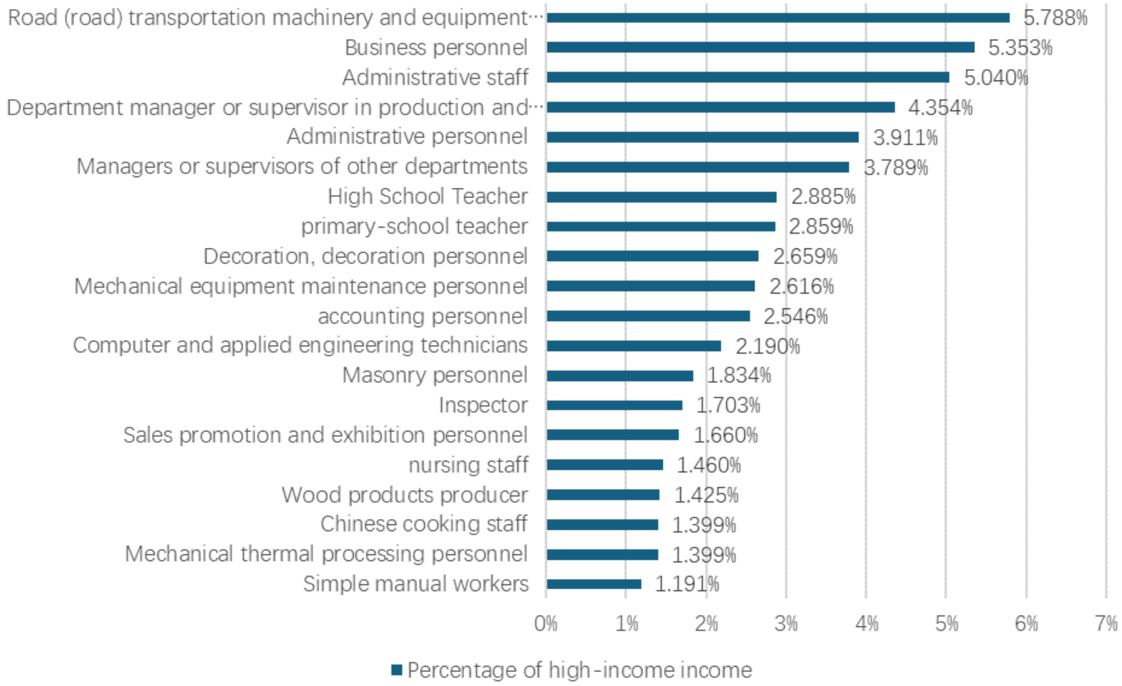


Figure 3. Top 20 occupations with the highest frequency of occurrence in the highest income bracket for 2022, along with their respective percentages.

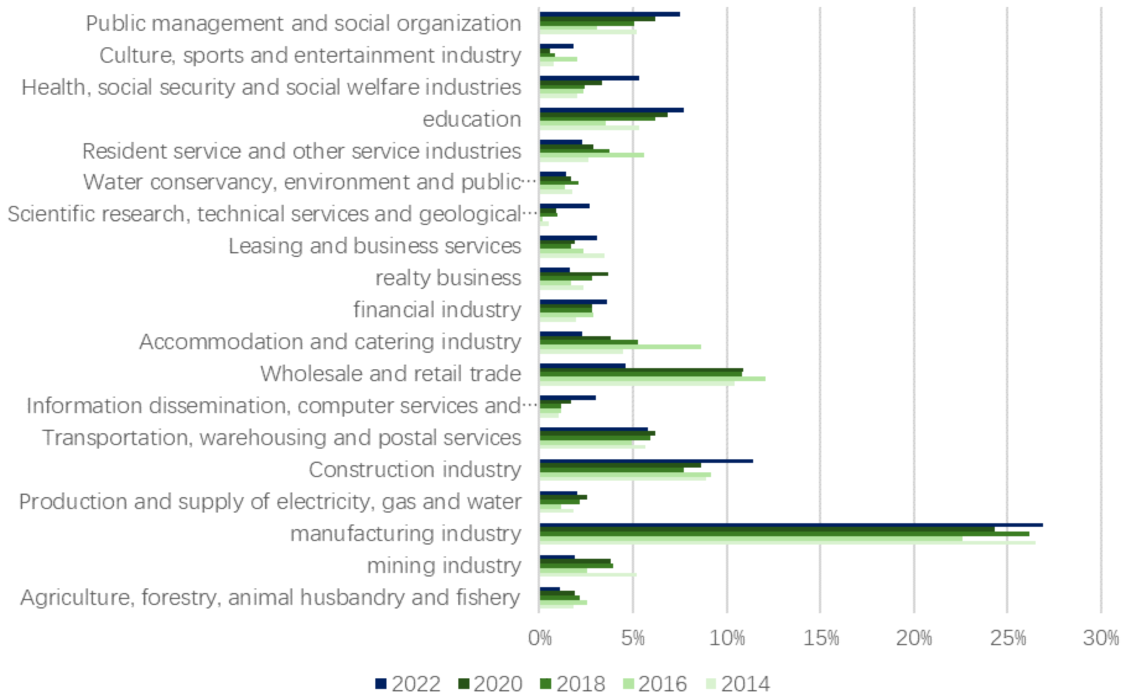


Figure 4. Distribution of top earning industries for the five years 2014, 2016, 2018, 2020, and 2022, respectively.

Operators of public road transport machinery and equipment, along with related personnel, are those involved in driving passenger and freight vehicles, as well as support staff. Their main duties include the following: (1) operating vehicles for passenger and cargo transportation in compliance with traffic regulations; (2) analyzing and summarizing the technical condition of the vehicle being driven, and suggesting maintenance and repairs; (3) replacing minor parts and troubleshooting during operations; (4) examining and discussing the causes of driving accidents and abnormal tire wear, and proposing preventive measures; (5) analyzing the components of transport costs and conducting single-vehicle economic accounting; and (6) suggesting methods for transporting oversized goods and participating in the development of transport plans. This occupational group may earn higher incomes in certain instances, potentially due to a shortage of qualified personnel. The requirement for operators of public road transport machinery and equipment to possess advanced driving skills, a thorough understanding of the vehicle's technical condition, and the ability to analyze it contributes to their higher earning potential. They bear the crucial responsibility of ensuring the safe and timely delivery of passengers and goods, which necessitates a high level of professionalism and accountability. Moreover, with economic growth and the acceleration of urbanization, the demand for public road transport is continually increasing. This demand is particularly strong for truck drivers, especially with the rapid expansion of e-commerce, logistics, and other industries. Due to competition within the sector, some skilled drivers may receive higher wages based on their professional expertise, service attitude, or work efficiency. In certain regions or periods, market supply and demand dynamics may lead to higher wages due to a scarcity of drivers. For instance, during peak logistics seasons or in specific sectors such as cold chain transport, the increased demand for drivers can lead to higher pay scales.

Between 2014 and 2022, the distribution of high incomes in China was marked by a preponderance in the manufacturing industry, with relatively high levels also found in construction, education, wholesale and retail, and public administration and social organizations. Other industries exhibited lower levels of high income. Notably, the education and public administration and social organizations sectors saw a gradual rise in the proportion of top incomes. According to the data, the manufacturing industry consistently accounted for the largest share of high-income earners in China in 2014, 2016, 2018, 2020, and 2022, respectively. As a vital component of the global manufacturing sector, China's manufacturing industry has made significant strides in transformation, technological innovation, and market expansion, leading to improved employment prospects for its workers. The wholesale and retail sector's share of high-income earners exceeded 10% in the five years but fell below 5% in 2022. Due to COVID-19 impacting the development of this sector, the incomes of those employed within it were affected too. Similarly, the accommodation and catering sector experienced the lowest share of high-income earners in the five-year period in 2022 due to the pandemic. The National Bureau of Statistics Report found that China's investment in education increased by 7.3% in 2018, 17.4% in 2019, and 12.3% in 2020, respectively. To reinforce the enduring role of education, numerous education reform documents and programs have been issued by the Chinese Government, covering a wide range of educational areas. These reforms have expanded the audience for education and enhanced the labor remuneration for education industry practitioners. In contrast, industries such as agriculture, forestry, animal husbandry, fisheries, mining, electricity, gas, and water production and supply, information dissemination, computer services and software, accommodation and catering, finance, real estate, leasing and business services, scientific research, technical services, surveying, water conservancy, environmental and public facilities management, residential services, health, social security, social welfare, culture, sports, and others accounted for a relatively smaller proportion of the highest income earners.

5. Measurement and Decomposition Analysis of Occupational Income Inequality by Region

Next, the Pareto coefficients for the 10 most significant occupations in each region over the relevant five-year period are presented by region (Eastern region: Beijing, Tianjin, Hebei, Liaoning, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong, Guangxi, and Hainan; Central region: Shanxi, Inner Mongolia, Jilin, Heilongjiang, Anhui, Jiangxi, Henan, Hubei, and Hunan; Western region: Chongqing, Sichuan, Guizhou, Yunnan, Tibet, Shaanxi, Gansu, Ningxia, Qinghai, and Xinjiang). The significance of an occupation is determined by the frequency with which it exceeds the 70th percentile of local earnings in a given year; occupations with higher frequencies are considered more significant. The symbol $\hat{\alpha}^{-1}$ represents the income inequality among occupations that surpass the 70th percentile of local income for that year. For instance, in Shanghai in 2014, the $\hat{\alpha}^{-1}$ for the occupation of manager or supervisor of production and operation departments was 0.6509. This indicates that the income inequality among this group of high-income managers or supervisors, who exceeded the 70th percentile of Shanghai's income distribution in 2014, was 0.6509. Due to the length constraints of this paper, we only display the data for three provinces representing the eastern, central, and western regions (selected based on economic development and geographic location). The complete results are available upon request.

Table 4 displays the five-year Pareto coefficients for the 10 most significant occupations in the three provinces of the Eastern and Central regions. In Guangdong, the greatest inequality in five-year top incomes is concentrated in the secondary occupations of "buyer and seller", "head of enterprise", and "engineers and technicians". Among these, the "sales staff" profession falls under the "buyer and seller" category, while the "head of enterprise", "department managers or supervisors in production and operations", and "other department managers or supervisors" professions are classified under the secondary category of "head of enterprise". The "sales staff" under the "buyer and seller" category becomes the most unequal high-income occupation in Guangdong in 2014 with a Pareto coefficient of 0.541. Subsequently, over the five years of 2014, 2016, 2018, 2020, and 2022, the Pareto coefficient does not exceed 0.5, and its ranking among the top ten occupations with the highest income inequality in Hebei shows a nearly year-on-year downward trend. This indicates that the prominence of income inequality among high-income individuals in the "buyer and seller" occupational category weakened. Conversely, "computer and application engineers and technicians" begins to stand out in terms of high-income inequality starting in 2018, becoming the most unequal high-income occupation in the province with a coefficient of 0.689, and in 2020 and 2022, it ranked second in terms of inequality with coefficients of 0.609 and 0.735, respectively. Similarly, the occupational category of "head of enterprise" has seen a gradual increase in inequality issues. The professions under this category are the most unequal in terms of high income in 2020 and 2022. For example, the $\hat{\alpha}^{-1}$ for "other department managers or supervisors" is 0.612 in 2020, and the $\hat{\alpha}^{-1}$ for "Department managers or supervisors in production and operations" reaches as high as 0.807 in 2022.

Table 4. Pareto coefficients of top ten occupations in three provinces of eastern, central, and western regions over five years.

City \ Careers	2014		2016		2018		2020		2022	
	Careers	$\hat{\alpha}^{-1}$	**Careers**	$\hat{\alpha}^{-1}$	**Careers**	$\hat{\alpha}^{-1}$	**Careers**	$\hat{\alpha}^{-1}$	**Careers**	$\hat{\alpha}^{-1}$
Guangdong	Sales staff	0.541	Head of Enterprise	0.639	Computer and application engineers and technicians	0.689	Other department managers or supervisors	0.612	Department managers or supervisors in production and operations	0.807
	Administrative and operational staff	0.385	Department managers or supervisors in production and operations	0.268	Operators of public (road) transport machinery and equipment and related personnel	0.362	Teachers of higher education	0.336	Accountant	0.331
	Accountant	0.482	Other department managers or supervisors	0.511	Department managers or supervisors in production and operations	0.585	Secondary school teachers	0.585	Other department managers or supervisors	0.719
	Inspector	0.471	Administrative Services staff	0.444	Accountant	0.458	Sales staff	0.459	Promoters and exhibitors	0.692
	Administrative services staff	0.458	Computer and application engineers and technicians	0.331	Inspector	0.377	Department managers or supervisors in production and operations	0.457	Secondary school teachers	0.532

Table 4. *Cont.*

City \ Careers	2014		2016		2018		2020		2022	
	Careers	$\hat{\alpha}^{-1}$	**Careers**	$\hat{\alpha}^{-1}$	**Careers**	$\hat{\alpha}^{-1}$	**Careers**	$\hat{\alpha}^{-1}$	**Careers**	$\hat{\alpha}^{-1}$
Guangdong	Operators of public (road) transport machinery and equipment and related personnel	0.325	Sales staff	0.321	Sales staff	0.316	Administrative services staff	0.449	Sales staff	0.458
	Secondary school teachers	0.296	Promoters and exhibitors	0.292	Administrative services staff	0.254	Accountant	0.379	Administrative and operational staff	0.331
	Promoters and exhibitors	0.29	Operators of public (road) transport machinery and equipment and related personnel	0.22	Administrative and operational staff	0.246	Insurance operator	0.359	Administrative services staff	0.329
	Cutting and sewing staff	0.213	Inspector	0.119	Operators of public (road) transport machinery and equipment and related personnel	0.161	Promoters and exhibitors	0.343	Inspector	0.299
	Simple manual laborers	0.088	Cutting and sewing staff	0.104	Mechanical equipment maintenance staff	0.157	Primary school teachers	0.232	Operators of public (road) transport machinery and equipment and related personnel	0.065

Table 4. *Cont.*

City \ Careers	2014		2016		2018		2020		2022	
	Careers	$\hat{\alpha}^{-1}$	**Careers**	$\hat{\alpha}^{-1}$	**Careers**	$\hat{\alpha}^{-1}$	**Careers**	$\hat{\alpha}^{-1}$	**Careers**	$\hat{\alpha}^{-1}$
Henan	Administrative and operational staff	0.508	Sales staff	0.516	Adminstrative and operational staff	0.573	Other department managers or supervisors	0.441	Other department managers or supervisors	0.474
	Mechanical equipment maintenance staff	0.362	Other department managers or supervisors	0.423	Doctor trained in Western medicine	0.547	Administrative Services staff	0.413	Administrative services staff	0.391
	Decorators and fitters	0.311	Promoters and exhibitors	0.31	Other department managers or supervisors	0.356	Department managers or supervisors in production and operations	0.348	Sales staff	0.345
	Sales staff	0.277	Operators of public (road) transport machinery and equipment and related personnel	0.228	Administrative services staff	0.324	Administrative and operational staff	0.282	Mechanical equipment maintenance staff	0.313
	Administrative services staff	0.254	Decorators and fitters	0.188	Sales staff	0.311	Sales staff	0.266	Doctor trained in Western medicine	0.307
	Accountant	0.23	Administrative services staff	0.187	Primary school teachers	0.201	Decorators and fitters	0.254	Operators of public (road) transport machinery and equipment and related personnel	0.278

Table 4. *Cont.*

City \ Careers	2014		2016		2018		2020		2022	
	Careers	$\hat{\alpha}^{-1}$	**Careers**	$\hat{\alpha}^{-1}$	**Careers**	$\hat{\alpha}^{-1}$	**Careers**	$\hat{\alpha}^{-1}$	**Careers**	$\hat{\alpha}^{-1}$
Henan	Operators of public (road) transport machinery and equipment and related personnel	0.194	Mechanical equipment maintenance staff	0.145	Operators of public (road) transport machinery and equipment and related personnel	0.199	Accountant	0.243	Wood workers	0.229
	Masonry staff	0.168	Mechanical thermal processors	0.042	Decorators and fitters	0.188	Primary school teachers	0.232	Decorators and fitters	0.164
	Simple manual laborers	0.15	Accountant	0.04	Wood workers	0.099	Operators of public (road) transport machinery and equipment and related personnel	0.174	Accountant	0.096
	Administrative and operational staff	0.508	sales staff	0.516	Administrative and operational staff	0.573	Other department managers or supervisors	0.441	Other department managers or supervisors	0.474
Sichuan	Primary school teachers	0.445	Promoters and exhibitors	0.616	Sales staff	0.639	Sales staff	0.716	Other department managers or supervisors	0.586
	Operators of public (road) transport machinery and equipment and related personnel	0.427	Decorators and fitters	0.401	Accountant	0.581	Secondary school teachers	0.404	Computer and application engineers and technicians	0.505

Table 4. *Cont.*

City \ Careers	2014		2016		2018		2020		2022	
	Careers	$\hat{\alpha}^{-1}$	**Careers**	$\hat{\alpha}^{-1}$	**Careers**	$\hat{\alpha}^{-1}$	**Careers**	$\hat{\alpha}^{-1}$	**Careers**	$\hat{\alpha}^{-1}$
Sichuan	Sales staff	0.424	Operators of public (road) transport machinery and equipment and related personnel	0.292	Department managers or supervisors in production and operations	0.421	Administrative and operational staff	0.356	Department managers or supervisors in production and operations	0.408
	Administrative and operational staff	0.385	Department managers or supervisors in production and operations	0.268	Operators of public (road) transport machinery and equipment and related personnel	0.362	Teachers of higher education	0.336	Accountant	0.331
	Decorators and fitters	0.301	Administrative and operational staff	0.217	Other department managers or supervisors	0.344	Operators of public (road) transport machinery and equipment and related personnel	0.318	Administrative services staff	0.291
	Administrative services staff	0.216	accountant	0.156	Adminstrative and operational staff	0.297	Primary school teachers	0.271	Administrative and operational staff	0.278

Table 4. *Cont.*

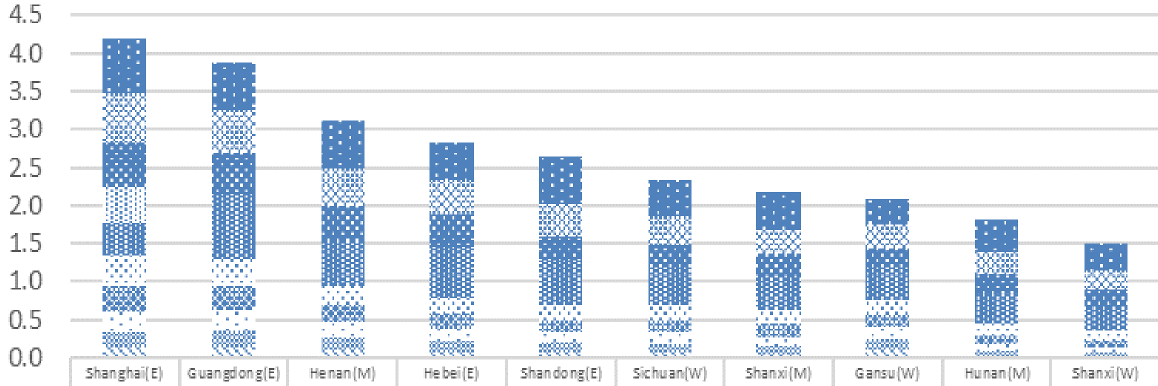
Careers / City	2014		2016		2018		2020		2022	
	Careers	$\hat{\alpha}^{-1}$	**Careers**	$\hat{\alpha}^{-1}$	**Careers**	$\hat{\alpha}^{-1}$	**Careers**	$\hat{\alpha}^{-1}$	**Careers**	$\hat{\alpha}^{-1}$
Sichuan	Department managers or supervisors in production and operations	0.203	Wood workers	0.118	Computer and application engineers and technicians	0.281	Administrative services staff	0.249	Decorators and fitters	0.139
	Masonry staff	0.165	Public order and security personnel	0.107	Wood workers	0.261	Department managers or supervisors in production and operations	0.162	Operators of public (road) transport machinery and equipment and related personnel	0.124
	Wood workers	0.128	Administrative services staff	0.079	Primary school teachers	0.211	Other department managers or supervisors	0.143	Sales staff	0.084
	Secondary school teachers	0.121	Primary school teachers	0.046	Mechanical thermal processors	0.142	Computer and application engineers and technicians	0.072	Simple manual laborers	0.058

In Henan, the secondary occupational category of “administrative office staff”, which includes “administrative and operational staff” and “administrative services staff”, is ranked highest in terms of income inequality with $\hat{\alpha}^{-1}$ values at second, first, second, fourth, and third in the years 2014, 2016, 2018, 2020, and 2022, respectively. This indicates that the issue of high-income inequality for “administrative office staff” in Henan is quite pronounced during the study years. In addition to the professions under the “head of enterprise” and “administrative office staff” categories, Shanxi also sees significant income inequality among certain skilled operational worker types. For instance, in 2014, “operators of public (road) transport machinery and equipment and related personnel” had a Pareto coefficient of 0.307, topping the list of high-income inequality in Shanxi that year. In 2016, “mineral extraction workers” had a coefficient of 0.3242, and in 2018, “mechanical equipment maintenance staff” had a coefficient of 0.4273, both ranking second in income inequality for their respective years. In 2020, “mineral extraction workers” again was ranked second with a coefficient of 0.2739.

In Sichuan, the “buyer and seller” occupational category, which includes “promoters and exhibitors” and “sales staff”, was the most unequal in terms of high income for the years 2016, 2018, and 2020, with an increasing trend in Pareto coefficients, indicating a worsening of high-income inequality issues for this category over those three years. In 2022, “other department managers or supervisors” became the most unequal occupation in Sichuan with a coefficient of 0.586. Additionally, it is noteworthy that the teaching profession in Sichuan had significant high-income inequality. For example, “primary school teachers” had a Pareto coefficient of 0.445 in 2014, making it the most unequal occupation of that year. In 2020, “secondary school teachers” was ranked second in terms of inequality with a coefficient of 0.404.

Figure 5 is a stacked plot showing the arithmetic mean of the Pareto coefficients for the 10 most important occupations with the highest incomes in each region, ranked in descending order of Pareto coefficients for four years at the same position. It can be observed that Shanghai has the most unequal distribution of top incomes, followed by Guangdong, with a minimal difference between these two regions. In contrast, the highest incomes are relatively more equal in Shaanxi. The graph suggests that top income inequality is more pronounced in the eastern part of the country, while the central and western parts exhibit relatively more equality, with no significant difference observed between the central and western regions. The rapid economic development and industrial innovation in the eastern region create an environment that easily fosters the enhancement of certain individuals’ skills, leading to a wider salary income gap. The central and western regions, where economic development lags behind the east, do not readily stimulate the acquisition of specific employable skills, or may lead to the loss of non-replaceable practitioners. As a result, the gap in the highest incomes between the workers in the central and western parts of the country and those in the eastern part is not as pronounced as in the eastern region.

Based on the GE index, this paper measures the results of regional decomposition and industry decomposition of the highest income gap in 31 provinces of China as shown in Tables 5 and 6, respectively. Table 5 presents the results of the measurement of top income inequality using the GE index for the entire country, as well as for the eastern, central, and western regions. The decomposition results indicate that top income inequality within regions was significantly greater than income inequality between regions in the years 2018, 2020, and 2022. This suggests that the top income disparities in the country are primarily driven by differences within regions rather than between them. The three-year sub-regional GE indices reveal that the intra-regional gaps are larger in the eastern and western regions, whereas the gap is smaller within the central region.



	Shanghai(E)	Guangdong(E)	Henan(M)	Hebei(E)	Shandong(E)	Sichuan(W)	Shanxi(M)	Gansu(W)	Hunan(M)	Shanxi(W)
NO.1	0.7154	0.6202	0.6299	0.4985	0.6217	0.4833	0.5003	0.3513	0.4256	0.3488
NO.2	0.6485	0.5588	0.5094	0.4472	0.4131	0.3627	0.3202	0.3041	0.3111	0.2621
NO.3	0.5761	0.5407	0.4362	0.4214	0.3265	0.2985	0.2872	0.2517	0.2442	0.2219
NO.4	0.4745	0.4580	0.3311	0.3669	0.3030	0.2702	0.2401	0.2183	0.2194	0.1744
NO.5	0.4271	0.4056	0.2779	0.2973	0.2750	0.2361	0.2037	0.2153	0.1845	0.1410
NO.6	0.4012	0.3526	0.2548	0.2140	0.1958	0.1878	0.1878	0.1858	0.1446	0.1176
NO.7	0.3282	0.3052	0.2180	0.1948	0.1686	0.1701	0.1623	0.1672	0.1189	0.0875
NO.8	0.2896	0.2788	0.1951	0.1651	0.1398	0.1391	0.1235	0.1631	0.0968	0.0749
NO.9	0.1973	0.2092	0.1577	0.1416	0.1304	0.1122	0.1066	0.1307	0.0526	0.0393
NO.10	0.1279	0.1453	0.1155	0.0754	0.0650	0.0760	0.0497	0.1105	0.0292	0.0298

Figure 5. Pile-up of five-year arithmetic averages of Pareto coefficients for the same occupation in all regions of the country.

Table 5. Regional decomposition of the top income gap in the 31 provinces of China.

Year / Region	2018		2020		2022	
	GE(0)	**Contribution**	**GE(0)**	**Contribution**	**GE(0)**	**Contribution**
National	0.043	100.0%	0.040	100.0%	0.39	100.0%
Between Regions	0.003	7.103%	0.015	37.873%	0.009	22.274%
Intra-Regional	0.04	92.897%	0.025	62.127%	0.03	77.726%
Eastern	0.028	24.734%	0.046	51.149%	0.045	48.787%
Central	0.018	9.429%	0.014	8.084%	0.014	8.443%
Western	0.066	59.706%	0.012	10.02%	0.027	24.383%

Table 6 uses the National Economic Industry Classification (GB/T 4754-2002) as employed in the CFPS database for industry classification. This coding system categorizes national economic industries into 20 distinct sectors. The decomposition results reveal that over the three years of 2018, 2020, and 2022, the greatest income disparities predominantly arose within industries. However, the contribution rate of the income gap between industries showed a gradual increase, while the contribution rate of the income gap within industries gradually decreased. Across all industries, the most significant income inequality was found within the manufacturing sector, with three-year contribution rates of 53.640%, 42.381%, and 20.429%, respectively. As a large industry, the manufacturing sector may exhibit segmentation in the internal labor market, where employees in different positions with varying skill requirements experience disparities in income. The manufacturing industry typically involves complex production processes and technical demands, and different positions necessitate different skills and experience from employees. Although they all belong to the high-income group, the income levels they earn are more likely to vary depending on the value they create for the enterprise. Additionally, we observe that the real estate industry's contribution has been on the rise year by year, likely due to the steady growth trend of China's economy and the continuous increase in residents' income levels over the past few years. As residents' disposable income has increased, so has the demand for housing, particularly in the context of accelerated urbanization. This has led to a significant influx of people into cities and a sharp surge in housing demand. In some major cities and popular areas, housing prices tend to be higher due to limited land resources and a relatively tight housing supply, which creates more opportunities and income sources for high-income earners in the property sector. Simultaneously, as population migration intensifies, the property market in certain regions is thriving, further boosting the number of high-income individuals in the real estate industry.

Table 6. Industry breakdown of the top income gap in China's 31 provinces.

Year / Region	2018		2020		2022	
	GE(0)	**Contribution**	**GE(0)**	**Contribution**	**GE(0)**	**Contribution**
National	0.136	100%	0.075	100%	0.084	100.0%
Between Industries	0.016	11.689%	0.012	16.554%	0.031	37.086%
Intra-industry	0.121	88.682%	0.063	83.446%	0.053	62.914%
Agriculture, forestry, animal husbandry, and fisheries	0.078	2.578%	0.015	0.274%	0.009	0.179%
Mining	0.044	0.521%	0.068	3.908%	0.079	2.979%
Manufacturing	0.189	53.640%	0.089	42.381%	0.052	20.429%
Electricity, gas and water production, and supply industry	0.114	1.382%	0.049	1.817%	0.037	0.647%
Construction	0.061	2.671%	0.024	2.311%	0.025	2.501%
Transport, storage, and postal services	0.112	4.953%	0.040	2.840%	0.075	4.637%
Information dissemination, computer services, and software	0.041	0.766%	0.026	0.592%	0.056	3.395%
Wholesale and retail trade	0.120	4.266%	0.024	1.039%	0.021	0.754%
Accommodation and catering	0.059	0.437%	0.000	0.000%	0.018	0.374%
Finance	0.035	0.468%	0.006	0.115%	0.260	21.588%
Real estate industry	0.005	0.016%	0.071	3.224%	0	0%
Rental and business services	0.057	1.714%	0.007	0.190%	0.055	1.838%
Scientific research, technical services, and geological survey industry	0.061	1.278%	0.085	4.461%	0.070	4.254%
Water conservancy, environment, and public facilities management industry	0.042	0.765%	0.078	3.119%	0.019	0.405%
Residential and other services	0.041	0.425%	0.057	1.113%	0.016	0.192%
Education	0.058	1.438%	0.008	0.374%	0.006	0.211%
Health, social security, and social welfare	0.042	1.283%	0.043	3.431%	0.044	1.660%
Culture, sports, and recreation	0.004	0.083%	0.115	7.671%	0.035	1.096%
Public administration and social organizations	0.147	9.552%	0.068	7.285%	0.065	8.461%

6. Conclusions

By measuring the maximum income Pareto coefficients across China's 31 provinces in 2014, 2016, 2018, 2020, and 2022, respectively, this paper finds that most of the provinces with greater inter-occupational income inequality are located in the more economically developed central and eastern parts of the country, whereas the western part has lower levels of inter-occupational income inequality.

The results of the occupational analysis show that it is common to earn a higher income in the occupation of "operators of public (road) transport machinery and equipment and related personnel"; this occupation accounted for 5.788% of the highest incomes in the five-year sample. This is followed by "salespersons" and "administrators" at 5.353% and 5.040%, respectively. There are three occupations with proportions between 3% and 5%: "managers or supervisors of departments in production and operations", "administrative and business personnel", and "managers or supervisors of other departments". Over the period from 2014 to 2022, the distribution of high incomes in China is characterized by a predominance of the manufacturing sector, with relatively high levels also found in construction, education, wholesale and retail trade, and public administration and social organizations, and relatively lower levels in other sectors. Among these, the proportion of the highest income in the education industry and public administration and social organizations industry shows a gradual increase.

Regionally, Shanghai has the most unequal top incomes, followed closely by Guangdong. In contrast, the highest income is relatively more equal in Shaanxi. Income inequality at the top is more pronounced in the eastern region, while it is less severe in the central and western parts of the country, with no significant difference observed between the central and western regions.

The top income inequality was decomposed by region and industry. In 2018, 2020, and 2022, income inequality within regions was much greater than inequality between regions, and the top income gaps across the country primarily stemmed from within regions. The gap was larger within the eastern and western regions, while it was smaller within the central region. The top income gap mainly arose from within industries, although the contribution of the gap between industries is gradually increasing, while the contribution from within industries is gradually decreasing. Among all industries, the manufacturing industry exhibits the most prominent income inequality at the top.

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