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Article

Investigating the main factors responsible for changes in income inequality in China between 2000 and 2018

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Abstract: Poverty, and especially the widening disparity between the rich and the poor, leads to social unrest that can interrupt the harmonious development of human society. Understanding the reasons for income inequality, and supporting the development of an effective strategy to reduce this inequality, have been major goals in socioeconomic research around the world. To identify the determinants of the income gap, we calculated the Gini coefficients for Chinese provinces and performed regression analysis and contribution analysis for heterogeneity, using data from 30 Chinese provinces from 2002 to 2018. We found that urbanization, higher education, and foreign direct investment in eastern China and energy in central and western China were important factors that increased the Gini coefficient (i.e., decreased equality). Therefore, paying more attention to the fair distribution of the factors that can increase the Gini coefficient and investing more in the factors that can reduce the Gini coefficient will be the keys to narrowing the income gap. Our approach revealed factors that should be targeted for solutions both in China and in other developing countries that are facing similar difficulties, although the details will vary among countries and contexts.

Keywords: Gini coefficient; marketization; urbanization; education; economic development; China

1. Introduction

Economic development has reduced the problem of absolute poverty (based on a threshold for the minimum income that is necessary for survival), but the risk of relative poverty (earning less than 60% of the median income within a country) has increased (Katikireddi and Dundas, 2017; Mao and Fu, 2024; Ravallion and Chen, 2019; Whalley and Yue, 2009). This income inequality has emerged as a primary catalyst for social unrest and has hindered efforts toward achieving sustainable development of human society and improving economic development at both national and regional levels. Compared with absolute poverty, relative poverty is more likely to reduce a person's ability to cope with risk (Alderman and Paxson, 1992), to increase social inequality (O'Boyle, 2003), and to undermine economic growth (Wang, 2006). In a context of growing risk due to factors such as climate change and government instability, relative poverty cannot be ignored. Over the past decade, more than 80% of the world's wealth has been owned by less than 10% of the population (CSRI, 2022). Income inequality, as a trigger for relative poverty, always emerges in developing countries during economic growth (Heshmati, 2007). Therefore, understanding the causes of this gap can provide targeted policy recommendations for developing countries that are trying to prevent widening of the income gap.

In 1978, China initiated reform and opening to the west policy, which has been continuously applied since then. China's rapid economic growth has been accompanied by a rapidly widening income gap (Kanbur et al., 2021; Yu and Li, 2021). Deng's slogan "let some people get rich first" has been realized, but other Chinese citizens have less benefited from that slogan (Zhang, 2016). China's Gini coefficient has exceeded 0.4 (i.e., moderate to high inequality) since 1994 and continues to increase (CSRI, 2022). Despite the government's efforts to reduce poverty, national efforts such as measures to balance inter-regional development and measures to better integrate migrant workers who move to cities in search of work have not targeted the key structural elements responsible for inequality. In part, this is because the dominant causes of the income gap are unclear. For example, it is difficult for the government to balance the two important goals of GDP growth and reducing the income gap without knowing what factors are responsible for the gap (Espadero Dulam et al., 2021). If it is clear which factors that underlie economic growth are conducive to reducing the income gap, it will be easier to reduce the gap by developing policies that target those factors.

For these reasons, it's important to analyze the current situation for China's income gap and identify the underlying determinants. To provide this knowledge, we first calculated China's Gini coefficient from existing grouped income data, and used the Gini coefficient to represent the income inequality. To understand the causes of changes in the Gini coefficient, we selected socioeconomic data for 30 Chinese provinces from 2002 to 2018, and calculated the contribution of these changes to the Gini coefficient based on a fixed-effect model and on panel quantile regression. In addition, we analyzed the spatial heterogeneity of the results to support a detailed comparison of variations in the contributions of the key influencing factors across China's regions and reveal the causes of income gaps between regions. Our method provides a basis for more effectively mitigating the income gap not only in China but also elsewhere in the world.

2. Literature review

Kuznets (1955) proposed a classic theory of income inequality based on an inverted-U curve. In this hypothesis, income inequality increases in the early stages of economic development but decreases in the later stages. However, this theory only considered the effects of industrialization and urbanization, and did not include the effects of other potentially important factors. Subsequently, functionalist theory was developed to account for the fact that society is a complex system in which the parts are interrelated and work together to maintain a stable order (Gómez-Diago, 2020). Under this theory, a nation's social system and the structural factors that result from this system and other factors such as resource endowments affect the change of an individual's income that result from economic development, and the theory inherently assumes that the causes of income inequality are multi-dimensional. This more holistic approach is an important component of the method developed in the present study. At the level of individual workers, the difference in human capital input will lead to income inequality, and this inequality will be passed on to subsequent generations (cumulative inequality theory (Merton, 1968) and human capital theory (Becker, 2009)) because wealthier individuals have better access to superior education and thus, to superior job opportunities (Stiglitz and Kanbur, 2015). Human capital theory and cumulative inequality theory share the income inequality of individuals. When income differences between individuals continue to grow over time, income inequality persists until the root causes of growing inequality are addressed (Kanbur and Tuomala, 1994).

There has been no standard definition of how income inequality is measured in China because of a lack of detailed official data. Many scholars use the urban-rural income gap to express this inequality (Sutherland and Yao, 2011; Su and Heshmati, 2014; Yu and Li, 2021), but this approach cannot comprehensively represent this gap. The Gini coefficient provides a better metric. The coefficient was developed by Corrado Gini and established by the United Nations as a standard way to compare the inequality of income distribution in societies (Chen, 2019). Previous calculations of China's Gini coefficient were based on the graded income data published by the National Bureau of Statistics (Chen et al., 2010; Chen, 2019; Tian, 2012; Wang, 2006). This method improves data accuracy, and is acceptable for nationwide measurements.

Many scholars have studied the factors that influence China's income gap, and their research results provide an important reference for the present study. For example, urbanization has transferred many surplus rural laborers to cities, where there is a deficit of workers, thereby increasing the rural laborers' salary and narrowing the income gap between urban and rural areas (Su et al., 2015). The poverty households with unemployed people worse income distribution (Xue and Zhong, 2003). Unequal access to higher education widens the income gap because uneducated workers cannot apply for high-paying jobs that require this education (Chan and Ngok, 2011). Unconstrained profit-seeking behavior and endogenous corruption resulting from state ownership of certain industries have also led to serious income inequality (Wu and Yao, 2015). Foreign direct investment also widens the urban-rural income gap because most of this investment is concentrated in eastern China, and has little impact on the central and western regions (Song et al., 2021).

To support the present study, we reviewed the literature on the methods used to identify the factors that influence income inequality. In early research on these factors, the factor decomposition method (Kanbur and Zhao, 1999; Yang, 1999) and ordinary least-squares regression (Li, 2009; Yang and Zhou, 1999) were used widely to find the underline impact of urbanization and industrialization on income inequality according to Kuznets theory. Other scholars began to consider the roles of other factors. For example, Yao et al. (2005) used a Granger causality model to analyze the interaction between finance and the urban-rural income gap. Su and Heshmati (2014) included the effect of education in their analysis using ordinary least-squares regression, conditional quantile regression, and Blinder-Oaxaca decomposition. However, most studies continue to focus on only one or a few explanatory variables to analyze their impact on income inequality, and these studies have mostly used regression methods, with some variants such as a hierarchical model (Igawa and Managi, 2022). Other scholars have used the factor decomposition method to analyze the factors that play the strongest role in income inequality (Luo et al., 2020).

However, most of the existing research has investigated the role of these and other factors in isolation (i.e., without accounting for their interactions or differences in their relative strength), leading to an unbalanced analysis that pays too much attention to one factor and ignores the influence of other factors. For example, although many studies have shown that urbanization can narrow the income gap between urban and rural areas, serious unemployment of migrant workers has widened the income gap within cities (Wu and Yao, 2015). Therefore, a comprehensive understanding of the relative contributions of several factors that may simultaneously affect the income gap can help the government develop more precisely targeted policies that affect multiple key factors simultaneously. We designed the present study to perform this analysis, but also analyzed the heterogeneity of the income gap, thereby clarifying both the relative contributions of multiple factors to the income gap and the spatial variation of these contributions (i.e., regional differences). Compared with other literature, our study has two novel contributions. First, we consider many structural factors, including factors in economic, social, and policy categories, to produce a more comprehensive analysis than was possible from the smaller number of indicators used in previous research. Second, we quantified the relative importance of the indicators ("contribution analysis") to quantify their impact on income inequality. This quantitative ranking was not performed in previous research.

3. Methods

3.1. Gini coefficient calculation

China doesn't publish values of the Gini coefficient for individual provinces, so there is no official data available for an empirical analysis. However, most of China's published income distribution data are available in an aggregated form. Tian (2012) used different income levels to calculate the Gini coefficient based on the Lorentz curve, a method commonly used by Chinese scholars to measure the Gini coefficient (G) of the provinces:

$$G_m = 1 - \frac{1}{P_m W_m} \sum_{i=1}^{n} (W_{m,(i-1)} + W_{m,i}) \times P_{m,i} \tag{1}$$

where G_m is the Gini coefficient in province *m*, P_m is the total population in province *m*, W_m is the total income in province *m*, and *n* is the number of groups with different levels of income in province *m* (and *n* is generally 5 or 7 groups). *i* refers to the ranking in the income of the *n* groups from the highest to the lowest. $W_{m,i}$ is the income of group *i* in province *m*, and $P_{m,i}$ is the population of group *i* in province *m*.

In most provinces, group income data were collected separately for urban and rural workers, so Tian (2012) combined the rural and urban Gini coefficients using the following formula:

$$G_m = P_{m,u}^2 \frac{u_{m,u}}{u_m} G_{m,c} + P_{m,r}^2 \frac{u_{m,r}}{u_m} G_{m,r} + P_{c,m} P_{r,m} \frac{u_{m,u} + u_{m,r}}{u_m} \tag{2}$$

where $G_{m,u}$ and $G_{m,r}$ are the Gini coefficients for the urban residents and rural residents in province *m*, respectively. $G_{m,u}$ and $G_{m,r}$ are calculated from Equation (1). $P_{m,c}$ and $P_{m,r}$ represent the proportions of the total population accounted for by the urban and rural populations, respectively; $u_{m,u}$ and $u_{m,r}$ represent the per capita income of urban and rural residents, respectively, in province *m*; and u_m represents the per capita income of province *m*.

3.2. Selection of factors responsible for inequality

We chose the explanatory variables for our analysis based on their potential influence on changes in the Gini coefficient. We used 10 factors that had been previously recognized as significant in the literature, with choices from economic, social, and policy categories to provide insights into the contributions of these domains to the observed changes in income inequality.

Economic development can directly increase income levels and reduce poverty, but its effect on income inequality is uncertain (Seghezza, 2002). We chose the investment in fixed assets (Wang, 2006), foreign direct investment (FDI) (Chen, 2016), urbanization level (Lee et al., 2019; Yuan et al., 2020), unemployment rate (Feriyanto et al., 2020; Xue and Zhong, 2003), energy production (Buccellato and Alessandrini, 2009), and agricultural mechanization (Wang et al., 2016) as representative factors that drive economic growth. We mainly considered social development from the perspective of the richness of social public resources. Specifically, we chose highway density (Huang et al., 2020; Weng et al., 2021) to represent the soundness of the infrastructure, and used the proportion of residents of an area who graduated from higher education, which we defined as college graduates (Chan and Ngok, 2011; Suhendra et al., 2020; Yang and Gao, 2017), to represent the degree of education. Policy factors determine the attitude of local government towards addressing relative poverty. We chose two indicators in this category: marketization (Wu and Yao, 2015), which represents the central government's priority policy of developing a private-sector economy, and financial transfer payments, which represent government investments to improve some aspect of a local economy (Lei et al., 2016). **Table 1** defines the 10 indicators and presents their statistical characteristics.

Table 1. The descriptive statistics for the overall sample for China's 30 provincial-level administrative regions from 2002–2018.

Variable	Calculation method	n	Mean	Std.Dev.	Min.	Max.
INV (Investment in fixed assets)	Total investment in fixed assets / regional GDP	510	0.647	0.248	0.233	1.48
FDI (Foreign direct investment)	Foreign direct investment / regional GDP	510	0.024	0.021	0	0.146
URB (Urbanization)	Total population living in an urban area / total population	510	0.699	0.135	0.203	0.921
UNE (Unemployment rate)	Unemployment rate in urban area	510	0.036	0.007	0.012	0.068
MAR (Marketization)	(Employees of private enterprises + self-employed individuals) / total employment	510	0.705	0.136	0.203	0.944
PAY (Financial transfer payments)	Financial transfer payment / total population (RMB/person)	510	3214.345	2924.224	61.965	20,416.58
EDU (Higher education)	Number of college and university graduates / total population	510	0.004	0.002	0	0.021
TRA (Highways)	Length of highways / regional area (km/km^2)	510	0.743	0.484	0.033	2.454
ENE(Energy)	Primary energy output / total population (ton of standard coal equivalent/person)	510	2.911	4.518	0.024	25.714
AGR (Agricultural modernization)	Total power of agricultural machinery / total population (kW/10,000 person)	510	1.29	0.714	0.057	3.816

Because the 10 indicators had different units of measurement and magnitudes of values, it was necessary to standardize their values. We used the following equation:

$$stdvar_j = \frac{var_j - \overline{var}}{\sqrt{\frac{1}{n-1}\sum_{j=1}^{n}(var_j - \overline{var})^2}} \tag{3}$$

where $stdvar_j$ represents the standardized value of each variable j, var_j represents the original value of variable j, $\overline{var}$ represents the mean value of the non-standardized variable, and n is the total sample size, which equaled 510 in this study. **Table 2** summarizes the standardized values of the variables.

Table 2. Values of the variables in **Table 1** after standardization using Equation (3).

Variable	n	Mean	Std.Dev.	Min.	Max.
INV	510	0	1	−1.666	3.352
FDI	510	0	1	−0.795	3.529
URB	510	0	1	−2.428	2.617
UNE	510	0	1	−0.274	5.207
MAR	510	0	1	−3.693	1.754
PAY	510	0	1	−1.078	5.883
EDU	510	0	1	−1.723	8.311
TRA	510	0	1	−1.466	3.536
ENE	510	0	1	−0.639	5.047
ARG	510	0	1	−0.192	9.963

3.3. Data sources

We collected panel data from 2002 to 2018 (i.e., from the beginning of data collection for all provinces to the most recent data available) for China's 30 provinces. We excluded Tibet because of missing data. We obtained the data from China's statistical yearbooks for each province from 2003 to 2019 (NBSC, 2019).

3.4. Methodology

First, we use a two-way fixed-effects model as the basic model (the following Equation (4)). Then, to quantify the heterogeneity of how the Gini coefficient responded to changes in the influencing factors in provinces with the largest and smallest Gini coefficient values, we conducted two-way fixed-effects quantile regression analyses (Canay, 2011; Galvao, 2011; Koenker, 2004) based on ranking of the provinces using their Gini coefficient distributions (25%, 50%, and 75% quantiles). We used the following equations for these regressions:

Fixed-effect model:

$$G_{it} = \alpha_i + \sum_{k}^{k}\beta_k x_{kit} + z_i + s_t + \varepsilon_{it} \tag{4}$$

Panel quantile regression:

$$Q_{G_{it}}(\tau|\alpha_i, \varepsilon_{it}, x_{kit}) = \alpha_i + \sum_{k=1}^{K}\beta_k x_{kit} + z_i + s_t + \varepsilon_{it} \tag{5}$$

where G_{it} is the dependent variable (the Gini coefficient) for province i in year t; τ represents the quantile (25%, 50%, and 75%); α is the constant; x_{kit} is the value of indicator k that may influence Gini in province i in year t; β is the regression coefficient for that indicator; z_i is the individual effect; s_t is the time effect; and ε_{it} are random error terms. We then divided the data into eastern, central, and western China region (**Figure 1**). In this system, provinces are classified based on their economic development level. We then repeated the analysis for the three regions.

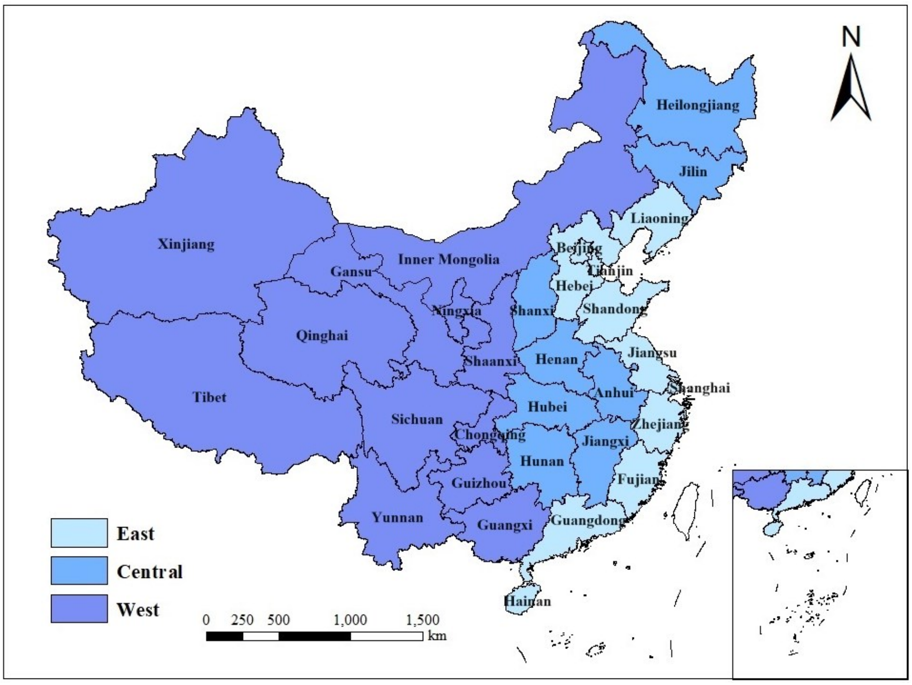

Figure 1. Chinese National Bureau of Statistics divides the eastern, central and western regions of China. The division was based on economic development and geographic location.

Although the statistical significance of each indicator and the direction of the corresponding coefficients can be observed in the regression results, the relative contribution of each indicator to the Gini coefficient cannot be determined. We therefore used the absolute values of the coefficients to calculate the contribution of the different indicators to changes in the Gini coefficient for the whole China and for eastern, central, western regions independently (Feng et al., 2015). The contribution was calculated as follows:

$$Con_k = \frac{AC_k}{\sum_{k=1}^{10} AC_k} \times 100\% \tag{6}$$

where Con_k is the contribution of variable k (the 10 economic, social, and policy indicators) to the dependent variable G and AC_k is the absolute value of the coefficient β_k.

4. Results

We observed both spatial variation (**Figure 2**) and changes over time (**Table 2**) in the Gini coefficient. The Gini coefficient in 2018 was much higher than that in 2002 in all 30 provinces. Although the Gini coefficient varied geographically, the highest values were found in eastern China, followed by central China, with the lowest values in western China. The average values were 0.55, 0.47, and 0.46, respectively in 2018. The Gini coefficient increased much more rapidly in eastern China (256.5%) than in western and central China (88.8% and 59.6%, respectively; **Table 3**). The spatial and temporal changes in the Gini coefficient highlight the need to investigate its heterogeneity in future research.

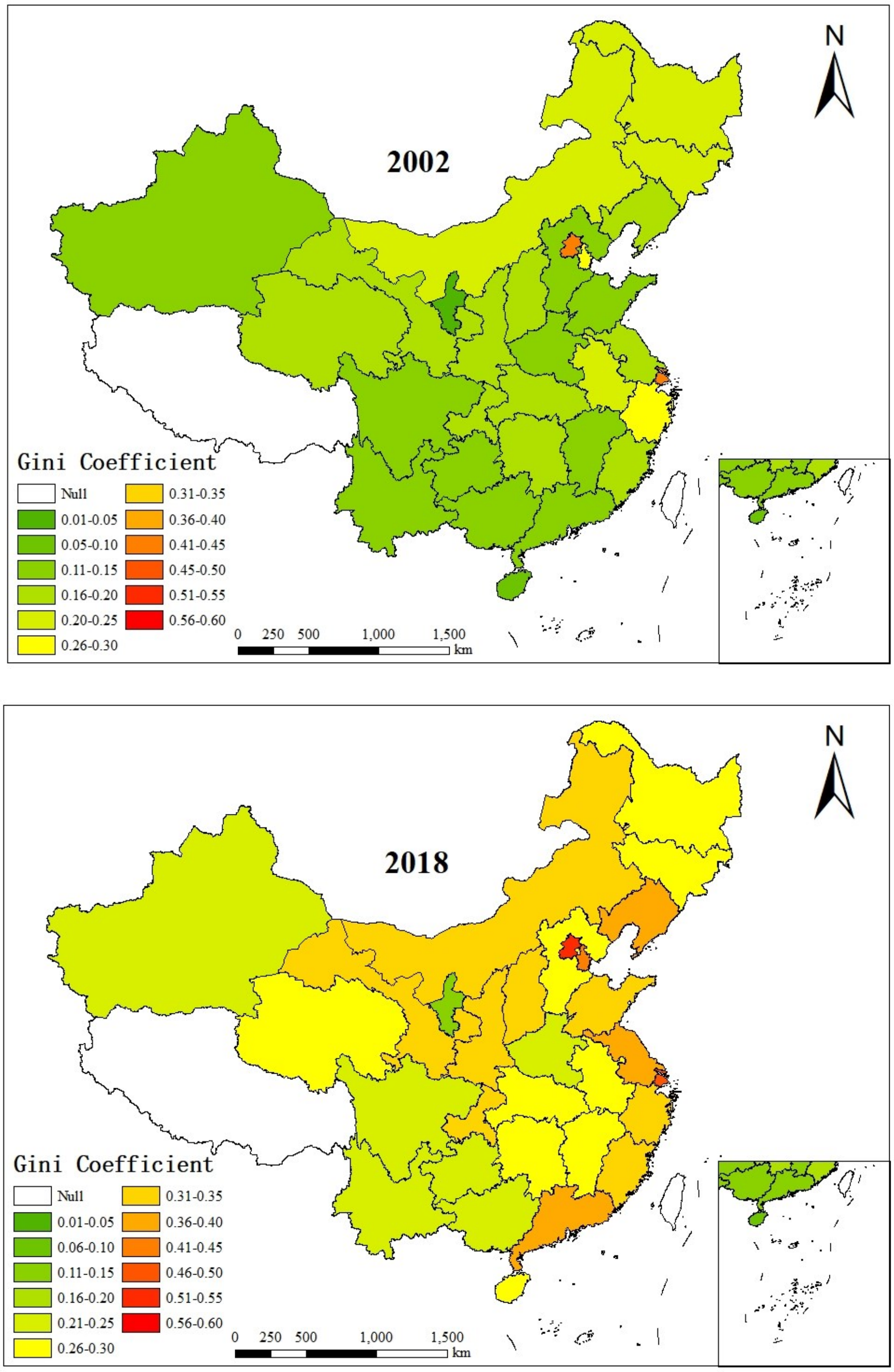

Figure 2. Spatial distribution of the Gini coefficient of China's provinces in 2002 and 2018 calculated using Equations 1 and 2.

Table 3. Changes of the Gini coefficient in China from 2002 to 2018. The Gini coefficient was calculated using Equations (1) and (2).

Region	Province	Gini coefficient		±SE	Growth rate (%)
		2002	2018		
Eastern region	Beijing	0.401	0.543	0.011	35.41
	Tianjin	0.273	0.436	0.012	59.71
	Hebei	0.127	0.292	0.012	129.92
	Liaoning	0.186	0.374	0.015	101.08
	Shanghai	0.407	0.458	0.038	12.53
	Jiangsu	0.154	0.378	0.017	145.45
	Zhejiang	0.252	0.345	0.007	36.9
	Fujian	0.179	0.339	0.012	89.39
	Guangdong	0.136	0.371	0.019	172.79
	Hainan	0.067	0.274	0.013	308.96
	Shandong	0.143	0.312	0.012	118.18
Central region	Shanxi	0.170	0.324	0.012	90.59
	Jilin	0.237	0.290	0.003	22.36
	Heilongjiang	0.236	0.300	0.005	27.12
	Anhui	0.247	0.264	0.008	6.88
	Jiangxi	0.106	0.262	0.011	147.17
	Henan	0.150	0.243	0.007	62
	Hubei	0.177	0.281	0.008	58.76
	Hunan	0.176	0.286	0.009	62.5
Western region	Inner Mongolia	0.209	0.343	0.011	64.11
	Guangxi	0.135	0.243	0.008	80
	Chongqing	0.182	0.337	0.01	85.16
	Sichuan	0.138	0.247	0.008	78.99
	Guizhou	0.127	0.241	0.008	89.76
	Yunnan	0.137	0.237	0.008	72.99
	Shaanxi	0.165	0.301	0.01	82.42
	Gansu	0.197	0.342	0.011	73.6
	Qinghai	0.166	0.291	0.009	75.3
	Ningxia	0.046	0.127	0.006	176.09
	Xinjiang	0.120	0.240	0.008	100

Many of the factors were statistically significant. For China as a whole (**Table 4**), urbanization increased the Gini coefficient (accounting for 27.9% of the change), and the effect became more obvious as the quantile of the Gini coefficient increased. Higher education (15.9%) and FDI (9.2%) also increased the Gini coefficient, but the role of higher education in increasing the gap decreased as the quantile increased. Financial transfer payments (9.2%), marketization (8.8%), and the investment in fixed assets were the main factors that decreased the Gini coefficient, but they showed the opposite trend in the quantile regression: when the Gini coefficient was higher, the contribution of marketization was higher but the contribution of financial transfer payments was smaller. Transportation (9.6%), investment in fixed assets (8.0%), and agricultural mechanization (3.2%) also played a role in decreasing the Gini coefficient, and both contributions decreased with increasing quantile.

Table 4. Regression results of the 10 indicators and their contributions to changes in the Gini coefficient for all Chinese provinces combined. TWFE, two-way fixed-effects model; Q25, Q50, and Q75, quantile regression models. Variable names are defined in **Table 1**.

Variable	TWFE		Q25		Q50		Q75	
	Coefficient	**Contribution (%)**	**Coefficient**	**Contribution (%)**	**Coefficient**	**Contribution (%)**	**Coefficient**	**Contribution (%)**
INV	−0.02*	7.97	0.005*	9.09	0.007	5.88	0.004	2.55
FDI	0.023***	9.16	0.003	5.45	0.02***	16.81	0.025***	15.92
URB	0.07**	27.89	−0.009**	16.36	0.031*	26.05	0.046*	29.30
UNE	−0.004	1.59	0.002	3.64	0.001	0.84	0	0
MAR	−0.022***	8.76	−0.009**	16.36	−0.022*	18.49	−0.04***	25.48
PAY	−0.023***	9.16	−0.012***	21.82	−0.014***	11.76	−0.012***	7.64
EDU	0.040***	15.94	0.007*	12.73	0.012*	10.08	0.015**	9.55
TRA	−0.024***	9.56	−0.004	7.27	−0.006	5.04	−0.007*	4.46
ARG	−0.008*	3.19	0	0	0	0	0	0
ENE	−0.017	6.77	0.004	7.27	0.006	5.04	0.008	5.1

Note: The coefficients were calculated using Equations (4) and (5). The contribution was calculated using Equation (6). See the Methods section for details. *, **, and *** represent 10%, 5%, and 1% significant levels, respectively.

From the regional perspective (**Table 5**), there were some commonalities in the three regions; for example, marketization significantly decreased the Gini coefficient in most models. Urbanization and higher education increased the Gini coefficient, except for a decrease due to urbanization in western China, and the higher the quantile, the greater their contribution. However, regional differences were more common than similarities. FDI only significantly increased the Gini coefficient in the eastern region (12.1%). The effect of transportation was not significant in the western region, but significantly decreased the Gini coefficient in the eastern region and the central region in the fixed-effect model (14.0% and 7.2%, respectively). Energy only significantly increased the Gini coefficient in the central region and the western region in the fixed-effect model (11.8% and 15.5%, respectively). Financial transfer payments did not significantly affect the Gini coefficient in the eastern region, but strongly and significantly decreased the Gini coefficient in the central region and the western region (34.6% and 24.1%, respectively).

Table 5. Regression results and contributions to the Gini coefficient for the 10 indicators for the three regions of China. TWFE, two-way fixed-effects model; Q25, Q50, and Q75, quantile regression models. Variable names are defined in **Table 1**.

Variable	TWFE		Q25		Q50		Q75	
	Coefficient	Contribution (%)	Coefficient	Contribution (%)	Coefficient	Contribution (%)	Coefficient	Contribution (%)
	Eastern							
INV	0.001	0.24	0.001	1.15	0.01	8.4	0.011	7.91
FDI	0.054*	12.08	0.007*	8.05	0.016*	13.45	0.013**	9.35
URB	0.127*	30.09	0.018**	20.69	0.032**	26.89	0.043*	30.94
UNE	−0.01	2.37	−0.01	11.49	−0.01	8.4	−0.01	7.19
MAR	−0.091***	21.56	−0.007	8.05	−0.017***	14.29	−0.026**	18.71
PAY	−0.001	0.24	0.013	14.94	0.008	6.72	0.01	6.80
EDU	0.026***	6.16	0.004*	4.60	0.006**	5.04	0.008*	5.44
TRA	−0.059***	13.98	−0.013	14.94	−0.015**	12.61	−0.018**	12.95
ARG	−0.020***	4.74	0.003	3.45	0.002	1.68	0.002	1.44
RES	−0.033	7.82	−0.011	12.64	0.003	2.52	−0.006	4.32
	Central							
INV	−0.003	1.96	0.000	0	0.000	0	0.000	0
FDI	0	0	0.002	1.87	0.001	0.98	−0.001	0.99
URB	0.028*	18.3	0.021**	19.63	0.02**	19.61	0.021**	20.79
UNE	0	0	0.002	1.87	0.001	0.98	0	0
MAR	−0.018***	11.76	−0.017***	15.89	−0.014***	13.73	−0.011**	10.89
PAY	−0.053***	34.64	−0.036***	33.33	−0.03***	29.41	−0.03***	29.70
EDU	0.02*	13.07	0.004	3.70	0.011**	10.78	0.013*	12.87
TRA	−0.011***	7.19	−0.009*	8.41	−0.009**	8.82	−0.009*	8.91
ARG	−0.002	1.31	0.001	0.93	−0.001	0.98	−0.002	1.98
RES	0.018***	11.76	0.016**	14.95	0.015***	14.71	0.014**	13.86
	Western							
INV	−0.008	4.28	0.002	5.71	0.002	3.39	0.002	4.35
FDI	−0.004	2.14	−0.002	5.71	−0.002	3.39	−0.002	4.35
URB	−0.023*	12.3	0.002	5.71	0.008**	13.56	−0.007*	15.22
UNE	0.003	1.6	−0.002	5.71	−0.003	5.08	−0.003	6.52
MAR	−0.026***	13.9	−0.001	2.86	−0.01**	16.95	−0.005*	10.87
PAY	−0.045***	24.06	−0.007***	20	−0.012***	20.34	−0.01**	21.74
EDU	0.03*	16.04	0.004*	11.43	0.009*	15.25	0.008**	17.39
TRA	−0.01	5.35	0.005*	14.29	0.004	6.78	0.002	4.35
ARG	−0.009*	4.81	−0.002	5.71	−0.002	3.39	−0.001	2.17
RES	0.029***	15.51	0.008***	22.86	0.007***	11.86	0.006**	13.04

Note: The coefficients were calculated using Equations (4) and (5). The contribution was calculated using Equation (6). See the Methods section for details. *, **, and *** represent 10%, 5%, and 1% significant levels, respectively.

5. Discussion

In this study, we added to the industrialization and urbanization factors emphasized by Kuznets and many subsequent researchers by adding eight more structural elements that extended the functionalist approach from a purely economic perspective to include social and economic perspectives. This more holistic analysis makes it possible for governments to identify the key factors that should be targeted by policies designed to mitigate income equality.

Our contribution analysis showed that urbanization and higher education widened the income gap, whereas marketization narrowed the income gap both for China as a whole and for the three regions separately. This and the relatively high contributions of marketization together suggest that the national government should continue its marketization strategy. The results of our analysis differed among the three regions due to their different geographical locations and the resulting differences in their development history and in their influencing factors (e.g., proximity to ports), resource endowments (here, energy), and policy orientations. For example, eastern China was the earliest region to open to the west, and its proximity to the coast encouraged foreign investment. China's central and western regions have more energy reserves than the eastern region, and energy mining is the core industry of many cities in these regions. It will be interesting to see how the income gap changes in response to Chinese policies such as Deng's belief that allowing some people to get rich first increases the chances for other people to get rich later.

Many studies have shown that urbanization can significantly reduce the urban-rural income gap (Lu and Chen, 2004; Su et al., 2015; Yuan et al., 2020). However, our research showed that urbanization was a large contributor to increases of the Gini coefficient (i.e., increased inequality). The urban-rural income gap in China has tended to narrow since 2009 (NBSC, 2003–2019), but the Gini coefficient is gradually increasing throughout China. The urban-rural income gap does not reflect differences in the income gap within urban or rural areas, and the widening of the income gap within cities is obvious (Zhou, 2009). Interestingly, we found that in western China, urbanization could reduce the Gini coefficient. This may be because the Chinese government has implemented the Western Development Project in the western region, which has brought a large number of rural people to work in the urban industrial sector, which has gradually expanded the region's small cities. This suggests the need for economic policies that take into account the interests of the majority of the population. Therefore, to develop urbanization in a way that decreases the Gini coefficient, we should not only pay attention to the transformation from rural to urban areas (i.e., urbanization), but should also pay more attention to the fair distribution of income within cities. For example, migrant workers who move to urban areas currently lack access to the benefits provided to urban residents, such as children education and medical care.

The expansion of higher education has enabled China to accumulate a large number of trained worked (Ge and Chen, 2010). However, as in the research by Chan and Ngok (2011) and Yang and Gao (2017), we found that higher education widened the income gap. Economic disparities between regions directly lead to unequal educational opportunities for students in different regions (Chan and Ngok, 2011). Mycos (2009) investigated the starting salaries of graduates and found that the inequality of educational opportunities led directly to inequality of salaries. Our results showed that the income inequality caused by higher education was most obvious in western China, which had the lowest percentage of college students (NBSC, 2003–2019), and the mean income of residents with higher education was much greater than that for the majority of local residents, leading to widening of the income gap. Improving the educational opportunities of disadvantaged groups in less-developed areas will decrease the social differentiation caused by the existing differences in access to higher education.

Due to differences in geographical locations and resource endowments, FDI has flourished in eastern China, whereas energy production has remained more important in the central and western regions. However, this development pattern has led to widening of the income gap in both the latter regions. Eastern region is rich in highly trained workers (Li et al., 2020), but needs foreign investment to support its industrial development in terms of technology and innovation. Such capital deepening and skills-biased FDI generates a large number of highly paid jobs in eastern China, but also marginalizes other workers, thereby increasing the income gap (Lin et al., 2013). Improving eastern China's innovation ability and reducing its dependence on technology from developed countries would decrease technology-related FDI in eastern China, thereby reducing the income gap. Natural resources extracted in the central and western regions mostly undergo primary processing (Liu and Zhang, 2020), which makes it easier for a few people to control the revenues from natural resources extraction and increases the income gap (Buccellato and Alessandrini, 2009). More intensive processing of local natural resources (e.g., transforming iron ore into steel) could reduce the income gap.

Although the Gini coefficient increased in all Chinese provinces during our study period, our results revealed that several factors can reduce the Gini coefficient and that these factors therefore deserve more attention in government efforts to narrow the income gap. Marketization significantly decreased the Gini coefficient both for China as a whole and separately for each region, and its contribution was greatest in the eastern region because the reform and opening up policy was first implemented in this region (Li et al., 2020). The increase of road density provides more opportunities for labor mobility, and the floating labor force (workers who move to cities to find jobs) supports marketization development, thereby reducing relative poverty (Fan and Chan-Kang, 2008). Agricultural mechanization improves labor productivity (Wang et al., 2016), and indirectly gives farmers more opportunities to obtain other income, such as income from migrant work, by reducing the time required for crop and livestock management (Fang et al., 2018).

The financial transfer payments that were intended to narrow the income gap were only effective in central and western China, because both regions received much higher transfer payments than eastern China (NBSC, 2003–2019). However, achieving social income equity should not rely on financial transfer payments, because our results showed that as the Gini coefficient increased, the role of these transfers has gradually decreased both for China and for all three regions.

6. Conclusion

To narrow the income gap, China must learn the reasons for these trends by identifying the key factors that widen the urban-rural income gap so that the government can develop policies that focus on these factors. Although the present study is preliminary, our research provides some useful insights into possible policy choices. For example, the government should pay more attention to welfare equity during urbanization. Increasing access to universities for disadvantaged groups in less-developed areas will also narrow the income gap. The eastern region should try to reduce technology-dependent FDI, whereas the central and western regions should develop natural resources such as energy by processing raw materials into intermediate and finished products rather than focusing on extraction of these materials. The government should continue to invest more in the factors that can reduce the income gap (marketization, transportation, and agricultural mechanization), and should find ways to reduce the importance of financial transfers, which contributed relatively little to reducing the income gap at higher quantiles for the Gini coefficient.

Analysis of the heterogeneity of the Gini coefficient (e.g., the results of the quantile regression that we performed) and measurement of the relative contribution of multiple indicators provided unique insights into the regional differences in income disparities and their driving factors, and can thereby help governments find the overall and relative importance of various indicators. However, due to lack of data, we could not obtain data on the Gini coefficient and related structural indicators at a sub-regional level; thus, we could only discuss the differences between eastern, central, and western China. In future research, finer-resolution data should be used as it becomes available. In addition, since we discuss the influence of structural factors on income inequality from a macro perspective, we could not discuss the income gap caused by individual human differences. These limitations mean that our analysis should be extended to a more micro level to provide better support for future policy development. Despite these limitations, our method and our results could provide useful references for other countries and regions with large income disparities. In addition to our economic results, it's important to note that income inequality is an important component of overall socioeconomic inequality, and reducing this inequality in developing countries will contribute to achieving the 10th Sustainable Development Goal of the United Nations.

A number of policies have been developed to reduce the income gap in China, such as the East-West Cooperation Policy and the Rural Revitalization Policy. These policies have triggered structural changes, but their impact on income inequality is unclear. In future studies, we hope to discuss the implementation of these policies separately, as well as their impact on income inequality.

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