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Measurement and Analysis of Opportunity Inequality in Residents' Income

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Abstract

Based on data from the China Family Panel Studies (CFPS), this study employs a parametric method to measure the degree of opportunity inequality in residents' income. It analyzes the spatial distribution characteristics across eight regions and delves into the contribution mechanisms of grouped environmental variables to income inequality. The empirical findings reveal that family environment factors consistently serve as the core driving force behind income opportunity inequality, with a persistently stable and significant contribution, underscoring the enduring impact of intergenerational transmission. Regional environmental factors exhibit significant fluctuations in their contributions, which are closely synchronized with the evolution of the overall inequality index, highlighting the pivotal role of regional development disparities in shaping inequality patterns. The contribution of individually controllable factors shows a gradual upward trend, providing a buffering effect, particularly during phases of declining opportunity inequality. Overall, the influence of environmental groupings on income inequality is characterized by a three-dimensional dynamic pattern of "family dominance, regional fluctuation, and individual enhancement."

Keywords: income inequality, opportunity inequality

1. Introduction

Common prosperity is a crucial goal for building a modern socialist nation and represents a vital pathway for China to advance social equity and justice while enhancing the well-being of all citizens. However, despite rapid economic and social development, significant income disparities persist among Chinese residents, with opportunity inequality emerging as a critical factor influencing income distribution. Opportunity inequality not only directly impacts individual income levels but also perpetuates social stratification through intergenerational transmission, reducing social mobility and hindering the realization of common prosperity.

The formation of opportunity inequality is complex and multifaceted, encompassing the long-term influence of family background on education and resource allocation, regional economic disparities, individual differences in ability, and social environmental factors. Therefore, measuring and analyzing income opportunity inequality from the perspective of environmental groupings can clarify the specific mechanisms by which family, regional, individual, and societal factors shape income distribution, providing a scientific basis for formulating more precise and effective income distribution policies.

Current research on opportunity inequality mainly focuses on its measurement and impacts. Romer (1993) introduced the innovative "circumstance-effort" dual framework to define opportunity inequality as income inequality driven by environmental factors. Building on this foundation, several measurement methods for opportunity inequality have been developed, including the ex-ante approach (Van de Gaer, 1993; Kranich, 1996), the ex-post approach (Romer, 1993, 1998; Fleurbaey, 1995), parametric methods (Ferreira & Gignoux, 2011), and non-parametric methods (Checchi & Peragine, 2010; Lefranc et al., 2008).

In recent years, the ex-ante parametric method has become the predominant approach in the literature. For example, scholars in China have adopted modified parametric methods to measure opportunity inequality. Lei Xin (2018) improved the parametric approach by considering the impacts of unobservable environmental and effort variables and addressing the correlation between these variables. Li Jinye (2019) utilized regression tree models for measurement, while Wan Xiangyu (2023) employed machine learning models based on integrated regression trees and introduced quantile regression forests to extend the analysis of opportunity inequality from income means to income distributions.

On the other hand, existing studies have also highlighted the impacts of opportunity inequality on household consumption expenditure, employment levels and hierarchies, mental health, and wealth inequality (Zhang Mingzhi, 2023; Yang Biyun, 2024; Li Qiaoge, 2025; Sun Sanbai, 2023). Against the backdrop of common prosperity, this study revisits the measurement and analysis of opportunity inequality in residents' income, focusing on the influence of different environmental variable groupings on income inequality. The findings aim to reveal the structural causes of inequality and provide theoretical support for policy design and optimization, ultimately promoting the equitable sharing of development outcomes across society and achieving the grand vision of common prosperity.

2. Research Methodology

2.1 Parametric Measurement Method for Opportunity Inequality

This study adopts the mainstream parametric measurement method for opportunity inequality as proposed by Bourguignon (2007) and Ferreira and Gignoux (2011) to quantify the degree of opportunity inequality in individual incomes. Based on Roemer's "circumstance-effort" dual theoretical framework of opportunity inequality, a Mincer income equation is constructed as follows:

$$\ln Y_i = \alpha_0 C + \beta E_i + \mu_i \tag{1}$$

Yi represents an individual's total income, C denotes the vector of the individual's environmental variables, Ei represents the vector of the individual's effort variables, and μi captures unobservable factors such as luck. It is assumed that an individual's effort level is a linear function of their environmental variables:

$$E_i = \theta C + v_i \tag{2}$$

Substituting equation (2) into equation (1) and simplifying yields:

$$\ln Y_i = \alpha C + \varepsilon_i \tag{3}$$

Where $\alpha = \alpha_0 + \theta, \varepsilon_i = \beta v_i + \mu_i$, by estimating equation (3) to obtain fitted values and averaging all environmental variable vectors, the counterfactual income distribution is obtained:

$$\tilde{Y}_i = \exp(\hat{\alpha}\bar{C} + \hat{\varepsilon}) \tag{4}$$

Based on the results, the Theil T index and Theil L index are calculated respectively:

$$I_T(Y) = \frac{1}{N}\sum_{i=1}^{N}[(Y_i / \bar{Y})\ln(Y_i / \bar{Y})] \tag{5}$$

$$I_L(Y) = \frac{1}{N}\sum_{i=1}^{N}\left(\ln \bar{Y} - \ln Y_i\right) \tag{6}$$

This study uses the Theil index as a measure of income inequality and, based on it, calculates the opportunity inequality index. The Theil index is an indicator used to assess the degree of inequality in income or resource distribution and has two common forms: the T-shaped Theil index, which is more sensitive to inequality among high-income or high-resource holders, and the L-shaped Theil index, which is more sensitive to inequality among low-income or low-resource holders. By substituting the actual income distribution Y and the counterfactual income distribution $\tilde{Y}$ into equations (5) and (6) respectively, and since the individual environmental variables have been averaged, the opportunity inequality index is obtained by subtracting the Theil index of the counterfactual income distribution from that of the actual income distribution. Additionally, the relative share of opportunity inequality in total income inequality can be calculated as follows:

$$IO_T = I_T(Y) - I_T(\tilde{Y}) \tag{7}$$

$$IO_L = I_L(Y) - I_L(\tilde{Y}) \tag{8}$$

$$IOr_T = [I_T(Y) - I_T(\tilde{Y})] / I_T(Y) \tag{9}$$

$$IOr_L = [I_L(Y) - I_L(\tilde{Y})] / I_L(Y) \tag{10}$$

2.2 Shapley Value Regression Decomposition

The Shapley value, originating from game theory in the 1950s, is used to quantify the marginal contribution of each participant to the total payoff in a cooperative game. This method has been widely applied in economics and social sciences to achieve a fair distribution of gains or costs. In regression models, the Shapley value method independently and unbiasedly quantifies the marginal contribution of explanatory variables to the dependent variable by evaluating all possible combinations of variables. In machine learning, Shapley value decomposition calculates the average marginal contribution of each feature to the model's prediction by considering all possible feature combinations, thereby providing a fair explanation of the model's predictions.

Consider a cooperative game with M participants and a value function f(A). The Shapley value f assigns to each participant k their marginal contribution to the total payoff, defined by equation (11):

$$\psi_k = \sum_{A \subseteq M \setminus \{k\}} \frac{|A|! \cdot (m - |A| - 1)!}{m!} \cdot [f(A \cup \{k\}) - f(A)] \tag{11}$$

A is a subset of participants excluding participant k;

|A| is the size of subset A;

f(A) is the value of subset A;

$f(A \cup \{k\}) - f(A)$ is the marginal contribution of participant k to subset A;

$\frac{|A|! \cdot (m - |A| - 1)!}{m!}$ is the weighting factor.

3. Variables

3.1 Effort Variables

Following existing research (Ferreira and Gignoux, 2011) and considering data completeness and availability, this study selects the following variables as effort variables influencing individual income levels: marital status, weekly working hours, social status, and education level. Traditionally, the phrase "establishing a family and career" reflects the cultural importance of marriage, which is often used as a standard to evaluate whether a person is "successful." Marriage typically requires individuals to invest emotions, responsibilities, and time, which can indicate their willingness and degree of effort. Working hours directly reflect an individual's dedication to their profession; longer working hours generally imply greater effort and commitment to career development. Although it is recognized that disadvantaged environments contribute to about 30% of educational opportunity inequality, effort remains the dominant factor affecting education level (Yang Juan and Zhang Lifang, 2024). Under a relatively fair education examination system, the number of years of education an individual attains is usually related to the time and energy they are willing to invest in acquiring knowledge and skills. Higher education levels typically require prolonged learning, testing, and practice, all of which reflect individual effort.

3.2 Environmental Variables

Environmental variables are typically those that individuals cannot change through their own efforts. Drawing on the approaches of Dong Lixia (2025) and Zhang Tongjin et al. (2024), this study uses 10 environmental variables divided into four categories: regional environment variables (hukou type, province, region), personal environment variables (gender, age), family environment variables (family social status, family net assets, family size, parental education level), and social environment variables (economic development level, government support intensity). Individual income is influenced by many uncontrollable factors. Research on intergenerational income transmission (Peng Jun and Zhao Xiliang, 2024) shows that parents' income levels and related factors significantly affect their children's income. Gender and age, as innate characteristics, cannot be changed but have a clear impact on income levels. Family size, family social status, and family net assets influence the formation of an individual's abilities and personality, which in turn determine income capacity in adulthood. Since economically developed areas typically offer more high-paying opportunities and better resources, regional differences and economic development levels have a significant impact on income. Social status is often the result of long-term effort and resource accumulation. Although social status may also be influenced by family background and other external factors, personal effort plays an important role in its improvement.

3.3 Regional Variables

According to the division standards of the eight comprehensive economic zones set by the Development Research Center of the State Council in "Strategies and Policies for Regional Coordinated Development," the regions are divided as follows:

Northeast region: Liaoning, Jilin, Heilongjiang

Eastern coastal region: Shanghai, Jiangsu, Zhejiang

Northern coastal region: Beijing, Tianjin, Hebei, Shandong

Southern coastal region: Fujian, Guangdong, Hainan

Middle Yellow River region: Shaanxi, Shanxi, Henan, Inner Mongolia

Middle Yangtze River region: Hubei, Hunan, Jiangxi, Anhui

Southwest region: Yunnan, Guizhou, Sichuan, Chongqing, Guangxi

Northwest region: Gansu, Qinghai, Ningxia, Tibet, Xinjiang

3.4 Income Variable

When estimating the income determination equation, this study selects the total income reported by the individual in the past 12 months as the dependent variable. Compared to total wage income or labor income alone, total income more comprehensively reflects the part of individual income influenced by environmental variables, such as investment returns from family financial assets.

Table 1. Table of Key Variable Definitions

			Variable Names	Variable Definitions
Dependent Variable			Lnfinc	Personal Income Level
			Marrige	Marital Status
Effort Variables			Workhour	Weekly Working Hours
			Eduy	Education Level
	Regional Variables	Environmental	Urban	Hukou Type (household registration type)
			Region	Region
			Provcd	Province
	Personal Variables	Environmental	Age2	Age
			Gender	Gender
Environmental Variables	Family Variables	Environmental	Asset	Family Net Assets
			Dw	Family Social Status
			Size	Family Size
			Pareduy	Parental Education Level
	Social Variables	Environmental	Lngdp	Economic Development Level (logarithm of per capita GDP)
			Govsup	Government Support Intensity

4. Data

This study utilizes the five datasets released by the China Family Panel Studies (CFPS) covering the years 2014 to 2022 as its sample. The survey provides comprehensive data on individuals, families, society, and regions, which serve as a foundation for this research. The sample is restricted to individuals with economic income who have provided income data. Specifically, the variables included are as follows:

4.1 Income Variables

Individual income level: The logarithm of total income over the past 12 months, as reported in the survey questionnaire by each sampled individual.

4.2 Effort Variables

Marital status: A binary variable where married individuals are coded as 1 and unmarried as 0.

Education level: Corresponds to years of schooling based on respondents' highest education level, coded as 0 = illiterate/semi-illiterate, 6 = primary school, 9 = junior high school, 12 = high school/technical secondary school/vocational school, 15 = junior college, 16 = bachelor's degree, 19 = master's degree, 22 = doctoral degree.

Working hours: Number of hours worked by the respondent in the past week.

Social status: Ranked from 1 to 5, with 1 being lowest and 5 highest.

4.3 Environmental Variables

Age: Age squared divided by 10.

Gender: A binary variable coded 1 for male and 0 for female.

Hukou type: A binary variable coded 1 for urban residents and 0 for rural residents.

Province: Administrative region code of the People's Republic of China (GB/T2260—999).

Region: A binary variable generated from the province variable, dividing the sample into eight economic zones.

Family net assets: Logarithm of family net assets.

Family size: Number of family members.

Parental education level: Calculated similarly to the respondent's education level, by averaging the years of schooling of both parents.

Economic development level: Logarithm of the local per capita GDP of the respondent's area in the current year.

Government support intensity: Ratio of fiscal expenditure to GDP in the given year multiplied by 100.

In summary, the CFPS datasets during the sample period contain 86,294 observations. After excluding samples under 22 years of age and those with missing variables, and performing a 1% winsorization, the final sample size used in this study is 31,202 observations.

5. Analysis and Recommendations on Opportunity Inequality Measurement Results

5.1 Measurement Results

The income inequality results for the nation and various economic regions during the even years from 2014 to 2022, calculated using equations (5) and (6), are presented in Table 2.

Table 2. National and Regional Income Inequality Results

	Index	2014	2016	2018	2020	2022
Nationwide	Theil T Index	0.4490	0.4889	0.4463	0.4324	0.5288
	Theil L Index	0.4369	0.4914	0.4755	0.4693	0.4851
Northeast	Theil T Index	0.2627	0.2357	0.3551	0.3244	0.2682
	Theil L Index	0.2802	0.2828	0.3689	0.3709	0.3036
Northern Coastal	Theil T Index	0.4552	0.5181	0.5309	0.4078	0.4555
	Theil L Index	0.4574	0.4802	0.5229	0.4617	0.4717
Eastern Coastal	Theil T Index	0.4335	0.4489	0.3104	0.3377	0.6992
	Theil L Index	0.4074	0.3960	0.3555	0.3783	0.4768
Southern Coastal	Theil T Index	0.4160	0.4348	0.4398	0.4246	0.3690
	Theil L Index	0.4412	0.4580	0.4548	0.4594	0.4192
Middle Yellow River	Theil T Index	0.2974	0.3426	0.3485	0.3358	0.3739
	Theil L Index	0.3463	0.4093	0.3943	0.3874	0.4287
	Index	2014	2016	2018	2020	2022
Middle Yangtze River	Theil T Index	0.3280	0.4541	0.3751	0.3908	0.2910
	Theil L Index	0.3745	0.4784	0.4084	0.4206	0.3555
Southwest	Theil T Index	0.3640	0.6600	0.4492	0.5032	0.3521
	Theil L Index	0.4259	0.6709	0.5161	0.5360	0.4293
Northwest	Theil T Index	0.7444	0.3580	0.4292	0.3054	0.5928
	Theil L Index	0.5165	0.3862	0.4264	0.3541	0.4835

The national T-shaped Theil index increased from 0.4490 in 2014 to 0.5288 in 2022, showing a trend of first decreasing and then rising, indicating a slight increase in income inequality. The L-shaped Theil index fluctuated slightly between 0.4369 and 0.4851 from 2014 to 2020, rising modestly to 0.4851 in 2022, suggesting a slight strengthening of inequality fluctuations nationwide, especially in interregional inequality.

Regional characteristics are as follows:

Northeast region: The T-shaped Theil index decreased slightly from 0.2627 to 0.2682, with small changes, but showed significant volatility after 2016, possibly related to economic transformation and other factors.

Northern coastal region: The T-shaped Theil index peaked at 0.5181 in 2016, then dropped to 0.4078 in 2020, potentially reflecting the effects of economic development and policy regulation.

Eastern coastal region: The index remained relatively stable between 2014 and 2018, then sharply increased to 0.6992 in 2022, indicating a notable rise in inequality possibly related to economic slowdown and regional imbalances.

Northwestern region: The index was 0.7444 in 2014, declined to 0.3054 in 2020, and rebounded to 0.5928 in 2022, showing that inequality was influenced by resource-based economies and population mobility.

Southern coastal and middle Yellow River regions: The index mostly ranged between 0.3 and 0.4, with small fluctuations, indicating relatively balanced income distribution.

Using equations (7) to (10), the income opportunity inequality index and its relative share of income inequality were calculated nationally and by region, as shown in the accompanying figure. The results indicate that both the national level and most regions (Northeast, Eastern coastal, Southern coastal, and Southwest) exhibit an inverted U-shaped distribution in opportunity inequality index and its share, while the middle Yangtze River and Northwest regions show a W-shaped pattern.

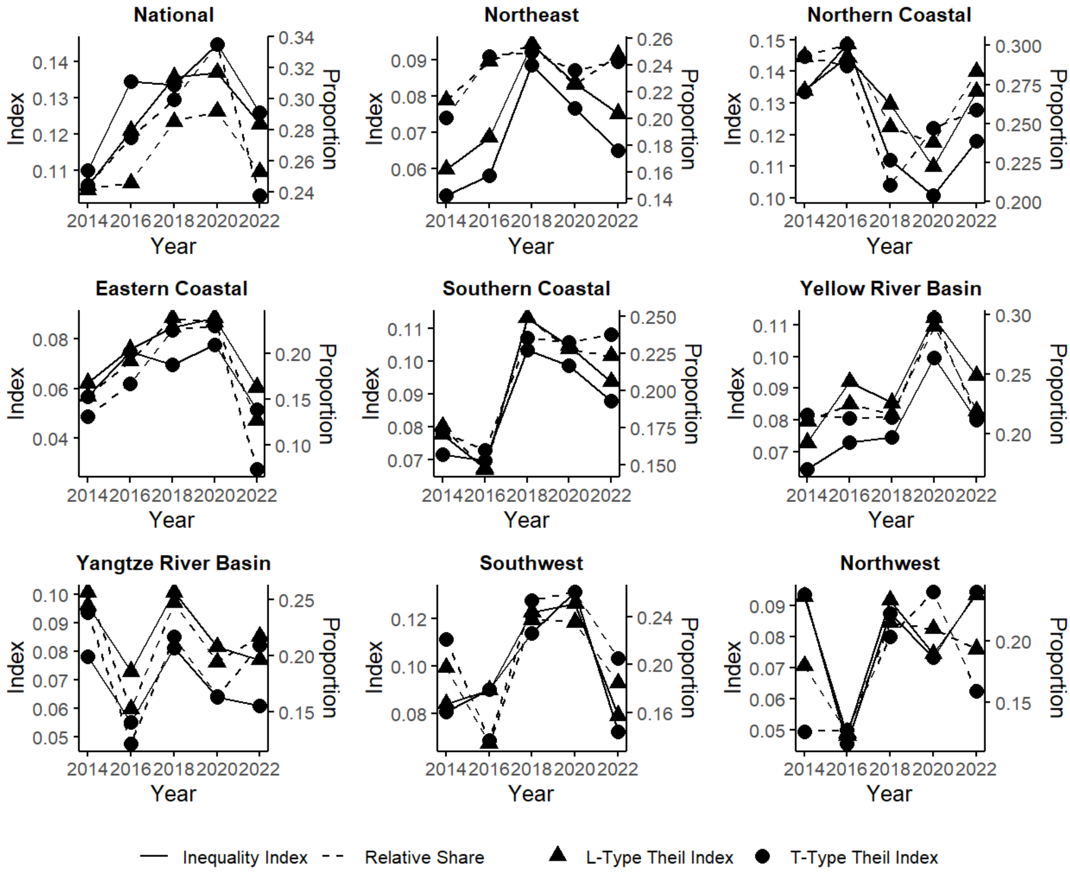

Figure 1. Results of National and Regional Opportunity Inequality and Its Proportion

From 2014 to 2022, the national high-income sensitive and low-income sensitive opportunity inequality indices generally fluctuated, without a clear unidirectional trend across years, but significant regional differences were evident. High-income regions such as the Northern and Eastern coastal areas had relatively high opportunity inequality levels, especially with marked fluctuations between 2014 and 2018, followed by gradual stabilization, reflecting a gradual mitigation of inequality effects brought by economic development. In contrast, economically less developed regions like the Northwest and middle Yellow River areas exhibited lower absolute levels but greater volatility, with opportunity inequality having a stronger explanatory power for income inequality, peaking around 2020. This indicates that opportunity inequality issues were particularly prominent in these regions during their economic development.

In 2022, the proportion of the opportunity inequality index relative to the income inequality index declined significantly in multiple regions, possibly related to optimized economic policies, income distribution reforms, and structural adjustment measures. The Northeast region showed a low opportunity inequality index but a relatively high share, indicating that income inequality there stems more from unequal opportunities. Meanwhile, the Southern coastal and Southwest regions exhibited a gradually weakening explanatory power of opportunity inequality on income inequality, likely benefiting from regional economic structural adjustments and policy support. Overall, the widespread downward trend in 2022 reflects the preliminary effectiveness of policy interventions in alleviating income and opportunity inequalities, although regional imbalances persist.

5.2 Shapley Value Decomposition

Following established methodologies in the literature, this study employs Shapley value regression decomposition to estimate the contribution rates of various environmental factors to overall income inequality. According to the classification presented in Table 1, variables are categorized into four environmental groups: regional, social, family, and personal.

Within each environmental group, variables are processed using principal component analysis (PCA) to extract the first principal component as the cointegration result. The contribution rate of each environmental group's cointegration result to overall income inequality is then calculated.

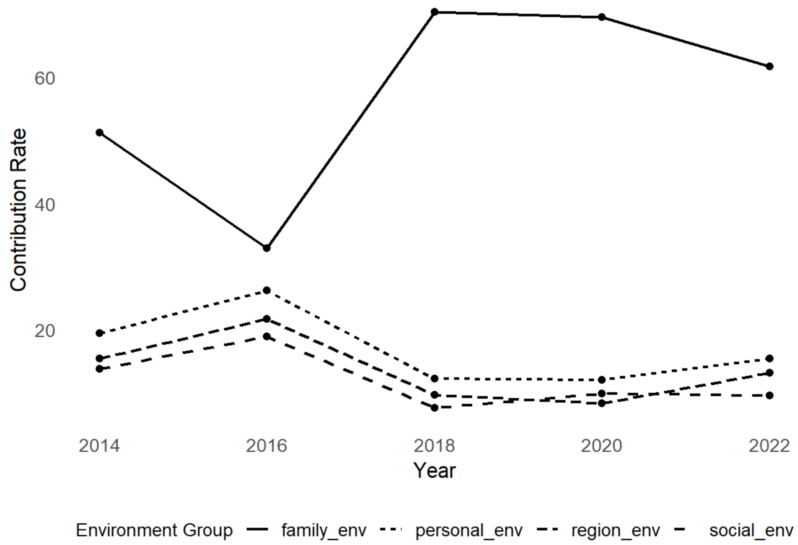

Figure 2. Contribution Rates of Environmental Groups to Income Inequality

The analysis of the contribution rates of environmental factors to income inequality indicates that the family environment has consistently been the primary driver of income inequality. Notably, in 2018 and 2020, its contribution rates reached 70.34% and 69.59%, respectively, corresponding to the high values of the opportunity inequality index in those years. This highlights the crucial role of family background in driving opportunity inequality. The contribution rate of the regional environment fluctuates significantly, aligning with the trend of the L-shaped Theil index, demonstrating the important impact of regional disparities on income inequality. Additionally, the contribution rate of personal factors was relatively high in 2022, while the opportunity inequality index declined, suggesting that improvements in individual capabilities have played a certain role in mitigating income gaps. Overall, the influence of environmental factors on income inequality shows characteristics of family dominance, regional fluctuations, and a gradually strengthening role of personal factors.

Based on the analysis of the contribution rates of environmental factors to income inequality and their underlying drivers, the following targeted policy recommendations are proposed:

Given the significant impact of the family environment on income inequality, efforts should be made to enhance educational equity. This can be achieved by optimizing the regional allocation of educational resources and increasing support for remote and economically underdeveloped areas to reduce disparities in educational opportunities caused by differences in family background. In addition, education subsidies and early childhood education support policies aimed at low-income families should be implemented to alleviate the intergenerational transmission effect on income inequality.

To reduce the contribution of regional environment to income inequality, further promotion of coordinated regional economic development is necessary. It is recommended to increase infrastructure and industrial support for underdeveloped regions to promote balanced economic development across regions. At the same time, mechanisms for cross-regional resource flow and distribution should be established to effectively reduce the negative effects of regional economic development disparities on income distribution.

The enhancement of personal capabilities has played a positive role in narrowing income gaps, and it is advisable to deepen vocational skills training and employment promotion policies. Targeted vocational training programs should be provided for low-income groups to help them integrate into high-quality employment markets. Meanwhile, the entrepreneurial environment should be improved through financial support and tax incentives to create more development opportunities for small and micro enterprises and individual entrepreneurs.

To reduce opportunity inequality, social mobility should be strengthened, ensuring fair employment and comprehensive social security coverage. Labor market regulation should be reinforced to eliminate employment discrimination and guarantee the fair distribution of labor opportunities. By expanding the coverage of the social welfare system, the medical, elderly care, and housing conditions of low-income groups should be improved to lower structural barriers to social mobility.

A dynamic monitoring mechanism should be established to track the evolving trends of income inequality and scientifically evaluate policy effectiveness. By regularly calculating the contribution rates and changing trends of each environmental factor to income inequality, precise data support for policy adjustment can be provided, ensuring the relevance and effectiveness of policies.

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