Dynamic Evolution and Configurational Heterogeneity of the Skill Wage Gap in China under Technological Transformation

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Abstract: Against the backdrop of the accelerated penetration of artificial intelligence and robotics technologies, the impact of technological shocks on income distribution has become a core issue in development economics and labor economics. Based on four waves of data from the China Family Panel Studies (CFPS) from 2022 to 2025, this study constructs an individual-level indicator of the skill wage gap and adopts an occupational task automation exposure index as a proxy variable for technological shocks. It systematically examines the heterogeneous effects of automation technology diffusion on wage structures and their micro-level transmission mechanisms. The results show that technological shocks significantly widen the skill wage gap, and wage growth for occupational groups with high exposure to automation lags markedly behind that of low-exposure groups. The task substitution mechanism is the core channel underlying these effects, as workers with a higher share of standardized routine tasks face more pronounced downward wage pressure. Vocational education background and participation in on-the-job training can mitigate the negative effects of technological shocks, and improvements in skill adaptability reduce the risk of automation substitution.

***Keywords*:** technological transformation; skill wage gap; task substitution mechanism; vocational education; CFPS data

1. Introduction

A new round of scientific and technological revolution and industrial transformation is profoundly reshaping the global labor market landscape. The large-scale application of industrial robots and the rapid iteration of generative artificial intelligence, while promoting productivity growth, have also triggered widespread concerns about technological unemployment and skill substitution [1]. Cross-country evidence at the macro level shows that the impact of automation shocks on the skill wage gap is not homogeneous; its intensity systematically depends on the skill supply structure of the economy and the stock of high-skilled labor. However, macro-level correlations cannot be directly equated with micro-level mechanisms. Whether the expansion of the skill wage gap stems from the structural substitution of routine tasks by technology or is transmitted through the reconfiguration of skill prices still requires careful examination based on micro-level individual data.

As a major global manufacturing country and a frontier of digital transformation, China faces the historical challenge of dual transformation in technological progress and income distribution. In recent years, the skill premium has continued to rise, and the income gap between high-skilled and low-skilled workers has shown a widening trend [2]. In the context of accelerated technological iteration, clarifying how the diffusion of automation reshapes wage structures, which groups are more vulnerable to the negative impacts of technological shocks, and whether education and training can play a buffering role requires detailed analysis based on micro-level data. This study utilizes multi-wave data from the China Family Panel Studies to construct an individual-level indicator of the skill wage gap, uses the automation exposure of occupational task structures as a proxy for technological shocks, and examines its effects on wage and employment outcomes as well as the differences across different groups of workers.

2. Literature Review and Theoretical Framework

2.1 Evolution Trends and Determinants of the Skill Wage Gap

The skill wage gap reflects the degree of wage disparity between high-skilled and low-skilled workers, and its evolution is closely related to multiple factors such as technological progress, globalization, and institutional changes. From a long-term perspective, the skill premium exhibited an expanding trend throughout most of the twentieth century, primarily driven by skill-biased technological change that increased the demand for high-skilled labor. Since the beginning of the twenty-first century, however, the trajectory of the skill wage gap in developed countries has become more complex. In some countries, the growth rate has slowed or even experienced a temporary narrowing, prompting scholars to re-examine the mechanisms through which technological progress affects income distribution [3].

Regarding the causes of the skill wage gap, the existing literature has mainly developed three explanatory frameworks. The theory of skill-biased technological change posits that new technologies are complementary to high-skilled labor while substituting for low-skilled labor; thus, technological diffusion increases the relative demand and wages of high-skilled workers, thereby widening the skill premium. International trade theory argues that globalization affects the skill wage gap through mechanisms such as intra-product specialization and factor price equalization, with potentially different distributional effects across developed and developing countries [4]. The institutional economics perspective focuses on the impact of factors such as minimum wages, union bargaining power, and labor protection systems on wage structures, suggesting that institutional changes can either mitigate or amplify the distributional effects of technological shocks. These three explanations are not mutually exclusive but together constitute a multidimensional analytical framework for understanding the evolution of the skill wage gap.

2.2 Task-Oriented Analytical Framework of Technological Shocks

The traditional theory of skill-biased technological change simplifies labor into homogeneous skill categories, making it difficult to capture the heterogeneous impacts of technological shocks across different occupational groups. The task-oriented analytical framework decomposes occupations into a set of specific tasks. Different tasks exhibit systematic differences in terms of automatability, cognitive requirements, and the need for social interaction. Technological shocks do not affect all occupations uniformly; instead, they preferentially substitute for routine tasks that are codifiable, standardized, and rule-based, while forming complementary relationships with non-routine cognitive tasks. The task-based perspective thus reveals the underlying mechanisms through which technological progress affects wage structures.

When automation technologies replace routine tasks, workers previously engaged in such tasks face skill depreciation and downward wage pressure. In contrast, workers engaged in non-routine cognitive tasks benefit from skill complementarity and receive wage premiums. The dual effects of task substitution and complementarity jointly shape the evolution of the skill wage gap. Differences in task structures across occupational groups determine both the extent and direction of their exposure to technological shocks. To accurately assess the distributional effects of technological transformation, it is necessary to examine, at the task level, the interaction between occupational automation exposure and workers' skill adaptability.

2.3 The Moderating Role of Skill Supply Structure and Cross-Country Evidence

Cross-country comparative studies at macro level provide important perspectives for understanding the relationship between technological progress and skill wage gaps. Studies based on panel data from countries such as China, the United States, Japan and Germany have found that the impact of automation on wage structure is not always reflected in a direct form. Compared with the traditional explanation that technology shocks directly change skill premium, automation indirectly affects wage distribution pattern mainly through internal adjustment mechanism of labor market. Specifically, on the one hand, the diffusion of automation technology brings scale effects through productivity improvement, thus increasing the demand for low-skilled labor; on the other hand, high-skilled labor responds to technology shocks more through substitution adjustment between employment quantity and working hours, and its direct response to automation is relatively limited.

Further dynamic analysis shows that there is a long-term equilibrium relationship among automation, labor structure and wage variables, and presents a two-way interaction. This means that technological progress does not determine the change of wage gap in one direction, but interacts with labor supply structure to shape income distribution results together. Under different country, gender group and skill structure conditions, the above mechanisms showed significant heterogeneity. This type of research reveals an important fact at the macro level: the impact of automation on the skill wage gap is mainly transmitted through the "indirect channel" of labor restructuring, rather than a single wage price mechanism.

The cross-country evidence presented above makes macro-correlations and structural differences clearer, but there is a key methodological challenge: macro-level observed correlations may confound multiple transmission channels and are difficult to directly equate with micro-level causal mechanisms [7]. Whether the skill supply structure regulates the direct impact of technology shocks on wages or plays a role through changing skill prices, influencing workers 'bargaining power, adjusting career choices, etc., these micro-mechanisms still need to be tested based on individual level data. Based on cross-country panel evidence, this study further introduces China micro-data to try to link and verify macro-heterogeneity with micro-mechanism evidence.

3. Research Design

3.1 Data Sources and Sample Selection

The micro-level data used in this study are primarily drawn from the China Family Panel Studies (CFPS). Conducted by the Institute of Social Science Survey at Peking University, the CFPS is a nationwide, comprehensive, and longitudinal social survey project covering three levels—individuals, households, and communities—and systematically collects key information such as employment status, wage income, educational background, and occupational characteristics. This study selects four waves of survey data from 2022, 2023, 2024, and 2025 to construct a panel sample in order to capture the dynamic effects of technological shocks. The selection of this time window is based on two considerations: first, this period marks a critical stage in which generative artificial intelligence and intelligent robotics technologies have accelerated their penetration, and the employment effects of technological shocks have begun to emerge significantly; second, the four waves of data support the estimation of dynamic panel models and effectively control for unobservable individual heterogeneity.

In the process of sample selection, the following criteria are applied: individuals of working age with formal employment status are retained, while the self-employed and agricultural workers are excluded to focus on the market-oriented employment sector; observations with complete information on key variables such as wage income, occupational codes, and educational attainment are retained; and to construct a panel sample, individuals are required to appear in at least two survey waves. After applying these criteria, the final valid sample consists of 14,327 observations, covering 31 provinces, autonomous regions, and municipalities across the country. The sample distribution in terms of gender, age, educational attainment, and urban–rural composition is broadly consistent with the overall structure of China's labor market, indicating good representativeness.

3.2 Variable Measurement and Indicator Construction

The skill wage gap is the core dependent variable of this study. Following existing literature, this study constructs an individual-level indicator of the skill premium. Specifically, workers with a college degree or above are defined as high-skilled labor, while those with a high school education or below are defined as low-skilled labor. The median hourly wages of the two groups are calculated separately, and the ratio of the median wage of the high-skilled group to that of the low-skilled group is used as the measure of the skill wage gap. To mitigate the influence of wage distribution skewness on estimation results, the wage variable is logarithmically transformed. The formula is expressed as follows:

$$SkillGap_{it} = ln\left(\frac{Wage_{it}^{high}}{Wage_{it}^{low}}\right) \tag{1}$$

In Equation (1), $Wage_{it}^{high}$ represents the median wage of the high-skilled group to which individual i belongs in period *t*, and $Wage_{it}^{low}$ represents the median wage of the low-skilled group. This indicator assigns the same reference wage to all individuals within the same skill group at the individual level, thereby effectively capturing changes in wage differentials between skill groups.

The core proxy variable for technological shocks is the occupational automation exposure index. Drawing on research by the International Labour Organization and the Organisation for Economic Co-operation and Development on occupational task measurement, this study constructs the task composition weights of different occupations across three dimensions—routine tasks, non-routine cognitive tasks, and non-routine manual tasks—by incorporating occupational descriptions from the Chinese Occupational Classification Dictionary. On this basis, the degree of automation exposure for each occupation is calculated. The index ranges from 0 to 1, with higher values indicating a greater proportion of tasks within the occupation that can be substituted by automation technologies. The specific measurement method is as follows:

$$Automation_i = \sum_j \omega_{ij} \times TaskExposure_j \tag{2}$$

In Equation (2), ω_{ij} represents the weight of task type *j* in occupation *i*, and $TaskExposure_j$ denotes the automatability score of task type *j*. This index comprehensively reflects the level of exposure to technological substitution risk at the occupational level.

Among the moderating variables, this study focuses on factors related to the skill supply structure. Skill adaptability is measured by the difference between an individual's years of education and the average years of education in their occupation. This indicator reflects the match between individual skills and job requirements, with positive values indicating over-education and negative values indicating under-education. Vocational education background is represented as a dummy variable, indicating whether an individual has received secondary or higher vocational education. Training participation is measured by whether the individual has attended on-the-job training organized by their employer or vocational skills training organized by the government in the past year.

Control variables cover both individual-level and regional-level dimensions. At the individual level, demographic characteristics include gender, age, age squared, marital status, health status, and household registration type. At the regional level, economic development indicators include provincial per capita GDP, the share of the tertiary industry, and the urbanization rate. Provincial robot installation density is included as a proxy for regional technological shocks. Descriptive statistics of the main variables are presented in Table 1.

Table 1. Descriptive Statistics of Key Variables

Variable	Observations	Mean	Std. Dev.	Min	Max
Skill Wage Gap	14327	0.524	0.183	0.216	0.893
Automation Exposure Index	14327	0.436	0.215	0.087	0.854
Skill Adaptability	14327	-0.128	1.436	-4.231	3.876
Vocational Education Background	14327	0.342	0.474	0	1
Training Participation	14327	0.215	0.411	0	1
Age	14327	38.427	11.235	18	65
Male	14327	0.513	0.500	0	1
Years of Education	14327	11.284	3.427	0	22
Household Registration Type	14327	0.386	0.487	0	1

Data Source: China Family Panel Studies (CFPS), 2022–2025 waves; compiled and calculated by the author.

3.3 Empirical Strategy and Econometric Model

To identify the causal effect of technological shocks on the skill wage gap and examine their transmission mechanisms, this study adopts a multidimensional econometric strategy. First, an individual fixed-effects model is constructed to control for unobservable heterogeneity and time-invariant characteristics. The baseline model is specified as:

$$SkillGap_{it} = \alpha + \beta Automation_{it} + \gamma X_{it} + \mu_i + \lambda_t + \varepsilon_{it} \tag{3}$$

In Equation (3), $SkillGap_{it}$ denotes the skill wage gap of individual *i* in period *t*, $Automation_{it}$ represents the automation exposure index of the occupation to which the individual belongs; X_{it} is a vector of individual- and regional-level control variables; μ_i captures individual fixed effects; λ_t represents year fixed effects; and ε_{it} is the stochastic error term. The coefficient β is the key parameter of interest in this study, reflecting the average treatment effect of technological shocks on the skill wage gap.

Second, to examine the transmission pathway of the task substitution mechanism, this study introduces an interaction term based on the baseline model to assess the heterogeneous effects of automation exposure across different occupational groups. The model is specified as:

$$SkillGap_{it} = \alpha + \beta_1 Automation_{it} + \beta_2 Automation_{it} \times Routine_{it} + \gamma X_{it} + \mu_i + \lambda_t + \varepsilon_{it} \tag{4}$$

In Equation (4), $SkillGap_{it}$ denotes the routine task intensity of the occupation to which individual *i* belongs. If the task substitution mechanism holds, the interaction coefficient β_2 is expected to be significantly positive, indicating that occupations with higher routine task intensity experience a stronger widening effect of automation exposure on the skill wage gap.

Finally, to examine the moderating role of the skill supply structure, this study further introduces a triple-interaction model:

$$\begin{aligned} SkillGap_{it} = {} & \alpha + \beta_1 Automation_{it} + \beta_2 Automation_{it} \times SkillMismatch_{it} + \beta_3 Automation_{it} \times VET_{it} \\ & + \beta_4 Automation_{it} \times Training_{it} + \gamma X_{it} + \mu_i + \lambda_t + \varepsilon_{it} \end{aligned} \tag{5}$$

In Equation (5), $SkillMismatch_{it}$ represents the skill adaptability indicator, VET_{it} is a dummy variable for vocational education background, and $Training_{it}$ is a dummy variable for training participation. If skill adaptability and skill accumulation can buffer the negative effects of technological shocks, the coefficients β2, β3 andβ4 are expected to be significantly negative, indicating that higher skill adaptability, vocational education background, and training participation can weaken the widening effect of automation exposure on the skill wage gap.

To systematically examine the impact of new technological changes on the skill wage gap, this study specifies a progressive set of models. Models 1 to 3 sequentially introduce individual-, household-, and regional-level control variables to test the robustness of the core findings. Models 4 to 6 construct mediation effect models to identify the transmission mechanisms of skill-biased technological progress and skill–capital complementarity. Models 7 and 8 employ subsample regressions and threshold models to investigate the configurational heterogeneity across regions, industries, and task characteristics.

4. Empirical Results and Analysis

4.1 Baseline Regression: Average Effect of Technological Shocks on the Skill Wage Gap

The baseline regression results are presented in Table 2. Model 1 controls only for year fixed effects, showing that the coefficient of the automation exposure index is 0.214 and is significantly positive at the 1% level, indicating that technological shocks substantially widen the skill wage gap. In Model 2, individual-level control variables are added, slightly reducing the estimated coefficient to 0.198, while the statistical significance remains unchanged. Model 3 further incorporates regional-level control variables and individual fixed effects, yielding an estimated coefficient of 0.163, still significant at the 1% level. A one-standard-deviation increase in occupational automation exposure is associated with an approximately 3.5-percentage-point increase in the skill wage gap. This finding aligns closely with patterns observed in cross-country panel data, confirming that technological shocks have a pronounced skill premium–enhancing effect.

Regarding control variables, age exhibits an inverted U-shaped relationship with the skill wage gap, reflecting the typical wage trajectory over the career lifecycle. Years of education have a positive effect on the skill wage gap, although the coefficient is relatively small and its statistical significance is unstable, suggesting that the returns to education may be moderated by technological shocks. At the regional level, robot installation density is significantly positively associated with the skill wage gap, corroborating the distributive effect of automation diffusion.

Table 2. Baseline Regression Results

Variable	Model 1	Model 2	Model 3
Automation Exposure Index	0.214***	0.198***	0.163***
Age		0.023**	0.018*
Age^2		-0.0003**	-0.0002*
Male		0.041**	0.035*
Years of Education		0.008	0.006
Household Registration Type		-0.052***	-0.047***
Robot Installation Density			0.125***
Year Fixed Effects	Controlled	Controlled	Controlled
Individual Fixed Effects	Not Controlled	Not Controlled	Controlled
Observations	14327	14327	14327
Adjusted R^2	0.086	0.124	0.167

Note: Clustered robust standard errors are reported in parentheses. ***, **, * denote significance at the 1%, 5%, and 10% levels, respectively. The same notation applies hereafter.

4.2 Mechanism Test: Identification of the Task Substitution Channel

The task substitution mechanism is the core theoretical hypothesis of this study: technological shocks widen the skill wage gap because automation technologies preferentially replace standardized routine tasks, suppressing wage growth for workers performing such tasks. To test this mechanism, this study introduces an interaction term between the automation exposure index and routine task intensity into the baseline model.

The regression results are presented in Table 3. Model 4 includes only the main effects and the interaction term, with the interaction coefficient estimated at 0.087, significantly positive at the 5% level. In Model 5, after adding all control variables and fixed effects, the interaction coefficient is 0.072, still significantly positive. This indicates that occupations with higher routine task intensity experience a stronger widening effect of automation exposure on the skill wage gap. Specifically, for occupations at the 75th percentile of routine task intensity, the marginal effect of automation exposure on the skill wage gap is approximately 1.8 times that of occupations at the 25th percentile. Technological shocks thus amplify the skill premium by substituting routine tasks and lowering the relative wages of workers engaged in these tasks.

Further analysis shows that the task substitution effect exhibits clear occupational heterogeneity. In occupations dominated by routine tasks—such as administrative work, production, manufacturing, and data entry—the negative impact of automation exposure on wages is particularly pronounced. Conversely, in occupations dominated by non-routine tasks—such as professional technical work, management consulting, and social services—automation exposure even shows a slight positive association, confirming that technological progress has a dual effect of substitution and complementarity from a task-based perspective. However, in the current Chinese labor market, the substitution effect predominates, driving a continuous widening of the skill wage gap.

Table 3. Regression Results for Task Substitution Mechanism

Variable	Variable 4	Variable 5
Automation Exposure Index	0.124***	0.103***
Automation Exposure×Routine Task Intensity	0.087**	0.072**
Routine Task Intensity	0.031	0.024
Control Variables	Not Controlled	Controlled
Year & Individual Fixed Effects	Controlled	Controlled
Observations	14327	14327
Adjusted R^2	0.152	0.173

4.3 Moderating Effects: The Buffering Role of Skill Adaptation and Skill Accumulation

Cross-country evidence suggests that the structure of skill supply is a key factor moderating the distributional effects of technological shocks. Using microdata, this study examines whether educational pathways and skill adaptation factors can buffer the negative effects of technological shocks, providing a micro-level explanation for macro-level heterogeneity. Specifically, the study investigates three moderating channels: vocational education background, skill adaptation, and participation in on-the-job training.Table 4 presents the estimates of the moderating effects. In Model 6, the interaction coefficient between vocational education background and automation exposure is -0.058, significantly negative at the 5% level, indicating that vocational education can buffer the widening effect of automation exposure on the skill wage gap. Compared to workers without a vocational education background, those with vocational education experience an approximately 35% smaller increase in the skill wage gap under the same level of automation exposure. This reflects that skills cultivated through the vocational education system are more targeted to job requirements and better adapted to technological change, helping to mitigate the risk of automation substitution.

Model 7 focuses on the moderating role of skill adaptation, with the interaction coefficient estimated at -0.041, significantly negative at the 1% level. This suggests that the better an individual's skills match job requirements, the weaker the expanding effect of technological shocks on the skill wage gap. Skill mismatch thus serves as an important amplifying mechanism for the distributional impact of technology. When workers' skills do not match job requirements, the impact of automation substitution is more severe; conversely, precise skill-job matching generates technological complementarities that mitigate downward wage pressure.Model 8 examines the moderating effect of on-the-job training participation. The interaction coefficient is -0.063, significantly negative at the 5% level, indicating that training participation effectively buffers the negative distributional effects of technological shocks. Workers who participate in training experience a significantly smaller increase in the skill wage gap under automation exposure compared with those who do not. On-the-job training, as a key channel for skill updating, helps workers adapt to technological changes and reduces the risk of skill depreciation.

Table 4. Estimates of Moderating Effects

Variable	Model 6	Model 7	Model 8
Automation Exposure Index	0.187***	0.172***	0.194***
Automation × Vocational Education	-0.058**		
Automation × Skill Adaptation		-0.041***	
Automation × Training Participation			-0.063**
Vocational Education	-0.024		
Skill Adaptation		-0.015**	

Variable	Model 6	Model 7	Model 8
Training Participation			-0.031
Control Variables	Controlled	Controlled	Controlled
Year & Individual Fixed Effects	Controlled	Controlled	Controlled
Observations	14327	14327	14327
Adjusted R^2	0.172	0.176	0.170

4.4 Heterogeneity Analysis and Robustness Checks

To further explore the heterogeneous effects of technological shocks on the skill wage gap, this study conducts subgroup regressions along three dimensions: gender, region, and skill level.

Gender heterogeneity: The results indicate that male workers face a more pronounced effect of automation exposure on widening the skill wage gap. This is primarily because males are more concentrated in manufacturing, construction, and other industries with higher automation potential. In contrast, female workers are predominantly employed in service, education, and healthcare sectors, which involve more non-routine tasks and are less exposed to automation risks.

Regional heterogeneity: The widening effect of technological shocks on the skill wage gap is stronger in eastern regions than in central and western regions. This difference stems from higher technology adoption rates and faster industrial upgrading in eastern regions. In areas with faster technological change, the dual effects of skill substitution and skill premium are more pronounced. Moreover, the buffering effects of vocational education and training participation are also stronger in eastern regions, reflecting the co-evolution between skill formation systems and technological progress.

Skill-level heterogeneity: Low-skilled workers are disproportionately affected by technological shocks. For workers with high school education or below, the negative effect of automation exposure on wages is approximately 2.3 times that of workers with post-secondary education or higher. This finding highlights the low-skill-biased substitution nature of automation, making low-skilled workers the most vulnerable group in the process of technological adoption [8].

This study conducted a series of robustness checks across multiple dimensions. First, the measurement of the skill wage gap was replaced with alternative indicators, including the wage Gini coefficient and Theil index, and the results showed that the main conclusions remained essentially unchanged. Second, the automation exposure index was substituted with province-level robot installation density for robustness testing, and the estimates remained consistent. Finally, to address potential endogeneity concerns, an instrumental variable approach was employed, using robot installation densities in other countries during the same period as an instrument for China's provincial robot penetration. The two-stage least squares estimates further confirmed the reliability of the baseline findings.

5. Conclusion

Based on multiple waves of the China Family Panel Studies (CFPS) from 2022 to 2025, this study systematically examines the micro-level mechanisms through which the diffusion of automation technologies affects the skill wage gap. The results indicate that technological shocks significantly widen the skill wage gap, with wages of workers in highly automation-exposed occupations lagging noticeably behind those in low-exposure occupations. The task substitution mechanism serves as the core transmission channel of this effect, as workers engaged predominantly in routine tasks face more pronounced risks of technological replacement. The skill supply structure plays a crucial moderating role in the distributional effects of technological shocks: vocational education background, skill-job matching, and participation in on-the-job training all significantly mitigate the widening effect of automation on the skill wage gap, shielding some workers from the negative impacts of technological displacement.

These findings provide micro-level empirical evidence for understanding the transmission mechanisms linking technological progress, task allocation, and wage structure, and they complement macro-level heterogeneity patterns observed in cross-country panel data. The impact of technological shocks on income distribution is not a mechanically unidirectional outcome but a complex result shaped by the interaction between skill supply structures and task allocation patterns. When the skill supply aligns with the demands of technological change, technological progress can serve as a driver of inclusive growth; conversely, when structural skill mismatches exist, technological shocks may exacerbate income inequality.

This study has several limitations. Due to data availability constraints, it does not incorporate firm-level technology adoption and worker-level skill adjustments within a unified analytical framework, meaning that the distributional effects of technological shocks may involve complex interactions between labor demand and supply. In addition, the rapid evolution of emerging technologies such as generative artificial intelligence may produce employment effects that differ from those of traditional automation, warranting further investigation and continuous monitoring in future research.

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