

The Impact of Inter-City Skill Polarization on Smart Manufacturing Labor Employment: Evidence Based on Chinese Cities

Guohui CHEN

School of Economics and Management, University of Chinese Academy of Sciences, Beijing 100190, China

E-mail: chenguohui19@mailsucas.ac.cn

Huajie JIANG*

School of Economics and Management, University of Chinese Academy of Sciences, Beijing 100190, China

E-mail: jianghuajie20@mailsucas.ac.cn

Qiguo GONG

School of Economics and Management, University of Chinese Academy of Sciences, Beijing 100190, China

E-mail: gonggg@ucas.ac.cn

Abstract Smart manufacturing is a key aspect of current urban sustainability concerns, with urban skills impacting the growth of smart manufacturing. This raises questions for sustainable urban development regarding the polarization of skills between cities. This study investigates the influence of inter-city skills polarization on the wages and employment of workers in smart manufacturing in China by examining social-cognitive skill score data. The regression results show that the social cognitive skill score of the city has a significant positive effect on local manufacturing wages. However, it reduces the number of local manufacturing jobs and the proportion of manufacturing in the industrial structure. Smart manufacturing development policies have a significant impact on local manufacturing employment but do not influence the wage levels of local manufacturing workers. In addition, productivity in the secondary industry may reduce local manufacturing wages and employment. Nevertheless, it has a negative skew when mediating the connection between intercity skill polarization and local manufacturing wages. The study reveals the reasons for workers participating in production during the smart manufacturing era, predicts future wage changes for these workers, and examines the differences in industrial layouts across cities.

Keywords inter-city skill polarization; smart manufacturing; employment; industrial layout

1 Introduction

Regional economic disparities are a critical concern that impacts sustainable development. In recent decades, with the acceleration of China's economic growth, the surge in domestic income inequality has gained the interest of scholars^[1–3]. Economic inequality is affected by the upgrading of industrial structure^[4] and changes in the labor force structure^[5]. Existing research has primarily focused on skill polarization within the labor market, but it may also exist across cities, potentially exacerbating economic inequality.

If we consider cities to be “abstract combinations of workplace tasks and skills”^[6], then their preference for certain occupational skills reflects regional differences in industrial structure. Therefore, some scholars have attempted to examine regional inequalities by combining cities and skills^[7]. The relationship between skill polarization and local economic and social development in different regions has been the focus of studies by both Xu et al.^[7] and Alabdulkareem et al.^[8].

Xu et al.^[7] even predicted the skills necessary for Chinese occupations based on job descriptions, calculated social-cognitive scores for 102 Chinese cities, and applied the data to analyze the correlation between inter-city skill polarization and regional gross domestic product (GDP). These works provide the research data and theoretical foundation for this study's analysis of regional economic development imbalances.

The occurrence of skill polarization results from alterations in the demand for technical abilities in job roles and duties within the job market^[9], which exhibits modifications in ability necessity across different occupations. Skill polarization occurs not only across the labor market but also within different cities, due to the varying industrial structures and reliance on different skills by each city's pillar industries, leading to disparities in skill preferences and polarization. For instance, the industrial structure of different Chinese cities in China significantly varies. Many major cities have already transitioned from a manufacturing-based industrial structure to one that is service-based. However, many small and medium-sized cities continue to prioritize the development of mining, manufacturing, and agriculture. This significant difference in industrial structure creates differing demands for workers with specialized skill sets from city to city. Focusing on occupational skill levels, this phenomenon reveals that skill distribution varies across cities. Large cities such as Beijing and Shanghai likely have a larger number of social-cognitive skills, while small and medium-sized cities like Luoyang in Henan Province are more likely to have sensory-physical skills. Technical term abbreviations are explained when first used to ensure comprehensibility. The language is objective and avoids biased, emotional, and ornamental language. The register is formal, and contractions, colloquialisms, and jargon are avoided. The text adheres to a conventional structure, including common academic sections and maintaining regular author and institution formatting.

Since the advent of Industry 4.0 and smart manufacturing and the issuance of China's made in China 2025 by the State Council in 2015, local governments of various provinces, autonomous regions, municipalities directly under the central government, and prefecture-level cities in China have disseminated policies to promote the development of smart manufacturing. For instance,

the 2015 “Notice of the Municipal Government on the Issuance of Several Policies to Promote the Transformation and Upgrading of the Industrial Economy of Taizhou City to Speed Up the Transformation and Upgrading” suggested that businesses pursued the “smart manufacturing” tactic and received an 8% subsidy for the acquisition of smart robot equipment. Although the specific policies to implement “smart manufacturing” may vary by location, the general objective is to utilize smart manufacturing to facilitate the transformation and upgrading of the local manufacturing industry, thereby promoting high-quality development within the sector. Under such circumstances, it’s crucial to investigate how skill polarization affects the labor force in various cities to aid city managers in comprehending local employment and wage performance in the context of policies promoting smart manufacturing.

Therefore, we utilize the data on skill polarization (measured from the perspective of levels of social-cognitive skills in cities) of Chinese cities, as quantified by Xu et al.^[7], to investigate the impact of smart manufacturing policies and inter-city skill polarization on manufacturing labor force employment and wages via econometric regression analysis.

At a theoretical level, this paper contributes to the understanding of labor demand and wages in smart manufacturing from the perspective of inter-city skill polarization. It enriches the theoretical study of skill polarization and the factors that influence labor demand and wages in smart manufacturing and aids in comprehending the disparities in industrial layouts between cities. At a practical level, the paper’s findings offer management insights and ideas to local government bodies that seek to encourage smart manufacturing transformation. Additionally, manufacturing enterprises can use these findings to implement smart factory transformation, while manufacturing workers can learn how to pass the employment test related to China’s smart manufacturing transformation.

The wage level of an occupation is positively correlated with its socially perceived skill score, and higher skill polarization in the labor market corresponds with greater wage polarization^[10]. According to Autor et al.^[6], cities can be viewed as abstract combinations of workplace tasks and skill sets, and thus this relationship should hold across different cities. Furthermore, because manufacturing jobs are frequently considered routine positions, employment in manufacturing should be inversely correlated with a city’s score on social-cognitive skills; When a city’s social-cognitive skills score is high, the number of manufacturing workers employed is relatively low.

In summary, the above analysis indicates that the phenomenon of inter-city skill polarization has a favorable impact on the wage rate of native manufacturing laborers and an unfavorable effect on the local manufacturing workforce. Therefore, we posit the subsequent two hypotheses:

H1 The phenomenon of inter-city skill polarization can significantly and positively affect the wage level of local manufacturing workers; The higher the socially perceived skill score of a city, the higher the wage level of manufacturing workers.

H2 The phenomenon of inter-city skill polarization can significantly and negatively affect the employment share of local manufacturing workers; The higher the socially perceived skill score of a city, the lower the number of manufacturing workers employed.

The impact of policies on the economy and society is a hot topic in public administration and political science. Williams and Kayaoglu^[11] argued that the temporary financial supported policy in European countries during the coronavirus pandemic stimulated the economy and supported employment and income. Zhang^[12] stated that the policies adopted by the Chinese government during the COVID-19 had the potential to affect employment. Therefore, in the context of Chinese cities actively promoting smart manufacturing, considering that local government policies to promote smart manufacturing usually take the form of economic incentives, awarding honorary titles to enterprises, and tax incentives, this has a certain promoting effect on enterprises to expand their production scale, and the process of manufacturing enterprises expanding their production scale increases the demand for labor to a certain extent, which means that it can increase the employment and wage level of the labor force. Taken together, the above analysis shows that the city's smart manufacturing policy will have a positive impact on the wage level and employment of local manufacturing workers. Therefore, we further propose the following hypothesis:

H3 Smart manufacturing policies in cities can significantly and positively affect the wage levels of local manufacturing workers.

H4 Smart manufacturing policies in cities can significantly and positively affect the employment of local manufacturing workers.

Considering that labor productivity is a common indicator of the economic development status of a country or region^[13], this paper focuses on the possible influence of secondary industry labor productivity in this context. Firstly, there may be a negative relationship between skill polarization between cities and secondary industry labor productivity for several reasons: First of all, if cities have higher levels of socio-cognitive skills, it reflects that the industrial structure of the region is biased toward industries that rely on socio-cognitive skills with workers who have higher socio-cognitive skills, while the secondary industry, to which manufacturing belongs, has an overall lower score for socio-cognitive skills. This means that the share of manufacturing in the region's industrial structure is relatively low, and the labor productivity of the secondary industry is also low. In the second place, cities with higher socio-cognitive skills are more willing to invest in industries with high socio-cognitive skills, while investment in manufacturing is relatively low, which ultimately leads to low labor productivity in secondary industries. Thirdly, higher levels of social-cognitive skills in cities indicate a higher level of upgrading of the local employment structure, which affects labor productivity^[14].

In theory, the labor productivity of secondary industry can reduce the employment share and wage level of manufacturing labor^[15–17]. Liu and Hu^[15] pointed out that the current technological progress had increased the relative labor productivity of the secondary industry, especially the manufacturing industry, released the remaining labor force in the manufacturing industry, and promoted the flow of labor to the tertiary industry. This is because, with the increase in labor productivity, the number of workers needed by manufacturing enterprises to produce the same number of products will be reduced, which means that the employment share

of workers will be reduced. As the number of workers needed in the manufacturing industry decreases, the labor market will have a situation where the supply exceeds the demand, and the wage level of workers will be lowered at this time. Of course, considering that labor productivity has been used as a mediating variable in many studies on wage levels, we also argue here that secondary industry labor productivity may have a mediating effect in the effect of the inter-city skill polarization phenomenon on local manufacturing wage levels.

The above analysis shows that the inter-city skill polarization phenomenon negatively affects secondary industry labor productivity, which in turn further negatively affects the employment share and wage level of manufacturing workers. Based on this, this paper proposes research hypotheses H5, H6 and H7:

H5 Secondary industry labor productivity has a significant negative effect on the wage level of local manufacturing workers.

H6 Labor productivity in the secondary sector has a significant negative effect on the employment of local manufacturing workers.

H7 The phenomenon of inter-city skill polarization affects the wage level of local manufacturing workers through secondary labor productivity.

The logic between the research hypotheses is shown in Figure 1.

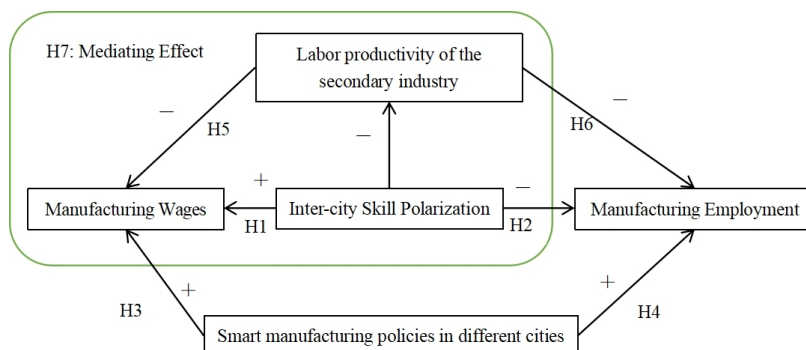


Figure 1 Mechanisms of the effect of inter-city skill polarization on labor under the background of smart manufacturing

2 Materials and Variables

2.1 Data Sources

The primary data used in this study are as follows:

Data on social-cognitive skills scores for 100 Chinese cities. This data were calculated by Xu et al.^[7] using machine learning techniques to classify Chinese workers' occupational skills into social-cognitive skills and sensory-physical skills and map them to O*NET to calculate the social-cognitive skills scores used by 102 cities in China (including Beijing, Shanghai, and Tianjin) that rely on social-cognitive skills scores. This data can be accessed at <https://github.com/Tutu-wq/China-s-first-skill-taxonomy>. They used the O*NET 23.0, which was released in

2018 after being revised by the United States Department of Labor according to the 2017 survey data. It should be explained that the data provided by Xu et al.^[7] for “YiZhou” could not be found in the existing prefecture-level cities in China, so some macro data are missing for Baoji. The data for 100 prefecture-level cities (including Beijing, Shanghai, and Tianjin municipalities directly under the central government) were retained.

Data at the prefecture-level city level. These include data on average manufacturing wage, number of manufacturing workers, regional GDP, unemployment rate, amount of FDI utilized, secondary industry GDP, secondary industry employment, number of industrial enterprises of the above-mentioned sizes, export volume, and proportion of secondary industry workers. All from the 2018 statistical yearbook of each city, the actual statistics are for 2017.

The 2017 government work report data of these cities. The main concern is whether the 2017 government work report is related to the promotion of smart manufacturing work arrangements and goals.

2.2 Variable Selection

2.2.1 Dependent Variable

Manufacturing employment. In the existing literature, total manufacturing employment is typically used directly to reflect the employment share of manufacturing workers. We continue this practice by directly using the total number of manufacturing workers employed in each location in 2017 as the data for this variable.

Manufacturing workers' wage. Existing studies usually use the industry or enterprise per capita wage to represent the wage level. For example, Wang et al.^[14] uses the annual enterprise per capita wage level as a proxy for the enterprise wage level. Therefore, the study in this paper adopts the average wage of manufacturing workers in 2017 as a proxy for the wage level of manufacturing workers.

In the subsequent study, the two dependent variables mentioned above were eliminated by taking their logarithms to eliminate the effect of heteroskedasticity and to improve the smoothness of the data.

2.2.2 Independent Variable

Inter-city skill polarization. From the existing literature, existing studies on measuring skill polarization between cities are still in the development stage, and related studies are only covered by Xu et al.^[7] and Alabdulkareem et al.^[8]. Considering that this study uses prefecture-level city-level data as the research object, it is difficult to collect data on the skill polarization of cities. Therefore, this study directly adopts the social-cognitive skill scores of Chinese cities (threshold value of 0.6) calculated by Xu et al.^[7] as a proxy for inter-city skill polarization.

2.2.3 Other Variables

Smart manufacturing policies in cities. In the existing literature, the policy variable is usually indicated by the presence or absence of relevant policies in the object of study^[18].

Therefore, in this study, the presence or absence of arrangements and goals to promote smart manufacturing in the government work report of each city in 2017 is used as a proxy for this variable.

Labor productivity of the secondary industry. Regarding the second labor productivity, this paper adopts the usual calculation in the existing literature, using the logarithm of the ratio of the GDP of the secondary industry to the number of people employed in the secondary industry in each location.

2.2.4 Control Variables

Unemployment rate. Many studies have confirmed the relationship between unemployment and wages^[19,20]. The unemployment rate situation reflects the relationship between labor supply and demand in the labor market, and the relationship between labor supply and demand indirectly affects the wage level of an occupation. In general, the higher the unemployment rate, the relatively larger the number of workers competing for the same job, leading to a decrease in the wage level of the corresponding occupation. On the other hand, the unemployment rate also reflects to some extent the development status of the regional economy. If the unemployment rate of a region increases, it means that the economic development level of the region is relatively low, and the wages that occupations can offer to employed people will be relatively low. Therefore, we use the unemployment rate as one of the control variables in this study.

GDP. GDP directly reflects the economic development of a region and is a common control variable and research object in macroeconomic analysis. In general research and perception, the better the regional economic conditions, the higher the corresponding labor wage level, which means that the regional GDP also affects the wage level of the manufacturing industry. Therefore, we use the regional GDP of each region in the corresponding year as a control variable that reflects the level of regional economic development.

Dependence on FDI (Foreign Direct Investment). From the investment perspective, FDI has an impact on local economic development and industrial restructuring. Existing studies have generally focused on the impact of FDI on economic development and the labor market^[21–24]. FDI dependence is calculated as the ratio of FDI to regional GDP, which can further reflect the extent to which the local economy and industrial structure are influenced by foreign investment. Therefore, we use the FDI dependence of each city in the corresponding year as a control variable.

Export volume. From the perspective of the regional economic structure, the export volume reflects the international trade of the region, and the export volume indirectly reflects the local industrial structure and drives the changes in the labor force employment structure and occupational wage level. Generally speaking, the higher the export volume, the higher the demand for foreign trade in the region, and the corresponding manufacturing industry providing foreign trade services develops better, which in turn affects the labor employment and wage level in related industries. Therefore, we use the logarithm of each city's export volume in the corresponding year as a control variable reflecting the level of trade.

The number of above-designated sizes industrial enterprises. The number of industrial enterprises over the designated size in a region directly reflects the quality and scale of manufacturing development in that region, and the number of industrial enterprises over the designated size is also related to the proportion of manufacturing labor force employment and wage level. Therefore, the logarithm of the number of industrial enterprises over the designated size is used as a control variable in this paper.

The proportion of employees in the secondary industry. Similar to the number of industrial enterprises of the above-mentioned sizes, the share of employees in the secondary industry is an important indicator that reflects the overall economic size of the manufacturing industry in the industrial economic structure of a region. A larger proportion of employees in the secondary industry means a larger proportion of employment in the secondary industry in the region, which usually means more employment in the local manufacturing industry. Therefore, the share of employment in the secondary sector is used as a control variable.

The definitions and descriptions of all variables are listed in Table 1.

Table 1 Summary definition of variables

Variable	Indicator	Definition
Manufacturing employment	$\ln(\text{ma-em})$	Dependent variable, taken as logarithm, representing regional manufacturing employment
Manufacturing workers' wage	$\ln(\text{ma-w})$	Dependent variable, taken as logarithm, reflects the regional manufacturing wage level
Inter-city skill polarization	socog6	Independent variable, cities' skill polarization (scores above 0.6 indicate high social cognitive skills)
Smart manufacturing policies	policy	Other variable, 1 if region has smart manufacturing policies, 0 otherwise
Labor productivity of secondary industry	2lp	Mediating variable, productivity of regional secondary industry
Unemployment rate	unemp	Control variable, overall local employment rate
GDP	$\ln \text{gdp}$	Control variable, overall economic development level of the region
Dependence on FDI	dfdi	Control variable, external dependence of the regional economy
Export volume	$\ln \text{expo}$	Control variable, logarithmic, reflecting regional foreign trade exports
Number of industrial enterprises	$\ln \text{nu-in-e}$	Control variable, logarithm, reflecting scale and quality of regional industry
Proportion of employees in secondary industry	pe2nd	Control variable, percentage, overall employment share of the secondary sector

3 The Impact of Inter-city Skill Polarization on Smart Manufacturing Labor Wages

3.1 Regression Model

As elaborated in the introduction of this paper, the issues of concern in this paper are: (1) the effect of inter-city skill polarization on manufacturing labor employment and wage levels, (2) the effect of smart manufacturing policies on manufacturing labor employment and wage levels, (3) the effect of secondary industry labor productivity on manufacturing labor employment and wage levels, and the effect of secondary industry labor productivity on inter-city skill polarization mediating effects in the impact on manufacturing wage levels. Therefore, we first consider a simple regression model that focuses on the effects of inter-city skill polarization and smart manufacturing policies on manufacturing wage levels in the following form:

$$\ln(\text{ma-w})_i = \alpha_0 + \alpha_1 \text{socog6}_i + \alpha_2 \text{policy}_i + \alpha_3 X_i + \varepsilon_1, \quad (1)$$

where $\ln(\text{ma-w})_i$ represents the logarithm of the manufacturing wage level in each city i , socog6_i is the socially perceived skill score in each city, reflecting skill polarization across cities, and policy_i is the support for smart manufacturing policies in each city. Not surprisingly, α_1 and α_2 are the estimated coefficients that we focus on in this study, reflecting the impact of skill polarization and smart manufacturing policy adoption on manufacturing wage level across cities. X_i represents each control variable, namely unemployment rate (unemp_i), regional GDP ($\ln \text{gdp}_i$), dependence on FDI (dfdi_i), export volume ($\ln \text{expo}_i$), number of industrial enterprises of the above-designated sizes ($\ln \text{nu-in-e}_i$) and proportion of employees in the secondary industry (pe2nd_i). ε_1 represents the random error term.

Based on the model (1), we further consider the effect of secondary industry labor productivity (2lp) in it. At this point, our first step is to construct the regression model (2) with secondary industry labor productivity as the dependent variable to examine the impact of intercity skill polarization on it, in the following form:

$$\ln(2\text{lp})_i = \beta_0 + \beta_1 \text{socog6}_i + \beta_2 X_i + \varepsilon_2. \quad (2)$$

In the second step, put the labor productivity of the secondary industry into the benchmark model:

$$\ln(\text{ma-w})_i = \phi_0 + \phi_1 \text{socog6}_i + \phi_2 \text{policy}_i + \phi_3 \ln(2\text{lp})_i + \phi_4 X_i + \varepsilon_3. \quad (3)$$

Such a model design is adopted to test whether secondary industry labor productivity has a mediating effect on the relationship between inter-city skill polarization and manufacturing wage. The theoretical logic of this design is to refer to the approach of Wen et al.^[25], which assumes that the correlation between the dependent variable manufacturing wage level and the independent variable inter-city skill polarization is significant through model (1) to model (3), i.e. the coefficient α_1 in regression model (1) is significant. From there, we start to discuss

whether the mediating effect of secondary sector labor productivity is significant, i.e. at this point, we first see whether the coefficient β_1 in the model (2) is significant. If the coefficient β_1 is not significant, it means that the variable labor productivity of the secondary industry is not a mediating variable; if β_1 is significant, then we will check whether the coefficient ϕ_3 in the model (3) is significant or not. At this point, if the coefficient ϕ_3 is not significant, it also means that the labor productivity of secondary industry is not a mediating variable, and if the coefficient ϕ_3 is significant, it means that the labor productivity of secondary industry is a mediating variable. Of course, if the coefficient ϕ_1 is not significant, the labor productivity of the secondary industry has a full mediating effect, otherwise it has a partial mediating effect.

In this paper, Stata 15.0 was used to conduct each econometric regression analysis. We first conducted descriptive statistics on the data characteristics of the main variables and calculated the correlations between the variables, and the detailed results are presented in Appendix Table A1. The results of the variable correlation analysis show that the independent variable inter-city skill polarization, the mediating variable secondary industry labor productivity, and the variable smart manufacturing policy selected for this study are all significantly correlated with the dependent variable manufacturing wage.

3.2 Regression Results

Column 1 of Table 2 reports the results of the regression considering only the independent variable and the mediating variable on the dependent variable. The results in column 1 show that the degree of skill polarization and the labor productivity of the secondary industry in each city significantly affect the manufacturing wage level in each city, but this result needs to be further tested by adding control variables. Columns 2–4 report the regression results for model (1) to model (3), respectively. In the regression results of model (1) (column 2 in Table 2), the coefficient of the independent variable, the skill polarization level of each city, on the manufacturing wage level is 1.186 and is significantly positive at the 1% level, with an R^2 of 0.345. This indicates that in the baseline model, higher socially perceived skill levels in cities are associated with higher manufacturing wages. The coefficient of 1.186 indicates that for every 0.01 unit increase in a city's socio-cognitive skill scores, the manufacturing wage level increases by 1.186% after including the relevant control variables. This indicates that inter-city skill polarization can significantly increase the wage level of the local manufacturing industry, and H1 passes the test. This result may be because higher social cognitive skill scores in cities imply that the industrial structure of the region is more skewed toward industries that rely on social cognitive skills and have a more rational industrial structure, which increases the wage level of manufacturing labor in general as the overall economic level improves, thus widening the manufacturing wage gap among skill-polarized cities.

Meanwhile, the regression coefficient of the variable smart manufacturing policy on the dependent variable manufacturing wage in each city is not significant, which indicates that the smart manufacturing policy introduced in the region does not have a significant impact on the wage level of the local manufacturing industry. This may be caused by two reasons: Firstly, the

Table 2 Empirical regression results on inter-city skill polarization and manufacturing wage

	(1)	(2)	(3)	(4)
	ln (ma-w)	ln (ma-w)	ln 2lp	ln (ma-w)
socog6	1.261*** (4.310)	1.186*** (4.610)	−73.130*** (−3.090)	0.807** (2.440)
ln 2lp	−0.005* (−1.700)			−0.005* (−1.950)
policy		−0.007 (−0.110)		−0.055 (−0.960)
ln gdp		0.095* (1.800)	5.951* (1.680)	0.131** (2.450)
dfdi		0.000 (1.170)	0.032 (1.650)	0.000* (1.920)
ln expo		−0.001 (−0.080)	0.758 (0.620)	0.003 (0.290)
uemp		0.082 (1.370)	−6.178 (−1.150)	0.048* (1.670)
ln nu-in-e		0.030 (0.580)	−8.175* (−1.750)	−0.005 (−0.130)
pe2nd		0.156 (0.730)		0.0552 (0.310)
_cons	11.180*** (29.510)	9.341*** (18.140)	65.990 (1.510)	9.678*** (38.790)
<i>N</i>	100	100	100	100
<i>R</i> ²	0.400	0.345	0.110	0.517

Note: *t*-value in parentheses, **p* < 0.10, ***p* < 0.05, ****p* < 0.01.

impact of the policy on the wage level has a certain lag, and the smart manufacturing policy in the current year may not be able to increase the wages. Secondly, the wage level is more determined by the supply and demand in the labor market, and the impact of policy on wages may indirectly affect the wage level of labor by encouraging enterprises to expand the scale of smart manufacturing production at the macro level. Therefore, the regression results reject H3.

The results of model (2) (column 3 in Table 2) show that the coefficient of the skill polarization level of the city on labor productivity in the secondary sector is significantly negative at the 1% level, with a coefficient of −73.13. This indicates that a higher level of social cognitive skills in a city corresponds to lower labor productivity in the secondary industry, and since the coefficient is −73.13, it indicates that after adding the relevant control variables, every 0.01 unit increase in the level of social cognitive skills of the city decreases the wage level in manufacturing by 0.7313, and H5 passes the test. The coefficient β_1 in the model (2) is significant, indicating that there may indeed be a mediating effect of labor productivity in the secondary

sector, which requires further validation. This is because an increase in labor productivity of secondary industry reduces the labor force in the secondary sector, including manufacturing, and promotes labor mobility to the tertiary sector when total output remains constant^[16,17]. There is an oversupply of workers in the manufacturing industry, and the wage level of workers will also fall at this time.

At this point, the regression results in column 4 of Table 2 show that the coefficients of the degree of skill polarization and the labor productivity of the secondary industry on the manufacturing wage level in each city are 0.807 and -0.005 , respectively, and are significant at the 5% and 10% levels. Firstly, based on the significantly negative regression coefficient of the mediating variable, the labor productivity of the secondary industry, on the dependent variable, the manufacturing wage level in each city, it is known that the labor productivity of the secondary industry plays a negative mediating effect in the relationship between the skill polarization between cities and the manufacturing wage in each city. Secondly, since the regression coefficient of inter-city skill polarization on the manufacturing wage level of each city is still significantly positive, the coefficient decreases from 1.186 to 0.807 and the significant level also decreases, indicating that the labor productivity of the secondary industry has a partial mediating effect. Thus, inter-city skill polarization affects the wage level of local manufacturing workers through the labor productivity of the secondary industry, and the labor productivity of the secondary industry plays a partial mediating role. Thus, H7 passes the test.

4 The Impact of Inter-city Skill Polarization on Smart Manufacturing Labor Force Employment

4.1 Regression Model

This section focuses on the relationship between inter-city skill polarization and manufacturing worker employment. Similar to Section 3.1, we consider both the independent variable inter-city skill polarization, the variables secondary industry labor productivity and smart manufacturing policies, and the dependent variable share of manufacturing labor employment across cities to construct a regression model of the following form:

$$\ln(\text{ma-em})_i = \psi_0 + \psi_1 \text{socog6}_i + \psi_2 \text{policy}_i + \psi_3 \ln(2\text{lp})_i + \psi_4 X_i + \varepsilon_4, \quad (4)$$

where $\ln(\text{ma-em})_i$ represents the logarithm of the manufacturing employment of each city, the meanings of socog6_i , policy_i , $\ln(2\text{lp})_i$, and X_i in the model are consistent with those in Section 3.1 and ε_4 is a random error term.

It is also easy to see that ψ_1 , ψ_2 , and ψ_3 are the estimated coefficients that are the focus of this study, capturing the degree of skill polarization across cities, the status of smart manufacturing policies, and the impact of secondary industry labor productivity on the share of manufacturing employment. Again, the control variables include the unemployment rate (unemp_i), regional GDP ($\ln \text{gdp}_i$), dependence on FDI (dfdi_i), export volume ($\ln \text{expo}_i$), the number of industrial enterprises above the size threshold ($\ln \text{nu-in-e}_i$), and the share of employment in the secondary

industry ($pe2nd_i$).

In this section, descriptive statistics were conducted on the data characteristics of the main variables, correlations between the variables were calculated, and the detailed results are presented in Appendix Table A2. The results of the variable correlation analysis show that the independent variable inter-city skill polarization, the variable secondary industry labor productivity, and the variable smart manufacturing policies, all selected for this study, are significantly correlated with the dependent variable share of manufacturing workers employed in each city.

4.2 Regression Results

Column 1 of Table 3 reports the regression results for model (4). The results show that the coefficient of inter-city skill polarization (cities' social-cognitive skill scores) on manufacturing wage levels is significantly negative at the 10% level, with a specific coefficient of -1.649 and an

Table 3 Regression results in cities' skill polarization and manufacturing employment

	(1) ln (ma-em)	(2) socog6	(3) prop-manu-gdp
socog6	-1.649^* (-1.700)		-0.410^{**} (-2.310)
ln 2lp	-0.006^{***} (-2.770)		0.001 (0.900)
policy	0.303^* (1.770)	0.044^{**} (2.140)	0.018 (0.230)
ln gdp	0.987^{***} (6.730)		
dfdi	-0.000 (-0.360)		0.000 (1.240)
ln expo	-0.003 (-0.060)		0.002 (0.280)
uemp	0.040 (0.460)	-0.024^{**} (-2.170)	
ln nu-in-e	0.215^{**} (2.080)	0.005 (0.330)	0.009 (0.760)
ln mgdp		0.039^{**} (2.490)	
pe2nd	1.606^{***} (2.800)	-0.093 (-1.290)	
_cons	2.159^{***} (2.670)	0.014 (0.180)	0.381^{***} (3.800)
N	100	99	100
R ²	0.754	0.287	0.043

Note: t -value in parentheses, $*p < 0.10$, $**p < 0.05$, $***p < 0.01$.

R^2 of 0.754. This indicates that higher social-cognitive skills scores in cities (i.e., greater skill polarization across cities) correspond to a lower share of manufacturing workers' employment, as their regression coefficient is -1.649 , which implies that the share of manufacturing workers' employment decreases by 1.649% for every 0.01 unit increase in a city's social-cognitive skills scores after including the relevant control variables. This suggests that skill polarization across cities can significantly reduce the share of local manufacturing employment, and H2 passes the test. This may be because manufacturing jobs are usually categorized as procedural jobs with relatively low social cognitive skills scores, and higher social cognitive skills scores of cities indicate that the share of manufacturing in the local industrial structure is relatively low, and thus manufacturing employment will be low.

Unlike in Section 3.2, the regression coefficient of smart manufacturing policies on manufacturing employment in each city is significantly positive at the 10% level with a coefficient of 0.303. This indicates that smart manufacturing policies introduced in the region can have a significant positive impact on local manufacturing employment, and when the intensity of smart manufacturing policies introduced in the region increases by 0.1 units, the share of local manufacturing employment will increase by 3.03%. The completely different result from the effect of wage level may be because around 2017, smart manufacturing policies will mainly be introduced in the form of economic incentives, which, once announced, will be more attractive to manufacturing enterprises and directly encourage them to implement the smart transformation, thus enabling an increase in labor demand in that year. Therefore, the regression results confirm H4.

Similarly, the regression coefficient of secondary industry labor productivity on manufacturing employment in each city is -0.006 and is significant at the 1% level. This implies that the labor productivity of the secondary industry in each city has a significant negative effect on local manufacturing employment. If each percentage point increases in the labor productivity of the secondary industry in a city will reduce the manufacturing labor employment in that area by 0.6%. This indicates that secondary industry labor productivity plays a significant role in reducing manufacturing employment, and H6 is also tested. This may be because, in most cities, the labor productivity of the secondary industry is mainly influenced by the labor productivity of the manufacturing industry, that is, the labor productivity of the secondary industry reflects the high level of labor productivity of the manufacturing industry. When labor productivity is high, manufacturing firms need fewer workers to produce the same number of products, which means that the demand for labor decreases, releasing the remaining labor force in the manufacturing industry, and promoting the flow of labor to the tertiary industry^[15].

Column 2 of Table 3 reports the regression results with inter-city skill polarization as the dependent variable, smart manufacturing policies as the independent variable, and the unemployment rate, the number of above-mentioned size industrial enterprises, manufacturing GDP, and secondary industry employment as control variables. The results show that smart manufacturing policies have a significant positive contribution to inter-city skill polarization (the

coefficient is 0.044 and significant at the 5% level). This indicates that when the government encourages the transformation of smart manufacturing, the phenomenon of skill polarization among different cities is intensified. This may be because cities with good economic conditions and a good foundation for manufacturing transformation are more likely to provide financial support for smart manufacturing policies and guarantee policy implementation when promoting smart manufacturing transformation, which improves the smartness of local manufacturing industries and eventually improves the social-cognitive skill scores of the region and intensifies the skill polarization phenomenon among different cities.

Column 3 of Table 3 then reports the regression results with the share of manufacturing GDP in regional GDP as the dependent variable, inter-city skill polarization as the independent variable, and secondary industry labor productivity, smart manufacturing policy, dependence on FDI, export volume, and the number of above-mentioned size industrial enterprises as control variables. Despite the poor fit of the model, the results still reflect a negative effect of inter-city skill polarization on the size of local manufacturing industries in the industrial layout (the coefficient is -0.410 and significant at the 5% level). This suggests that the degree of skill polarization among cities reflects the differences in the industrial layout of local governments in promoting the smart transformation of local manufacturing industries. Specifically, cities with high social cognitive skill scores have a lower share of manufacturing in the industrial layout.

In addition, the regression results also reveal the internal logic of why workers still need to participate in production in the era of smart manufacturing from the perspective of skill polarization among cities. From the perspective of skill polarization among cities, there are policy differences among different cities in the process of promoting smart manufacturing, which leads to different industrial structures and even the progress of smart transformation of manufacturing industry in each region, which leads to differences in the occupational skill demand for workers and employment demand for manufacturing industry in different cities. In regions where the degree of intelligent transformation of manufacturing industry is low, workers are still required to participate directly in production, while in regions where the degree of intelligent transformation of manufacturing industry is high, workers are still required to cooperate with intelligent machines to participate in production.

5 Robustness Tests

To mitigate the endogeneity problem of the model, we need to test the robustness of the regression results. In terms of model robustness tests, common practices include replacing the proxies for the dependent variable or the independent variables, etc. In this section, we have replaced the independent variables in model (3) and model (4), respectively. Specifically, the regression analysis was conducted on the social cognitive skills scores of each city using 0.8 (socog8) and 0.5 (socog5) as the new independent variables. The correlation results are shown in Table 4.

Table 4 Robustness tests

	Robust(1)	Robust(2)	Robust(3)	Robust(4)
	ln (ma-em)	ln (ma-w)	ln (ma-em)	ln (ma-w)
socog8	-5.761*	2.335**		
	(-1.730)	(2.190)		
socog5			-1.485*	0.747**
			(-1.730)	(2.530)
ln 2lp	-0.006***	-0.006**	-0.006***	-0.005*
	(-2.720)	(-2.110)	(-2.780)	(-1.920)
policy	0.292*	-0.047	0.301*	-0.054
	(1.730)	(-0.810)	(1.770)	(-0.960)
ln gdp	0.986***	0.139**	0.993***	0.126**
	(7.000)	(2.600)	(6.770)	(2.330)
dfdi	-0.000	0.000	-0.000	0.000*
	(-0.230)	(1.600)	(-0.330)	(1.890)
ln expo	-0.012	0.008	-0.003	0.003
	(-0.280)	(0.690)	(-0.070)	(0.280)
uemp	0.059	0.038	0.040	0.049*
	(0.670)	(1.270)	(0.460)	(1.680)
ln nu-in-e	0.211**	-0.006	0.212**	-0.003
	(2.040)	(-0.150)	(2.060)	(-0.070)
pe2nd	1.560**	0.062	1.575***	0.073
	(2.610)	(0.350)	(2.710)	(0.420)
_cons	2.222***	9.642***	2.161***	9.679***
	(2.750)	(37.650)	(2.680)	(39.140)
<i>N</i>	100	100	100	100
<i>R</i> ²	0.754	0.506	0.755	0.521

Note: *t*-value in parentheses, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

The results in Table 4 show that the social-cognitive skills scores of each city have a significant positive effect on the local manufacturing wage level and a significant negative effect on the local manufacturing employment, which means that the labor productivity of the secondary industry can reduce the local manufacturing wage and employment share and that smart manufacturing policies can increase the local manufacturing employment share. The results of the robustness test are consistent with the benchmark model. In other words, the results of this study are highly robust despite the replacement of two new independent variables that are larger than the threshold of 0.6 and smaller than the threshold of 0.6, respectively, in the regression model.

6 Conclusion

Unlike previous literature, this paper does not limit itself to skill polarization within the labor market but focuses on skill polarization across cities, which to some extent reflects differences

in the industrial structure of different cities. Using inter-city skill polarization as measured by the occupational skill importance score, this paper makes a new attempt to examine the issue of economic inequality from the perspective of differences in the skill needs of workers in the industries on which different regions depend.

This paper reveals the inner logic of why workers still needed to participate in production in the era of smart manufacturing, the future wage changes of smart manufacturing practitioners, and the differences in industrial layouts in different cities. It provides some management inspiration and ideas for local governments to promote smart manufacturing transformation, manufacturing enterprises to implement smart factory transformation, and manufacturing workers to cope with the employment problem in the smart transformation of China's manufacturing industry.

Firstly, this paper finds that cities' social-cognitive skills scores significantly and positively affect local manufacturing wages and significantly reduce local manufacturing employment and the share of manufacturing in the industrial structure. This suggests that the stronger the skill polarization between cities (the higher the city's social-cognitive skills scores), the lower the city's manufacturing employment and the lower the share of manufacturing GDP in regional GDP, but the higher the manufacturing wage, which in turn widens the manufacturing wage gap between skill-polarized cities. This is because, on the one hand, cities with higher social-cognitive skill scores have relatively better overall economic conditions, and thus the overall labor market wage level is higher than elsewhere, and the manufacturing wage is somewhat higher. On the other hand, industries that rely on social cognitive skills account for a larger share of the industrial structure in these cities, and they also tend to have more investment and technological accumulation in new technologies such as artificial intelligence. Therefore, local manufacturing enterprises that meet the conditions of smart transformation are more likely to transform successfully, and the process of such transformation has an impact on the employment and wage levels of manufacturing workers.

Secondly, the regression results show that smart manufacturing policies have a significant positive effect on local manufacturing employment, but do not affect the wage level of local manufacturing workers. This indicates that the better the smart manufacturing policy situation in a city, the higher the manufacturing employment in that area, but does not affect the manufacturing wage. This is because local governments have sufficient funds to provide affordable economic subsidies, tax incentives, and other policies to motivate enterprises in the process of promoting the smart transformation of local manufacturing industries, which is an important factor in attracting local manufacturing enterprises to carry out the smart transformation, and thus have an impact on manufacturing employment.

Finally, we investigate the issue of the effect of secondary industry labor productivity on local manufacturing wage and employment and examine the mediating effect of secondary industry labor productivity in the relationship between inter-city skill polarization and local manufacturing wage level. The results show that the labor productivity of the secondary industry can

reduce the wage level and employment of local manufacturing workers, and at the same time, it has a negative partial mediating effect in the relationship between the effect of inter-city skill polarization on the local manufacturing wage. This means that the phenomenon of inter-city skill polarization can affect the wages of local manufacturing workers through the labor productivity of the secondary industry.

In concrete practice, city governments not only bear the responsibility of promoting healthy and high-quality local economic growth but also the responsibility of ensuring stable employment in the region. Manufacturing is an important absorbing sector for labor employment in China, and the value added of China's secondary industry will still account for 39.9% of GDP in 2022¹. Therefore, local governments must understand the impact of smart manufacturing policies on manufacturing employment and wage levels, while promoting the smart transformation of manufacturing industries and achieving high-quality development to stabilize local employment and labor income levels. The research results of this paper on the relationship between inter-urban skill polarization, smart manufacturing policies, secondary industry labor productivity, and manufacturing employment and wages provide local governments with certain references for governance practices and guidance. In the short term, the government needs to monitor the impact of policies on the employment of manufacturing workers; in the long term, it needs to further monitor the impact of policy implementation on the wage level of manufacturing workers. At the same time, the government can also find the reference object for local industrial structure optimization and transformation and upgrading from inter-city skill polarization, and coordinate different industries to do a good job of regional high-quality development.

In addition, manufacturing workers are the group directly affected by the smart transformation of the manufacturing industry, and the conclusion of this paper also provides useful help for them to assess the impact of the smart transformation of the manufacturing industry on themselves. On the one hand, if workers' energy and economic conditions allow, they can combine their occupations, positions, and skill levels, select their ideal positions suitable for them in the smart manufacturing scenario in advance, and participate in relevant vocational training to adapt to the employment demand after the smart transformation of their enterprises. On the other hand, due to the existence of inter-city skill polarization, in the short term, manufacturing workers can also seek suitable manufacturing positions in cities with similar social-cognitive skill levels.

Last but not least, this study also has certain limitations. For example, the research data used is only the cross-sectional data of 2017, and the data source of the core variables relies on the publicly available measurement data of other research teams, which affects the reliability of the regression analysis results in this paper. Subsequent studies can further analyze the phenomenon of intercity skill polarization in China by independently measuring the social cognitive skill scores of different cities in China, which can be used to validate this study.

¹Data are from the website of the National Bureau of Statistics, <https://data.stats.gov.cn/easyquery.htm?cn=C01>.

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Appendix

Table A1 Results of descriptive analysis of variables where the dependent variable is wage

	lnmw	socog6	ln2lp	policy	lngdp	dfdi	lnexpo	uemp	lnnu-i-e	pe2nd
lnmw	1									
socog6	0.455***	1								
ln2lp	-0.516***	-0.185*	1							
policy	0.223**	0.302***	-0.215**	1						
lngdp	0.478***	0.532***	-0.101	0.380***	1					
dfdi	0.0920	-0.0760	0.0720	-0.0420	-0.0390	1				
lnexpo	0.259***	0.359***	-0.0520	0.195*	0.473***	-0.0770	1			
uemp	0.0620	-0.231**	-0.121	-0.0430	-0.190*	0.109	-0.130	1		
lnnu-in-e	0.384***	0.270***	-0.176*	0.297***	0.713***	0.117	0.426***	-0.108	1	
pe2nd	0.153	0.0130	-0.149	0.222**	0.240**	0.0260	0.212**	-0.103	0.438***	1

Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.**Table A2** Results of descriptive analysis of variables where the dependent variable is the employment

	lnma-em	socog6	ln2lp	policy	lngdp	fdii	lnexpo	uemp	lnnm	pe2nd
lnma-em	1									
socog6	0.328***	1								
ln2lp	-0.252**	-0.185*	1							
policy	0.429***	0.302***	-0.215**	1						
lngdp	0.800***	0.532***	-0.101	0.380***	1					
fdii	-0.031	-0.076	0.072	-0.042	-0.039	1				
lnexpo	0.396***	0.359***	-0.052	0.195*	0.473***	-0.077	1			
uemp	-0.101	-0.231**	-0.121	-0.043	-0.190*	0.109	-0.130	1		
lnnu-in-e		0.722***	0.270***	-0.176*	0.297***	0.713***	0.117	0.426***	-0.108	1
pe2nd	0.436***	0.0130	-0.149	0.222**	0.240**	0.026	0.212**	-0.103	0.438***	1

Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.