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How does digital transformation relieve the employment pressure in China? Empirical evidence from the national smart city pilot policy

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The impact of digital transformation on employment has been increasingly noticed by the academic community, while the internal mechanism still remains as a black box, especially in terms of specific pilot policy, such as the national smart city pilots policy in China. Based on the city-level and firm-level panel data, we investigate the impact of China's national smart city pilot on the employment pressure of urban job seekers using difference-in-differences model. The results show that the national smart city pilots significantly reduces the employment pressure in the pilot cities. In addition, by bringing configuration optimization and technological upgrading, smart city pilots affect firm selection at the micro level, generating siphoning effects, factor substitution effects, and efficiency gains, and further affect the macro economy by promoting urban economic agglomeration, industrial structure transformation, and regional innovation thereby affecting employment pressure. Furthermore, the reduction effect of China's national smart city pilot on employment pressure are heterogeneous in terms of cities, firms, and workers' education levels. Finally, conclusions and policy implementations are provided to highlight the theoretical and practical values.

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Introduction

Unemployment is one of the social phenomena that citizens and public administrators in developing countries are most concerned about. The global economic crisis and the recession associated with COVID-19 have brought hitherto unknown unemployment rates (Manuchehr, 2023). According to the International Labor Organization(ILO), in 2020, global hours of work decreased by 4.3% from pre-pandemic levels, equivalent to a reduction of 255 million full-time jobs. This will directly lead to a loss of about 700,000 new jobs in urban areas, which exacerbates the severity and complexity of the employment situation and puts great pressure on the working-age population to find employment.

Kryiacou and Sutcliffe (1978) considers stress as a sense of personal tension or the possibility of future external threats stimulating personal activity. Industrial transformation, economic recession, and pandemic outbreaks bring strong shocks to the labor market (Sima et al., 2020; Dengler and Matthes, 2019; Nicola et al. 2020), and individuals generate a negative emotional state in the employment process out of unclear self-perceptions and concerns about current socioeconomic uncertainty, which some scholars refer to as employment pressure (Li et al., 2023; Chen et al., 2020). The causes of this negative emotional state include self and external factors. From the external factors, employment pressure is inversely proportional to labor demand, fewer jobs in the job market means a worse economic environment and less labor demand, when job seekers face greater employment pressure. From the internal factors, changes in the market environment affect the possibility of job opportunities for individuals. When job seekers do not think they can get more resources and opportunities, the more likely they are to treat employment with a negative attitude, and the more employment pressure they feel. Deteriorating mental health is one of the effects of high labor market instability. Scholars have argued that it is important to reduce job seekers' job insecurity, and this study attempts to provide a strong initial attempt in this direction.

One of the drivers of employment stress is changes in the use of technology in organizations (Greenspan, 1996). New technologies may create threat perceptions among employees, and people worry whether they are still working (Nam, 2019). The fourth industrial revolution and artificial intelligence bring about a global and irreversible digital transformation, the rapid development of the digital economy is causing profound social change, and the traditional urban form, industrial structure, and job market are all subject to the huge impact of digital technology change (Ghobakhloo, 2020; Liu et al. 2022; Ma and Zhu, 2022; Wu and Yang, 2022). Digital technologies represented by big data, cloud computing and artificial intelligence have rapidly penetrated the economic cycle, bringing about a region-wide digital transformation of the economy, society and government, reshaping human production and lifestyle, and triggering a new workforce allocation effect(Vial, 2019; Niu, 2022; Feroz et al., 2021; Nambisan et al. 2019; Janowski, 2015). Does digital transformation aggravate or reduce the pressure of employment in society? This question is increasingly worrying.

The established literature is concerned with the complex impact of the development of digital transformation on employment. Theoretical and empirical studies by Autor et al. (2003) suggest that technology can have both positive and negative substitution effects on labor demand. Some scholars' studies argue that the application of new technological paradigms such as digital transformation, digital technology, and technology will have substitution effects on employment (Autor and Duggan, 2006; Autor et al., 1998; Beaudry et al., 2016). Autor and Salomons (2018) use cross-country data to find that industrial intelligence reduces employment and labor income. And the employment substitution effects of technological revolutions tend to be greatest for middle-skilled workers (Autor and Dorn, 2013). However, not all technological revolutions increase the demand for high-skilled labor, and some scholarly studies have concluded that digital transformation, digital technology, and emerging technology have a positive impact on labor demand and can create new labor demand (Lordan and Neumark, 2018; Graetz et al., 2018), which is mainly due to the substitution and complementary relationship between emerging technologies and unskilled labor (Acemoglu and Micheals, 2002; Machin and Van Reenen, 1998). Dauth et al. (2018) show, based on data from the German labor market, that digital technologies affect the distribution of labor across industries and that robotics applications can increase service sector jobs while reducing manufacturing jobs. Dengler and Matthes (2021) study the impact of digital transformation on labor force employment in Germany based on detailed occupational data and argue that there is an irreplaceable component in almost all occupations and that employment growth slows down with increasing substitution potential. Furthermore, the digital economy can reduce information asymmetries (Kuhn and Mansour, 2014), reduce the risk of frictional unemployment (Lederman and Zouaidi, 2022), increase service jobs and benefit low-skilled labor (Lee and Clarke, 2019), improve regional innovation (Guo and Zhong, 2022), encourage entrepreneurial behavior (Atasoy, 2013), improve the quality of human capital (Rageth and Renold, 2020), and optimize the long-term employment structure (Wu and Yang, 2022).

In summary, the existing literature suggests that digital transformation has the potential to both exacerbate employment pressure through substitution effects and to reduce job anxiety among job seekers through creation effects. However, few studies have focused on the mechanisms through which digital transformation has an impact on employment pressure. Smart cities are an important vehicle for digital transformation. Between 2012 and 2014, the Chinese government announced three consecutive batches of smart city pilots (SCP), signaling that China is attempting to accelerate the digital transformation process of its cities at the national level. In this large-scale project led by government forces (Tai, 2019), many employed people in traditional and emerging industries have had to face job restructuring, so an important and unanswered question is: Have the smart city pilot policies effectively impacted employment? With this question as a starting point, we creatively incorporate smart city pilot policies and employment into the same research framework, and use the DID methodology to analyze the relationship between the two as well as the policy effects of smart city pilot policies.

We consider the smart city pilot policy as a natural experiment and measure the average treatment effect of SCP on employment with time-varying DID using panel data of Chinese cities and listed companies from 2003–2019, with pilot cities as the experimental group and non-pilot cities as the control group, to measure the average treatment effect of SCP on employment using difference-in-difference model (DID). To better explain the impact of SCP on employment, we sort out its potential impact mechanism from micro-selection to macro-performance levels and make a theoretical analysis. We find that SCP brings about the siphoning effect, factor substitution, and efficiency improvement at the micro level, and further forms economic agglomeration, industrial structure transformation, and regional innovation at the macro level, which together have an impact on employment under the superposition of multiple effects. In addition, we further find that SCP can drive enterprises to undergo digital transformation, and workers' wages will be reduced by SCP. These findings have a positive policy and theoretical implications for the construction of smart cities in developing countries and can guide for optimizing digital industrial policies.

The potential marginal contribution manifests itself in three ways. First, we examine in depth the theoretical mechanisms of SCP's impact on employment pressure from micro to macro levels, based on the "creation effect" and "substitution effect" from smart city policy effects. In contrast to previous research, this study examines the distinct effects of SCP at various levels while incorporating macro and micro effects into the same analytical framework. Second, we estimate the net effect of SCP on employment pressure using multi-period DID. It is found that SCP has a positive effect on employment stress relief. As an emerging research area, there are few empirical studies on the impact of smart cities on employment pressure, and our analysis fills the gap in current research and enriches the existing literature. Finally, on the basis of theoretical analysis and empirical tests, we explore the mechanisms of smart city pilot policies affecting employment pressure from the perspectives of configuration optimization, technology upgrading, siphon effect, factor substitution, efficiency improvement, economic agglomeration, industrial structure transformation, and regional innovation, bridging the gap of existing studies on mechanism exploration.

The remainder of the paper is organized as follows: Section 2 provides a review and analysis of the theoretical mechanism of SCP's impact on employment; Section 3 presents the methodology, data, and identification strategy; Section 4 reports the results of the empirical analysis of SCP's impact on employment pressure and a series of robustness tests; Section 5 reports the results of the empirical analysis of SCP's impact mechanism on employment pressure; Section 6 provides a discussion and analysis of heterogeneity; Section 7 provides further analysis and discusses the impact of SCP on the digital transformation of firms and workers' wages; and Section 8 gives conclusions.

Policy background and theoretical analysis

Policy background. Smart city construction aims to achieve sustainable urban development by building an environment and ecological model that is conducive to enterprise development and human habitation, and is a city form supported by information technology, using information technology to integrate and optimize various resources (Albino et al., 2015). With the rapid development of the Internet of Things, Internet, cloud computing and other information technologies, the wave of smart city construction has been launched worldwide. In view of the continuous improvement of smart city construction and urban management level in developed countries such as Europe, America and Japan, China's policy has followed suit. In China, from the timeline of smart city pilot implementation, China started to design, implement and build China's smart cities in 2010, and the principle of construction wanted to be gradual, piloting first and then promoting. 2012, China's national Ministry of Housing and Construction and Ministry of Science and Technology promulgated the Notice on National Smart City Pilot Work and launched the first batch of 90 smart city pilots. Based on the construction results of the first batch of pilots, the central government announced the second batch of pilots for the policy in 2013, and increased the scale of the pilots, identifying 103 cities for the second batch of pilots. In 2014, the government issued the *Guidance on Promoting the Healthy Development of Smart Cities* and started the third batch of policy pilots in 2015, which has brought the number of smart city construction across China to more than seven hundred.

Theoretical analysis. As a new model of urban governance, smart cities widely use the Internet of Things, the Internet and other high technologies to accelerate the development speed and operational efficiency of cities (Vanolo, 2014; Ramaswami et al., 2016). Smart city pilots policy uses a series of technical means to promote the city into the digital stage, such as the use of various types of sensors embedded in the infrastructure to form the Internet of Things, to real-time dynamic monitoring of the operation of various elements of the city system, and then use supercomputer and cloud computing technology to analyze the big data generated by the operation of the city, to achieve the efficient allocation of urban resources.

Smart cities are supported by powerful information technology that can respond to complex and dense citizen needs and achieve optimization of governance processes with organic collaboration among multiple subjects (Li et al., 2015; Rathore et al., 2018), thus attracting the flow of capital, talent, and other factor resources, bringing about production technology upgrades and organizational changes, and achieving optimal resource. The optimal allocation of resources. With intelligent infrastructure as the cornerstone, smart cities can bring more convenient and perfect public services with the help of advanced computer technology, further refine public management, greatly improve urban governance capacity, provide residents with a more livable living environment. At the same time, smart city policy is an important tool for transforming traditional industries, resolving excess capacity, and developing new industries such as high-tech industries. The information technology used in smart city policy has extensive and permeable characteristics, and the resulting technological innovation will improve the resource endowment of various industries, drive the improvement of local total factor productivity, and promote the upgrading of traditional industrial structures from multiple perspectives (Cui and Cao, 2022). The existing literature focuses on the policy effects of smart cities from macro perspectives such as public services, governance models, innovation outputs and emission reduction effects (Barrutia et al. 2022; Wang and Deng, 2022; Cheng et al. 2022), and in recent years some scholars have started to analyze how smart cities affect entrepreneurial dynamics from a micro perspective (Li et al. 2023). and whether the interactive experience of smart cities enhances the happiness of residents (Wang and Deng, 2023; Chen et al. 2020). However, there is little literature that integrates both macro and micro perspectives to study the impact of smart cities on employment pressure. In fact, the impact of SCP on employment pressure is complex, as it can both alleviate employment pressure through employment creation effects and increase employment pressure through employment substitution effects. We will analyze the intrinsic mechanism of SCP's impact on employment pressure from three aspects: the policy effect of SCP, and the impact on the choice of micro subjects on the macro economy.

Policy effects. Smart city pilot policy will have two major impact effects. One is the configuration optimization effect, and the other is the technology upgrading effect. The configuration optimization effect that word city can significantly reduce the transaction costs of the main body, thereby improving the efficiency of factor allocation. Smart city on the existing basis of urban development, the use of information technology, deep excavation, integration of information resources, so as to achieve fine management of urban management, industry development, public services, residents' lives and other areas (Silva et al., 2018; Ismagilova et al., 2019; Heidari et al. 2022), and promote the society and enterprises to intelligent, digital, which further enhance the city's management and operation capacity, promote the free flow of resources, and ultimately promote the efficiency of resource allocation. Specifically: on the one hand, the construction of smart cities will promote the continuous improvement of urban network infrastructure (Albino et al., 2015), and the improvement of such facilities will enable the full flow of information, which will further reduce the risk of resource mismatch and improve the efficiency of urban resource allocation. Moreover, the development of intelligent information systems in cities and the increasing ability of the government to provide public services will significantly reduce the cost of information flow, thus realizing the free flow of resource factors between different cities, regions and industries and increasing the probability of effective resource allocation. On the other hand, smart city construction will vigorously develop big data industry, "Internet+ " enterprises and other modern information technology enterprises, promoting the convergence of talents, capital and resources in this place, providing good conditions for effective resource allocation.

Technology upgrading effect means that smart city construction can promote production technology upgrading and organizational upgrading (Angelidou, 2017), and once advanced digital technology is applied to actual production, it can effectively replace traditional production technology and further bring modern organizational management technology. On the one hand smart cities use the new generation of information technology to technically penetrate various sectors of traditional industries, causing a huge change in the traditional industrial structure. On the other hand information technology penetrates into all aspects of production, manufacturing, transportation, management, and sales, completely changing the traditional production and management model, optimizing the organizational form of enterprises, and improving their productivity and reducing their operating costs by constantly turning to information-based scientific management (Cheng et al. 2023).

Micro Impacts. At the micro level, SCP will affect the choice of enterprises and thus employment. New economic geography theory suggests that the upgrading of infrastructure level may lead to the gathering of factors from surrounding regions to the central region, resulting in the slowdown of economic development in surrounding regions, a phenomenon known as the "siphon effect" (Han and Li, 2022). As a typical representative of traditional and new infrastructure upgrading, smart cities can realize the transformation and upgrading of traditional industries to intelligent industries and digital industries, thus causing the resources of the surrounding regions to be "sucked away" by the central region, and in the long run, high-quality resources will all be clustered in areas with higher marginal utility, resulting in the siphon effect (Batty et al., 2012; Globerman and Shapiro, 2002). Under the mechanism of "voting with one's feet", labor factors tend to have a tendency to be superior, and the construction of smart cities will lead to a large-scale influx of labor to cities with higher wage rates (Dashkevych and Portnov, 2023), especially high-skilled labor, which tends to cluster in cities that can bring them greater utility.

Second, lower factor costs and digital production technologies will produce a factor substitution effect. Digital tools and robots will replace traditional industrial workers, causing unemployment; new production methods will increase the demand for high-skilled labor and reduce the demand for low-skilled labor. The development of smart city construction increases the complexity of jobs and increases the demand for skilled personnel (Balsmeiera Woerter, 2019), which will also lead to the loss of some traditional jobs, if workers as a whole have a low level of education, are not equipped to quickly adapt to new positions, lack skills that are compatible with the jobs, and human capital cannot effectively match. This will lead to more serious structural unemployment in the short and medium term. Smart cities enable the widespread use of automation and artificial intelligence, causing a profound innovation in production methods, which leads to an increase in labor productivity and a decrease in the size of the labor force required for the same output, i.e., the "employment substitution effect" of the digital economy (Balsmeier and Woerter, 2019). At the same time, smart cities have changed the traditional organization and production methods of enterprises, making the organizational structure flatter, outsourcing procedural and support work in general and focusing on the development of core business, reducing the number of middle-skilled workers, who mainly play a supporting role, due to the streamlining of the organization, indirectly reducing the demand for labor and pushing labor out of the job market.

Third, the development of smart cities promotes the emergence of new businesses, new occupations, and new jobs, which create new jobs and employment opportunities while creating a substitution impact on jobs (Vivarelli, 2014; Calvino and Virgillito, 2018). On the one hand, the reduction in production costs of firms brought about by the technology effect leads to a decrease in the price of goods, which leads to an increase in market demand, and firms will therefore expand production, which means an increase in the demand for labor, providing more jobs (Lim and Lee, 2019). At the same time, the decrease in production costs and product prices actually increases the income of consumers, leading to an increase in demand for products and services, which leads to the expansion of the market size and ultimately promotes the increase of jobs. On the other hand, the expansion of digital technology in the practical application of smart cities has promoted the extension and optimization of the industrial chain of related industries, bringing new jobs such as urban information analysts and integration engineers, increasing the demand in the job market and gradually increasing the ability to absorb employment.

Macro Impacts. At the macro level, SCP will have an impact on the macro economy, which in turn will affect urban employment. First of all, SCP will generate economic agglomeration, and various factors such as people, capital and technology will flow to the pilot city. The agglomeration of factors will accelerate the expansion of industries, thus generating scale effects, and the larger the scale of industries means more jobs (Funderburg and Boarnet, 2008). On the one hand, with the further aggregation and proliferation of resources and elements in the smart city, some jobs created specifically for high-level workers with special professional skills gradually increase, thus generating the phenomenon of gathering highly skilled and skilled labor. High-quality and high-skilled personnel are conducive to improving the level of technological innovation and production efficiency in the city, thus attracting more corporate investment, bringing more jobs and increasing (Baaij et al., 2015). This attracts more enterprises to invest, bringing more jobs and increasing the employment density of the city. On the other hand, the concentration of labor force is conducive to the concentration of industries, and the stronger the concentration of industries, the stronger the ability to accommodate the number of labor force. The scale of industry will also have an impact on labor force employment, and areas with larger industry scale will require more labor force.

Secondly, SCP will promote the transformation of urban industrial structure, specifically the digitalization of industry and digital industrialization (Jo et al., 2021). Among them, the digitization of industry brings the deep integration of digital technology and real industry, which will give rise to new business models and new business modes, thus creating new jobs. A large number of digital R&D, management and camp positions will be created, increasing the demand for high-skilled labor (Fossen and Sorgner, 2022). The development of digital industrialization makes the industrial form with digital technology as the core

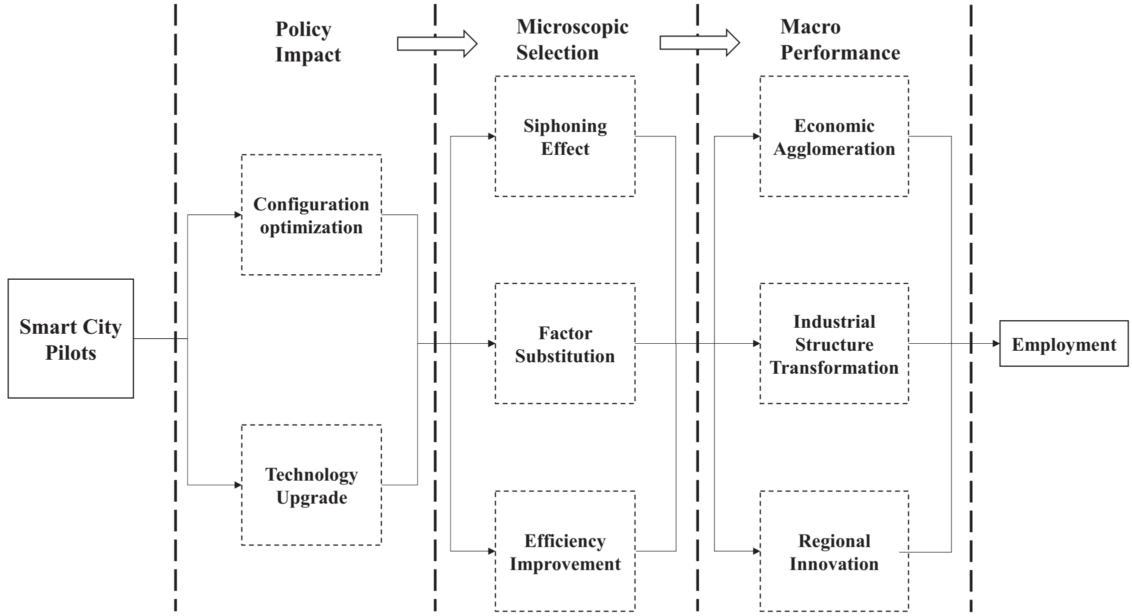

Fig. 1 Theoretical mechanism.

occupy an increasingly important position, and the popularity of digital industry brings a large number of new products, new models and new business modes of innovation, which constantly give rise to new employment opportunities and ways.

Third, SCP will raise the level of innovation in urban areas, bringing technological innovation, product innovation and market innovation. These innovations will bring a large amount of new consumer demand, while enterprises will tend to further expand their production scale for the purpose of profit maximization (Bianchini and Pellegrino, 2019). In addition, technological innovation can drive the development of related industries and labor force employment by innovating products and services, expanding production fields, and promoting industrial transformation and upgrading. Technological innovation effectively improves product production methods and enhances product production efficiency, leading to increased enterprise profits and production scale, which effectively promotes labor force employment (Zhu et al., 2021), while further expanding market share through product innovation, extending related industrial chains and creating more new jobs. Secondly, technological innovation will further trigger industrial structure changes, giving rise to new industries and new models, generating employment diffusion effects and creating more new jobs.

In sum, SCP brings employment creation effect and employment substitution effect to firms and cities at both micro and macro levels, and the impact of SCP on employment pressure depends on the net effect of the combined creation and substitution effects. Next, we test this impact effect through empirical analysis. The theoretical mechanism is demonstrated in Fig.1.

Methodology

Data. To investigate the impact of SCP on employment pressure, we chose the period 2003–2019 as the study interval and collected relevant data at both macro and micro levels. Specifically, to explore the impact of SCP on employment pressure at the macro level, we obtained data from the *China Statistical Yearbook* on the number of employed workers, household registration population, wages of employed workers, gross regional growth per capita, and total retail sales of social consumer goods, and collected data from 284 prefecture-level cities, with a total of 4828 samples. To explore the impact of SCP on employment pressure at the micro level, we obtained data on the number of employees, operating revenue growth rate, cost of sales, gearing ratio, return on net assets, and income tax expense for Chinese A-share listed companies in Shanghai and Shenzhen from the CSMAR database. To avoid the influence of abnormal data, we processed the data of listed companies as follows: first, eliminate companies with abnormal financial status and risk of delisting, i.e., companies with “ST” or “*ST” in front of their stock names; second, we excluded listed companies with serious missing data; third, we excluded listed companies with panel length. Fourth, we use linear interpolation to fill in the missing data. Finally, we obtained a total of 28707 data for 2329 listed companies. In addition, we also obtained the SCP pilot list from the MHURDC website.

Identification strategy. We consider the smart city pilots policy starting from 2012–2014 as a quasi-natural experiment to estimate the policy effect of SCP on employment pressure through multi-period DID. In this paper, we use panel data from a total of 30 provinces and cities across the country from 2003–2019 as the sample for the study, with the three batches of selected pilot cities as the experimental group and the remaining cities as the control group. The benchmark model is built at both city and firm levels.

A model for assessing the city-level employment effects of the SCP. We assess the employment impact of the SCP at the macro-city level to derive the overall employment effect of the pilot policy at the city level, and the model is set up as follows:

$$ln\left(citylabor_{ct}\right) = \alpha_1 + \theta_1 SCP \times Post_{ct} + \lambda_1 X_{ct} + \eta_c + \mu_t + \varepsilon_{ct} \tag{1}$$

where $citylabor_{ct}$ denotes the employment of city c in year t, expressed as the logarithm of the total number of workers employed in the city; $SCP \times Post_{ct}$ is the core explanatory variable, with a value of 1 if city c is included in the pilot list in year t and 0 otherwise;θ_1 is a DID estimator measuring the average treatment effect of SCP on urban employment; X_{ct} is the set of control variables; ηc and μ_t denote individual fixed effects and year fixed effects, respectively; and ε_{ct} is a random disturbance term affecting urban employment.

Table 1 Baseline regression.

	ln(city_labor)		*ln(labor)*	
	(1)	**(2)**	**(3)**	**(4)**
SCP × Post	0.1185*** (0.0107)	0.0743*** (0.0125)	0.1841*** (0.0182)	0.1690*** (0.0180)
Constant	3.3887*** (0.0032)	−5.1450*** (0.8990)	7.5507*** (0.0092)	7.5224*** (0.0097)
Control variable		Yes		Yes
Year fixed effect	Yes	Yes	Yes	Yes
Individual fixed effect	Yes	Yes	Yes	Yes
Observations	4828	4828	28707	28707
R-squared	0.9564	0.9735	0.8214	0.8245

*** denotes $p < 0.01$, and robust standard error is shown in brackets.

Model for assessing the impact of SCP on employment at the firm level. We assess the impact of SCP on employment at the micro-firm level to derive the policy effects of this pilot policy at the firm level, and the model is set up as follows:

$$ln\left(labor_{\mathrm{it}}\right) = \alpha_2 + \theta_2 SCP\times Post_{it} + \lambda_2 Z_{it} + \eta_i + \mu_t + \varepsilon_{it} \quad (2)$$

where $labor_{it}$ denotes the employment of firm i in year t, expressed as the logarithm of the number of employees in the firm; $SCP\times Post_{it}$ is the core explanatory variable, with a value of 1 if the city where firm i is located is included in the pilot list in year t and 0 otherwise; θ_2 is a DID estimator measuring the average treatment effect of SCP on firm employment; Z_{it} is the set of control variables; η_i and μ_t denote individual fixed effects and year fixed effects, respectively; and ε_{it} is a random disturbance term affecting firm employment.

The difference-in-difference model alleviates the endogeneity problem to some extent, but excludes the interaction between individuals, and strictly assumes that individuals are independent of each other. However, from the perspective of new economic geography, there is interaction between individuals, and there will be certain spatial spillover effects on smart city construction as well as high-quality urban economic development. The spatial difference-in-difference model, compared with the traditional difference-in-difference model, relaxes the assumption of individual treatment effect stability and is able to consider the spatial spillover effect of smart city construction (Feng et al., 2021). Therefore, we set up the following spatial difference-in-difference model:

$$\begin{aligned} ln\left(citylabor_{ct}\right) = \alpha_3 + \beta W\times ln\left(citylabor_{ct}\right) + \theta_3 SCP\times Post_{ct} \\ + \lambda_3 X_{ct} + \varphi W\times X_{\mathrm{ct}} + \eta_c + \mu_t + \varepsilon_{ct} \end{aligned} \quad (3)$$

where W denotes the spatial weight matrix; β is the spatial autocorrelation coefficient of the dependent variable; φ is the spillover effect of the control variable; η_c and μ_t denote individual fixed effects and year fixed effects, respectively; and ε_{ct} is the random disturbance term affecting urban employment.

Variables. The explained variable is the employment pressure. The total number of employed labor force is the most intuitive response to employment pressure. A higher number of employed people means a better economic environment and more labor demand, when job seekers face less employment pressure. The total number of employed urban workers is chosen as a proxy variable at the macro level, while the total number of employees of listed companies is chosen as a proxy variable at the micro level.

The explanatory variable is the smart city pilot policy, which is an interaction term between the smart city pilot and the time dummy variable. The dummy variable $SCP\times Post_{ct}$ is set to take the value of 1 if at least one district, county, or town in city c has implemented a pilot policy in year t, and 0 otherwise; the dummy variable $SCP\times Post_{ct}$ is set to take the value of 1 if at least one district, county or town in the city where enterprise i is located has implemented a pilot policy in year t, and 0 otherwise.

Control variables. For the city-level control variables we choose the number of employees in employment, household population, wages of employees in employment, gross regional growth per capita, and total retail sales of consumer goods. For firm-level control variables we chose the number of employees, operating revenue growth rate, cost of sales, gearing ratio, return on net assets, and income tax expense.

Spatial weights. With reference to Feng et al. (2019), we set the spatial proximity matrix ($W1$) and the inverse economic geography matrix ($W2$) in this paper. Among them, the spatial proximity matrix indicates that city i is taken as 1 when it is adjacent to city j, and 0 when it is vice versa. In addition, in order to perform robustness tests on the spatial difference-in-difference model, we also construct the economic geographic weight matrix, which mainly considers the influence of economic factors based on the inverse distance weight matrix, and the specific expressions are shown in Eqs. (4), (5), and (6), where y denotes the per capita GDP during 2003–2019.

$$W_0 = \begin{cases} 0 & i = j \\ \frac{1}{d_{ij}^2} & i \neq j \end{cases} \quad (4)$$

$$\overline{y_i} = \frac{1}{t_1 - t_0}\sum_{t_1}^{t_1} y_{it}, \overline{y} = \frac{1}{n\left(t_1 - t_0 + 1\right)}\sum_{i=1}^{n}\sum_{t_0}^{n} y_{it} \quad (5)$$

$$W_2 = W_0 \times diag\left(\frac{\overline{y_1}}{y}, \frac{\overline{y_2}}{y}, \frac{\overline{y_3}}{y} \ldots \frac{\overline{y_n}}{y}\right) \quad (6)$$

Empirical findings

Baseline results. Table 1 reveals the average treatment effect of China's SCP on employment at the city level and firm level. The regressions take year fixed effects and individual fixed effects into account and further include control variables to increase the robustness of the results. Columns (1) and (2) demonstrate the effect of SCP on urban labor employment, with DID coefficient values of 0.1185 and 0.0743 before and after the inclusion of control variables, respectively, and both pass the significance test at the 1% level, indicating that SCP increases employment in pilot cities by 7.43% compared to non-pilot cities when other factors are fully taken into account. Columns (3) and (4) show the effect of SCP on the employment of labor in enterprises, and the DID coefficient values before and after adding the control variables are 0.1841 and 0.1690, respectively, and both pass the significance test at 1% level, indicating that SCP increases the employment of enterprises in pilot cities by 16.9% compared to non-pilot cities when other factors are fully taken into account. That is, the new jobs created by the SCP policy are greater than the jobs lost, and in general is able to relieve employment pressure.

Parallel trend test. The key premise of the asymptotic difference-in-difference model is to satisfy the parallel trend assumption, which means that the trends of change in the pilot and non-pilot cities should be parallel before the implementation of the SCP. To avoid the subjective observation bias associated with the traditional observation approach of simply comparing employment changes in the treatment and control groups, we used the event study method proposed by Jacobson et al. (1993) to conduct parallel trend tests.

The city-level test model is constructed as follows:

$$ln\left(citylabor_{ct}\right) = \alpha_1 + \sum_{t=2007}^{2018} \delta_t D_{ct} + \lambda_1 X_{ct} + \eta_c + \mu_t + \varepsilon_{ct} \quad (7)$$

where D_{ct} is a set of dummy variables that takes the value of 1 if city c implemented the pilot policy in year t and 0 otherwise; δ_t reflects the employment difference between pilot and non-pilot cities in year t of SCP implementation; the remaining symbols have the same meaning as in Eq. (1).

The firm-level test model is constructed as follows:

$$ln\left(labor_{it}\right) = \alpha_2 + \sum_{t=2007}^{2018} \varphi_t D_{it} + \lambda_2 Z_{it} + \eta_i + \mu_t + \varepsilon_{it} \quad (8)$$

where D_{it} is a set of dummy variables that takes the value of 1 if the city in which the firm i is located implemented the pilot policy in year t and 0 otherwise; φ_t reflects the difference in employment between pilot and non-pilot firms in year t of SCP implementation; the remaining symbols have the same meaning as in Eq. (2).

Plots (a), (b) in Fig. 2 show the results of the parallel trend test at the city and firm level, respectively, and it can be found that the coefficient estimates of both groups are not significant before the policy shock occurs, which indicates that there is no significant difference between the experimental and control groups before the SCP implementation and the parallel trend hypothesis is satisfied.

Placebo test

Hypothetical policy shock. To avoid that the employment differences between the treatment and control groups are caused by time changes, we advance the implementation of SCP by 3, 4, and 5 years to construct dummy policy times, denoted as $SCP \times Post^{-false3}$, $SCP \times Post^{-false4}$, $SCP \times Post^{-false5}$, respectively. If none of the coefficients of the cross-product terms are significant under the dummy policy shock, it can be shown that the robustness of the previous estimation results is verified if there is no SCP and there is no systematic difference in the trend of the explanatory variables changes between the experimental and control groups. Table 2 shows the regression results under the hypothetical policy shock. It can be found that all the coefficients of the interaction terms are insignificant at the 10% level, which indicates the good robustness of the baseline estimation results above.

Randomly selected experimental group. To avoid regression results being influenced by unobservable random variables, referring to Cai et al. (2016), we randomly select 123 cities in the sample to constitute the dummy treatment group and the remaining cities to constitute the dummy control group, and run the baseline regression on them and repeat 500 times. Figure 3 shows the kernel density distribution of the estimated coefficients of the randomly sampled cross-product term, and the vertical line is the value of the true regression coefficient. It can be seen that the coefficient values estimated with random sampling are highly close to zero, which is significantly different from the true regression coefficient values. In addition, the vast majority of the results estimated under random sampling have p-values greater than 0.1, which indicates that the policy effect of SCP in random sampling trials is not significant. Therefore, it is possible to deny that the baseline regression results of this study are driven by unknown factors.

Robustness test

Sample data screening. The sample data were subjected to regressions with reduced tails at the 1% and 5% levels to avoid the effect of extreme values on the baseline regression results, and the results are shown in Table 3. After excluding the extreme data, all regressions were still significant at the 1% level, and this estimate was similar to the baseline regression.

Controlling for sample variation. The regression results of adding benchmark variables to mitigate the effects of selection are shown in Table 4. The ideal situation using the asymptotic difference-in-difference model is that pilot and non-pilot cities are selected randomly. If the list of smart city pilots is related to factors such as the city's level of economic development, historical mission, and geographic location, then differences in these factors may evolve to have different effects on business employment, causing estimation bias. Therefore, a set of dummy variables for city benchmark factors are included in the baseline regressions, including whether the city is a provincial capital, whether it is a special economic zone, and whether it is located east of the Hu line, etc. *Trend* is a time-trend term. The regression results are all significant, which indicates that the pilot policy significantly promotes employment, consistent with the benchmark results, whether by adding the interaction term of city benchmark factors and time trend one by one or all together. The pilot cities are located in different geographic locations with differentiated levels of economic development, and to some extent have selection randomness.

PSM-DID. We used PSM-DID to alleviate the endogeneity problem caused by sample selectivity bias, and the regression results are shown in Table 5. One-to-two nearest neighbor matching with a caliper distance of 0.05 was performed to find a control group for the experimental group that met the identification criteria, and the difference-in-difference regression was performed afterwards. The regression results showed that the coefficient estimates of the cross-product term still passed the significance test at the 1% level, which verified the robustness of the baseline regression results.

Excluding macro-systematic errors. We use the method of controlling for joint fixed effects to exclude macro systematic errors, and the regression results are presented in Table 6. We control for joint province and year-fixed effects in the city-level baseline regression, and joint industry and year-fixed effects in the firm-level benchmark regression. The regression results show that the coefficient estimates of the cross-product term is significant at the one percent level.

Mechanism Test

Configuration optimization and efficiency improvement. Total factor productivity is defined as the increase in output caused by factors such as technological progress and institutions, reflecting the portion of productivity growth caused by other factors such as technological level advancement and organizational management improvement after removing the influence of production factors such as capital and labor. In previous studies, many scholars have

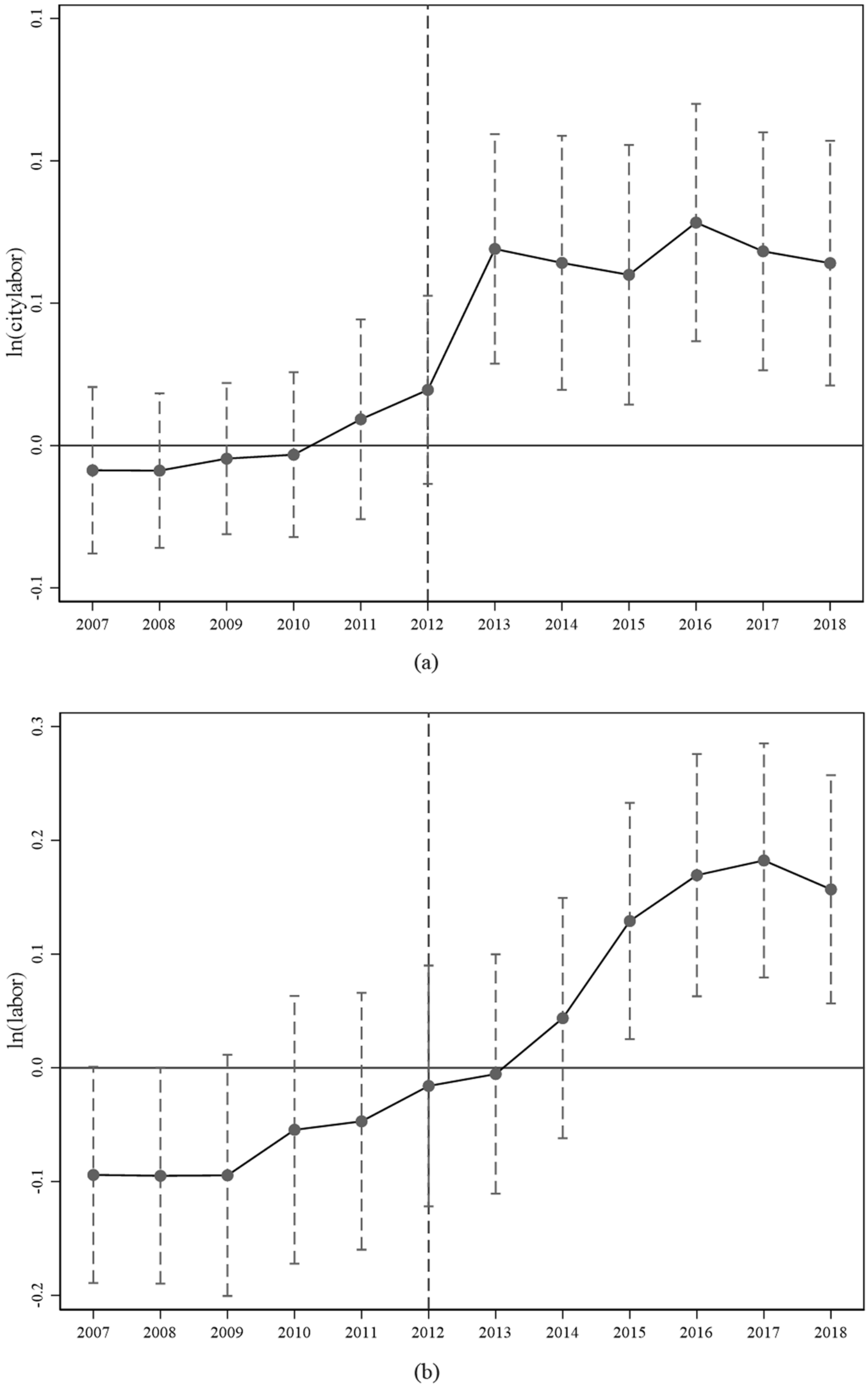

Fig. 2 Parallel trend test. a City-level parallel trend. **b** Firm-level parallel trend.

used total factor productivity to reflect the technological progress and input-output efficiency of firms). We choose the total factor productivity (TFP) of firms as a proxy variable for allocation optimization and efficiency improvement. Total factor productivity was measured using LP and regressed as the dependent variable, and the regression results are shown in Table 7. the results in column (1) indicate that the pilot policy significantly increased the total factor productivity of enterprises. To explore the impact of SCP on different types of firms, the sample is divided into three categories: capital-intensive, labor-intensive, and technology-intensive[1] for group regressions. The regression results in columns (2), (3), and (4) show that SCP does not have a significant impact on the TFP of capital-intensive and labor-intensive firms, but can increase the TFP of technology-intensive firms by 5.02% at the 5% significance level.

Technology Upgrade. Generally speaking, it is always difficult for enterprises to convert their R&D inputs into innovation outputs, and the number of patents can reflect the actual innovation outputs more objectively. Based on this, we use the total number of patents obtained in a year, the total number of patents applied in a year, the total number of inventions obtained in a year, and the total number of inventions applied in a year as proxy variables for technology upgrading. The regression results are shown in Table 8. The regression results all pass the significance test at the 1% level, which shows that SCP can significantly improve the

Table 2 Hypothetical policy impact.

	ln(labor)						ln(labor)					
	Three years in advance		Four years in advance		Five years in advance		Three years in advance		Four years in advance		Five years in advance	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
SCP × Post		0.0149	0.0133	0.0111	0.0136	0.0108	0.0095	0.0052	0.0015	0.0014	−0.0012	−0.0005
		(0.0134)	(0.0100)	(0.0096)	(0.0089)	(0.0086)	(0.0433)	(0.0429)	(0.0323)	(0.0320)	(0.0312)	(0.0309)
Constant		0.7073	3.2604***	0.7105	3.2595***	0.7117	7.3966***	7.3608***	7.3974***	7.3611***	7.3983***	7.3617***
		(0.8147)	(0.0024)	(0.8129)	(0.0027)	(0.8109)	(0.0083)	(0.0151)	(0.0104)	(0.0163)	(0.0135)	(0.0182)
Control variable		Yes		Yes		Yes		Yes		Yes		Yes
Regional fixed effect		Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual fixed effect		Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations		1988	1988	1988	1988	1988	7168	7168	7168	7168	7168	7168
R-squared	0.9848	0.9857	0.9848	0.9857	0.9848	0.9857	0.8986	0.9006	0.8986	0.9006	0.8986	0.9006

*** denotes $p < 0.01$, and robust standard error is shown in brackets.

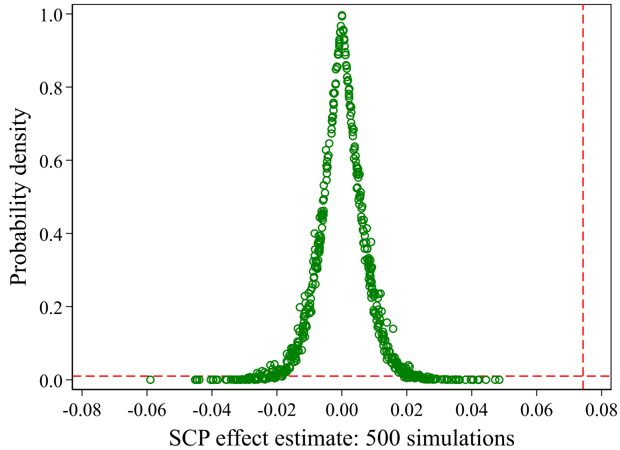

Fig. 3 Randomly selected experimental group.

innovation output of enterprises and promote technological upgrading.

Siphoning effect. We use a spatial econometric model to measure the "siphon effect" of smart city pilot policies. Table 9 shows the spatial difference-in-differencemodel estimation based on model (3). Column (1) is regressed using the spatial neighborhood matrix (W1), and the results show that the direct effect coefficient of the smart city policy is 0.0528, indicating that the number of employment in the pilot cities is significantly higher after the implementation of the smart city policy compared to the non-pilot cities, and the main explanatory variables pass the significance test at the 1% level after the inclusion of control variables. The indirect effect coefficient is −0.0213, which indicates that there is a negative feedback effect of smart city policy on the employment level in the neighborhood. Smart city pilot policies will accelerate the flow of labor from non-pilot cities to the pilot, intensifying the siphoning effect of pilot cities on non-cities, and promoting the growth of employment levels in pilot cities while also exacerbating the employment woes of other non-pilot cities.

To verify the robustness of the empirical results, we re-run the regression using the economic distance matrix (W2), and the results are shown in column (2) of Table 2, with a direct effect coefficient of 0.0757, an indirect effect coefficient of −0.0290, and a total effect of 0.0467, and all effects are significant at the 1% level of significance, indicating that the above empirical results are robust.

Element substitution. The regression results are presented in Table 10. The cross term of the DID term with the average wage of the firm is introduced to indirectly identify the substitution effect of digital transformation on the labor force. The coefficient of the cross term is negative and passes the significance test at the 1% level, which indicates that the higher the average wage level of the firm, the greater the proportion of digitally substituted labor.

The regression results are insignificant using the ratio of firms' purchased fixed assets and intangible assets to total assets as a proxy variable for factor substitution. We grouped the samples to further explore the factor substitution effects of capital-intensive, labor-intensive, and technology-intensive firms. The regression results show that the factor substitution effect of technology-intensive firms passes the significance test at the 1% level. That is, SCP produces a significant factor substitution effect on technology-intensive firms.

Table 3 Sample data screening.

	ln(city_labor)				ln(labor)			
	1%		5%		1%		5%	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
SCP × Post	0.1104***	0.0585***	0.0866***	0.0671***	0.1780***	0.1306***	0.1460***	0.1120***
	(0.0105)	(0.0080)	(0.0095)	(0.0070)	(0.0174)	(0.0166)	(0.0151)	(0.0135)
Constant	3.3878***	−.3384***	3.3807***	−5.1781***	7.5528***	7.0652***	7.5730***	6.9474***
	(0.0031)	(0.5358)	(0.0029)	(0.6444)	(0.0089)	(0.0217)	(0.0077)	(0.0169)
Control variable		Yes		Yes		Yes		Yes
Regional fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4828	4828	4828	4828	28707	28707	28707	28707
R-squared	0.9570	0.9813	0.9562	0.9782	0.8232	0.8399	0.8266	0.8607

*** denotes $p < 0.01$, and robust standard error is shown in brackets.

Table 4 Control sample variance.

	ln(city_labor)				ln(labor)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
SCP × Post	0.0734***	0.0692***	0.0759***	0.0689***	0.1535***	0.1600***	0.1697***	0.1394***
	(0.0123)	(0.0125)	(0.0124)	(0.0120)	(0.0183)	(0.0180)	(0.0180)	(0.0184)
Hu Line × Trend	0.0015			0.0027*	0.0163***			0.0180***
	(0.0017)			(0.0016)	(0.0049)			(0.0049)
PC × Trend		0.0074***		0.0078***		0.0100***		0.0132***
		(0.0019)		(0.0019)		(0.0022)		(0.0022)
SEZ × Trend			0.0094	0.0094			0.0155***	0.0148***
			(0.0079)	(0.0080)			(0.0039)	(0.0023)
Constant	−5.1365***	−5.0756***	−4.9828***	−4.8942***	7.5507***	7.5224***	7.5096***	7.3365***
	(0.9014)	(0.8951)	(0.9027)	(0.9001)	(0.0092)	(0.0097)	(0.0100)	(0.0360)
Control variable	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Regional fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4828	4828	4828	4828	28707	28707	28707	28707
R-squared	0.9735	0.9737	0.9736	0.9738	0.8246	0.8247	0.8247	0.8252

* and *** denote $p < 0.10$ & 0.01, and robust standard error is shown in brackets.

Table 5 PSM-DID regression.

	ln(city_labor)		*ln(labor)*	
	(1)	**(2)**	**(3)**	**(4)**
SCP × Post	0.1156*** (0.0106)	0.0402*** (0.0080)	0.1784*** (0.0182)	0.1506*** (0.0176)
Constant	3.3949*** (0.0031)	−7.2569*** (0.4958)	7.5029*** (0.0092)	7.3997*** (0.0105)
Control variable		Yes		Yes
Year fixed effect	Yes	Yes	Yes	Yes
Individual fixed effect	Yes	Yes	Yes	Yes
Observations	4804	4804	28284	28284
R-squared	0.9577	0.9843	0.8035	0.8162

*** denotes $p < 0.01$, and robust standard error is shown in brackets.

Table 6 Joint fixed effect.

	ln(city_labor)		*ln(labor)*	
	(1)	**(2)**	**(3)**	**(4)**
SCP × Post	0.1156*** (0.0106)	0.0402*** (0.0080)	0.1784*** (0.0182)	0.1506*** (0.0176)
Constant	3.3949*** (0.0031)	−7.2569*** (0.4958)	7.5029*** (0.0092)	7.3997*** (0.0105)
Control variable		Yes		Yes
Provincial × Year fixed effect	Yes	Yes		
Industry × Year fixed effect			Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes
Individual fixed effect	Yes	Yes	Yes	Yes
Observations	4804	4804	28284	28284
R-squared	0.9577	0.9843	0.8035	0.8162

*** denotes $p < 0.01$, and robust standard error is shown in brackets.

Table 7 Configuration optimization and efficiency improvement.

	(1)	**(2)**	**(3)**	**(4)**
SCP × Post	0.0340** (0.0145)	−0.0003 (0.0272)	0.0137 (0.0247)	0.0502** (0.0232)
Constant	8.6040*** (0.0212)	8.7897*** (0.0398)	8.6824*** (0.0421)	8.3995*** (0.0278)
Control variable	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes
Individual fixed effect	Yes	Yes	Yes	Yes
Observations	24046	5041	9350	9655
R-squared	0.8612	0.8751	0.8502	0.8679

Column (1) shows the regression results of the full sample, and columns (2), (3), and (4) respectively show the regression results of the samples of capital-intensive, labor-intensive, and technology-intensive enterprises. ** and *** denote $p < 0.05$ and 0.01, and robust standard error is shown in brackets.

Table 8 Technology upgrade.

	(1)	**(2)**	**(3)**	**(4)**
SCP × Post	4.3438*** (1.3521)	6.9002*** (1.9440)	2.3536*** (0.6886)	4.6585*** (1.2617)
Constant	1.6388 (2.3810)	0.6871 (4.2123)	−2.6974** (1.3461)	−3.2470 (2.6867)
Control variable	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes
Individual fixed effect	Yes	Yes	Yes	Yes
Observations	28707	28707	28707	28707
R-squared	0.7179	0.6655	0.6905	0.6545

Column (1) shows the regression results of patents obtained in the current year, column (2) shows the regression results of patents applied in the current year, column (3) shows the regression results of inventions obtained in the current year, and column (4) shows the regression results of inventions applied in the current year. ** and *** denote $p < 0.10$ and 0.01, and robust standard error is shown in brackets.

Industrial structure transformation. The regression results are shown in Table 11. First, we use the proportion of value added of the tertiary industry, the index of rationalization of industrial structure, and the index of advanced industrial structure as proxy variables for industrial structure transformation, and the regression results in columns (1)-(3) in Table 11 are not statistically significant, so they cannot indicate that SCP has increased the proportion of the tertiary industry. Digital industrialization and industrial digitization are the manifestation of the deep integration of digital economy and real economy, and have an important impact on the upgrading of industrial structure. The digital economy brings about changes in the proportional relationship between industries and the improvement of labor productivity, which in turn increases the proportion of output value of industries with high labor productivity and brings about the transformation of industrial structure. Next, we introduced the proportion of employees in information transmission computer services and software industry to the proportion of employees in the tertiary industry to measure the level of industrial digitization, and the *Digital Financial Inclusion Index* compiled by the Internet Finance Research Center of Peking University to measure the level of digital industrializationin which the Digital Inclusive Finance Index measures the degree of digital financial inclusion in each region of China in three aspects: breadth of financial coverage, depth of use, and degree of digitization, which to some extent characterizes the level of industrial digitization. The regression results in columns (4) and (5) are both significant at the 1% level,which indicates that SCP can promote the digitization of industries and digital industrialization in the pilot areas, and thus achieve industrial structure transformation.

Table 9 Siphoning effect.

	SAC-W1 (1)	*SAC-W2* (2)
Direct effects	0.0528***	0.0757***
Indirect effects	−0.0213***	−0.0290***
Total effect	0.0314***	0.0467***
Control variable	Yes	Yes
Year fixed effect	Yes	Yes
Individual fixed effect	Yes	Yes
Spa-rho	−0.5957***	−0.6292
$Sigma_2$	0.0140	0.0194
Observations	4828	4828
R-squared	0.5251	0.5668

*** denotes $p < 0.01$, and robust standard error is shown in brackets.

Regional Innovation. In general, compared with small cities, large cities tend to have the advantage of concentration of innovation factors and resources, and their industrial base, financialization level, and transportation level are also higher. These differences may lead to heterogeneity in the innovation effects of smart cities.We used the city-level innovation index from *China City and Industry Innovation Power Report* as a proxy variable for regional innovation, and the regression results are shown in Table 12. The regression results passed the significance test at the 1% level. Then, we divided the sample into large cities and medium and small cities and ran the regressions separately, and the results showed that the SCP had a stronger effect on improving the regional innovation level in large cities than in medium and small cities.

Heterogeneity test

City Heterogeneity

City Scale Heterogeneity. We use the classification caliber in the *Seventh Census Sub-county Data*, classifying mega-cities,

Table 10 Factor substitution.

	ln_labor (1)	*factor_sub* (2)	*factor_sub_C* (3)	*factor_sub_L* (4)	*factor_sub_T* (5)
SCP × Post × average wage	−0.0026*** (0.0009)				
SCP × Post	0.2047*** (0.0210)	−3.1212 (2.1511)	0.5592 (1.6807)	−0.0163 (0.0296)	0.0662* (0.0378)
Constant	7.5221*** (0.0097)	0.5762 (1.6815)	−40.8223*** (8.9545)	0.2787*** (0.0174)	0.3873*** (0.0475)
Control variable	Yes	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes	Yes
Individual fixed effect	Yes	Yes	Yes	Yes	Yes
Observations	28707	28707	6505	10963	11239
R-squared	0.8247	0.1588	0.8963	0.9162	0.1763

Column (1) shows the regression results of enterprise labor, column (2) shows the regression results of factor replacement, and columns (3), (4), and (5) show the regression results of factor replacement of capital-intensive enterprises, labor-intensive enterprises, and technology-intensive enterprises respectively. Standard errors clustered at the city level occur in parentheses. * and *** denote $p < 0.10$ and 0.01, and robust standard error is shown in brackets.

Table 11 Industrial structure transformation.

	(1)	(2)	(3)	(4)	(5)
SCP × Post	0.0278 (0.1936)	−0.0018 (0.0052)	0.0000 (0.0024)	0.0812*** (0.0171)	0.1146*** (0.0324)
Constant	73.8468*** (13.3644)	1.6681*** (0.2038)	1.6798*** (0.1411)	−5.5443*** (0.6702)	4.6567*** (0.7930)
Control variable	Yes	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes	Yes
Individual fixed effect	Yes	Yes	Yes	Yes	Yes
Observations	4828	4828	4828	4828	2556
R-squared	0.8777	0.8154	0.9165	0.6310	0.8969

Column (1) shows the regression results of the proportion of value-added of tertiary industry, column (2) shows the regression results of industrial structure rationalization, column (3) shows the regression results of industrial structure upgrading, column (4) shows the regression results of industrial digitalization, and column (5) shows the regression results of digital industrialization. *** denotes $p < 0.01$, and robust standard error is shown in brackets.

Table 12 Regional innovation.

	(1)	(2)	(3)
SCP × Post	0.2354*** (0.0236)	0.2886*** (0.0331)	0.2083*** (0.0338)
Constant	−10.9208*** (1.4744)	−12.5799*** (2.9693)	−10.7647*** (1.2453)
Control variable	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes
Individual fixed effect	Yes	Yes	Yes
Observations	4828	1717	3111
R-squared	0.9630	0.9733	0.9293

Column (1) shows the regression results of the full sample, column (2) shows the regression results of the samples of large cities, and column (3) shows the regression results of the samples of small and medium-sized cities. *** denotes $p<0.01$, and robust standard error is shown in brackets.

Table 13 Urban heterogeneity.

	City scale		Urban location		
	Large	Medium&Small	Eastern	Central	Western
SCP × Post	0.0797*** (0.0218)	0.0324*** (0.0114)	0.1164*** (0.0333)	0.0250** (0.0101)	0.1826*** (0.0324)
Constant	−4.8937** (1.9066)	−4.8987*** (0.8393)	−4.7041** (1.9383)	−8.6849*** (0.4017)	−0.9997 (1.1687)
Control variable	Yes	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes	Yes
Individual fixed effect	Yes	Yes	Yes	Yes	Yes
Observations	1717	3111	1700	2091	1037
R-squared	0.9606	0.9494	0.9700	0.9743	0.9747

	Human capital		Government intervention		Digital infrastructure	
	High	Low	High	Low	High	Low
SCP × Post	0.0537*** (0.0128)	0.0672*** (0.0123)	0.0363** (0.0141)	0.0785*** (0.0167)	0.1021*** (0.0290)	0.0595*** (0.0127)
Constant	−6.5753*** (0.8857)	−4.9340*** (0.7744)	−4.9588*** (1.0203)	−5.1862*** (1.0801)	−4.5548*** (1.5776)	−5.8589*** (0.9161)
Control variable	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Individual fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1580	3210	1590	3213	1613	3211
R-squared	0.9886	0.9716	0.9774	0.9759	0.9737	0.9751

** and *** denote $p<0.05$ and 0.01, and robust standard error is shown in brackets.

megacities, type I megacities, and type II megacities as large cities; and other cities as medium and small cities[2], and the regression results are shown in Table 13. The regression results show that SCP has a better and significantly stronger effect on employment in large cities than in medium and small cities.

City Location Heterogeneity. Chinese cities generally differ significantly in terms of their geographical location. Specifically, most cities in the western region are less economically developed than those in the central and eastern regions, making it easier for labor and other resource factors to move to a city with good infrastructure and economic development. To examine the policy effects of the pilot SCP on cities in different zones, we divided the sample into three groups: eastern cities, central cities, and western cities, and the regression results are shown in Table 13. The results show that the SCP has the highest employment stress relief effect in the western region, followed by the eastern region, and the weakest relief effect in the central region.

Human capital heterogeneity in cities. To examine the heterogeneous effects of SCP on employment in cities with different levels of human capital, we use the one-third quantile of the number of college students per 10,000 in the city and divide the cities into two groups with high and low education levels, and the regression results are shown in Table 13. The results show that the pilot policy has a stronger effect on promoting employment and alleviating employment pressure in cities with low education levels.

Heterogeneity of city government intervention. To explore the heterogeneity of SCP policy effects in cities with different levels of government intervention, we use the ratio of general public budget expenditure to regional GDP as a proxy variable for government intervention and use one-third quantile to divide the sample into two groups of high and low government intervention, and the regression results are shown in Table 13. The regression results indicate that SCP is more effective in promoting employment in cities with low government intervention.The possible reason is that local governments, motivated by the pursuit of GDP growth, tend to depress the price of land and capital, which increases the relative price of labor, thus leading to an increase in the substitution of capital for labor. At the same time, there is a distortion in the fiscal expenditure structure of local governments that "emphasizes capital construction at the

Table 14 Firm heterogeneity.

	Enterprise age		Enterprise ownership		
	New	Old	State-owned	Private	Foreign-funded
SCP × Post	0.0633** (0.0275)	0.1890*** (0.0211)	0.1426*** (0.0226)	0.1745*** (0.0287)	0.3953*** (0.0998)
Constant	7.1570*** (0.0546)	7.6112*** (0.0100)	7.8410*** (0.0129)	7.1835*** (0.0173)	7.3520*** (0.0524)
Control variable	Yes	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes	Yes
Individual fixed effect	Yes	Yes	Yes	Yes	Yes
Observations	9199	19508	15002	13187	1642
R-squared	0.9057	0.8008	0.8514	0.8283	0.8852

	Industry			Factor density		
	Primary	Secondary	Tertiary	capital-intensive	labor-intensive	technology-intensive
SCP × Post	0.5945*** (0.0891)	0.1535*** (0.0196)	0.1532*** (0.0429)	0.1502*** (0.0353)	0.1455*** (0.0312)	0.1665*** (0.0265)
Constant	6.5643*** (0.1289)	7.6578*** (0.0106)	7.2423*** (0.0244)	7.7897*** (0.0158)	7.4045*** (0.0176)	7.4734*** (0.0208)
Control variable	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Individual fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Observations	323	19124	9260	6505	10963	11239
R-squared	0.9345	0.8281	0.8155	0.8374	0.8176	0.8342

** and *** denote p <0.05 and 0.01, and robust standard error is shown in brackets.

Table 15 Heterogeneity of labor education level.

	(1)	(2)	(3)
SCP × Post	49.5359* (25.5589)	408.4945*** (109.5393)	−48.2773 (100.8629)
Constant	66.7343* (34.8273)	2041.2310*** (202.4685)	3174.1030*** (110.0677)
Control variable	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes
Individual fixed effect	Yes	Yes	Yes
Observations	10900	23630	23504
R-squared	0.8713	0.9145	0.9071

Column (1) shows the regression results of high-skilled workers, column (2) shows the regression results of medium-skilled workers, and Table (3) shows the regression results of low-skilled workers. * and *** denote p < 0.10 and 0.01, and robust standard error is shown in brackets.

expense of human capital investment and public services", and this distortion will reduce the employment absorption capacity of economic growth.

City Digital Infrastructure Heterogeneity. To explore the heterogeneous effects of SCP on employment in cities with different levels of digital infrastructure, we use the ratio of Internet broadband subscribers to the total population as a proxy variable for urban digital infrastructure and use one-third quantile to classify cities into two groups: high digital infrastructure and low digital infrastructure, and the regression results are shown in Table 13. The results show that the SCP of cities with high digital infrastructure has a stronger contribution to employment. The possible reason is that digital infrastructure, as an important part of the new infrastructure, can create a large number of flexible jobs by spawning related information industries. At the same time, digital infrastructure can take advantage of knowledge sharing on technology platforms to alleviate information asymmetry in the labor market, improve the probability of human-job matching, and enhance labor force employment through multiple channels.

Corporate heterogeneity

Corporate age heterogeneity. To explore the heterogeneity of SCP policy effects among firms of different ages, we used the median age of firms to divide them into two groups: new and old firms, and the regression results are presented in Table 14. The regression results indicate that SCP does not significantly promote employment in new firms, but significantly promotes higher employment levels in old firms.

Corporate ownership heterogeneity. To explore the heterogeneity of SCP policy effects across ownership, we divided the sample into three groups: state-owned enterprises, private enterprises, and foreign enterprises, and the regression results are shown in Table 14. The regression results indicate that the pilot policy has the strongest promotion effect on employment in foreign enterprises, followed by private enterprises, and the weakest promotion effect on state-owned enterprises. Compared to state-owned enterprises, foreign and private enterprises are more flexible and better at using digital technology to improve survival rates and thus social employment levels.

Industry heterogeneity. To explore the heterogeneity of SCP policy effects in different industries, we divided the sample into three groups: primary, secondary, and tertiary industries and the regression results are shown in Table 14. The regression results indicate that the pilot policy has the strongest promotion effect on employment in tertiary industry firms, followed by secondary industry firms, and the weakest promotion effect on employment in primary industry. The penetration of the social economy into agriculture and industry will change the original production characteristics, and the phenomenon of labor replacement is more common in the primary and secondary industries. In the tertiary industry, the digital economy gives rise to a large number of new productive services and high-end services, and the emergence of new industries brings a large number of new jobs.

Table 16 SCP promotes digital transformation of enterprises.

	(1)	(2)	(3)	(4)
SCP × Post	2.9510*** (0.3709)	1.6889*** (0.2634)	2.2137*** (0.4972)	2.2153** (0.9201)
Constant	6.0060*** (0.2075)	1.1653*** (0.2053)	4.6400*** (0.2487)	10.7699*** (0.5727)
Control variable	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes
Individual fixed effect	Yes	Yes	Yes	Yes
Observations	28678	6498	10952	11228
R-squared	0.6400	0.6082	0.6634	0.6379

Column (1) shows the regression results of the full sample, and columns (2), (3), and (4) respectively show the regression results of the samples of capital-intensive, labor-intensive, and technology-intensive enterprises. ** and *** denote $p<0.05$ and 0.01, and robust standard error is shown in brackets.

Table 17 Workers benefit from digitization.

	(1)	(2)	(3)	(4)
SCP × Post	−0.1364*** (0.0118)	−0.1288*** (0.0252)	−0.2008*** (0.0205)	−0.0680*** (0.0158)
Constant	2.2332*** (0.0061)	2.2717*** (0.0107)	2.2356*** (0.0103)	2.1876*** (0.0103)
Control variable	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes
Individual fixed effect	Yes	Yes	Yes	Yes
Observations	28707	6505	10963	11239
R-squared	0.7475	0.7577	0.7243	0.7795

Column (1) shows the regression results of the full sample, and columns (2), (3), and (4) respectively show the regression results of the samples of capital-intensive, labor-intensive, and technology-intensive enterprises. *** denotes $p<0.01$, and robust standard error is shown in brackets.

Heterogeneity of elemental intensity. To explore the heterogeneity of SCP policy effects across factor-intensive firms, we divided the sample into three groups: capital-intensive, labor-intensive, and technology-intensive, and the regression results are shown in Table 14. The regression results indicate that the pilot policy has the strongest employment promotion effect on technology-intensive firms, followed by labor-intensive firms, and the weakest employment promotion effect on capital-intensive firms.

Heterogeneity of labor's education level. To explore the heterogeneity of SCP policy effects under different workers' education levels, we classify the workers with a bachelor's degree or higher in enterprises as a highly educated labor force and those with less than a bachelor's degree as low-educated labor force, and the regression results are shown in Table 15. The regression results indicate that the pilot policy has a significant employment promotion effect on the highly educated labor force, but not on the low-educated labor force.

Further analysis

Has the pilot policy driving the digital transformation of enterprises. We use data from the CSMAR database, which uses textual analysis of keywords in firms' annual reports by crawlers, to construct an index of firms' digital transformation and put it into a benchmark regression as an explanatory variable. The regression results are shown in Table 16. The regression results show that the pilot policy significantly drives the digital transformation of enterprises, with the strongest digital push for technology-intensive enterprises, followed by labor-intensive enterprises, and the weakest push for capital-intensive enterprises.

whether workers benefit from digitization. To determine whether workers benefit from SCP, we examine the impact of the pilot policy on average employee pay, and the regression results are presented in Table 17. The regression results indicate that digital transformation significantly reduces employee wages, with labor-intensive firms experiencing the largest reduction in wages, followed by capital-intensive firms, and technology-intensive firms being the least affected.

Conclusion

This paper explores the impact of China's smart city pilot policy on employment pressure and its mechanisms. We empirically test the panel data from 2003–2019 using a multi-period DID. The results show that the three batches of smart city pilots established from 2012–2014 significantly increased employment in pilot cities, resulting in a 7.43% increase in employment in pilot cities compared to non-pilot cities, alleviating the employment pressure of the pilot cities, and a 16.9% increase in employment in listed companies in pilot cities compared to non-pilot cities. Parallel trend tests showed no significant differences between the experimental and control groups before the pilots began, ruling out systematic differences, and placebo tests confirmed that the results were not coincidental, while a series of robustness tests were also passed.

We also test the theoretical mechanism of SCP's impact on employment pressure. We find that SCP leads to allocation optimization and technology upgrading, influences firm selection at the micro level, generates siphoning effects, factor substitution effects, and efficiency gains, and further influences the macro economy, promoting urban economic agglomeration, industrial structure transformation, and regional innovation.

Next, we discuss heterogeneity. We find that SCP has stronger boosting effects on employment in large cities, cities in the western region, cities with low education levels, cities with low government intervention, and cities with high digital infrastructure; SCP has stronger boosting effects on employment in old firms, foreign and private firms, tertiary firms, and technology-intensive firms; and SCP has significant boosting effects on employment in highly educated labor. Finally, in further analysis, we find that SCP drives the digital transformation of enterprises, with the strongest boosting effect on technology-intensive enterprises in particular; SCP reduces the wages of enterprise employees, and labor-intensive enterprises are most affected.

To better play the role of smart city construction in alleviating employment pressure, the following aspects should be optimized: first, strengthen policy promotion in small and medium-sized cities and cities in the central region and monitor policy implementation to enhance policy effects; second, appropriately reduce administrative approval processes, broaden financing channels, and appropriately decentralize power to minimize the negative effects of excessive government intervention on policy effects; third, strengthen workforce skills training, optimize the workforce structure, and cultivate high-quality workers to adapt to the digital economy; finally, pay attention to the livelihood issues brought by digital transformation, introduce policies to relieve the unemployed, and reasonably compensate workers whose interests have been damaged.

Data availability

The datasets generated during and/or analyzed during the current study are not publicly available because they are subject to third-party restrictions.

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Notes

1 Technology-intensive industries: electrical machinery and equipment manufacturing, comprehensive utilization of waste resources, computer, communications and other electronic equipment manufacturing, metal products, other manufacturing, automotive manufacturing, software and information technology services, ecological protection and environmental management, railroad, ship, aerospace and other transport equipment manufacturing, rubber and plastic products industry, pharmaceutical manufacturing, instrumentation manufacturing Professional and technical services, special equipment manufacturing; labor-intensive industries: catering, warehousing, animal husbandry, road transportation, telecommunications, radio and television and satellite transmission services, real estate, housing construction, textiles, clothing, apparel, textiles, non-metallic mining, public facilities management, ferrous metal mining, Internet and related services, motor vehicles, electronic products and daily use products repair industry, furniture manufacturing, construction and installation industry, building decoration and other construction industry, education, wine, beverage and refined tea manufacturing, science and technology promotion and application services, forestry, retail trade, coal mining and washing industry, wood processing and wood, bamboo, rattan, palm and grass products industry, agriculture, forestry, animal husbandry and fishery services, agricultural and food processing industry, agriculture, wholesale trade, leather, fur, feathers and their products and footwear industry, the business services, food manufacturing, water production and supply, railroad transportation, general equipment manufacturing, civil engineering and construction, culture and art, education, industry, sports and recreational goods manufacturing, news and publishing, research and experimental development, printing and recording media reproduction, postal services, non-ferrous metal mining and quarrying, non-ferrous metal smelting and rolling processing industry, accommodation, handling and transportation Agency, integrated; capital-intensive industries: insurance, electricity, heat production and supply, non-metallic mineral products, radio, television, film and video recording production, air transport, ferrous metal smelting and rolling processing industry, chemical fiber manufacturing, chemical raw materials and chemical products manufacturing, monetary and financial services, mining auxiliary activities, other financial industries, gas production and supply, oil and Natural gas extraction, petroleum processing, coking and nuclear fuel processing industry, water transportation, sports, health, fisheries, paper and paper products, capital market services, leasing industry.

2 Cities with 10 million or more urban residents are considered megacities, cities with 5 million to 10 million are considered large cities, cities with 3 million to 5 million are considered Type I large cities, and cities with 1 million to 3 million are considered Type II large cities.

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