Employee allocation efficiency in the context of the digital economy: Evidence from "Broadband China" demonstration cities

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This study focuses on the "Broadband China" policy and its impact on employee allocation efficiency, specifically examining the influence of digital economy development on the optimization of human resource structures in enterprises. Using data from Chinese listed companies between 2011 and 2019, combined with city-level statistics from the China City Statistical Yearbooks, we employ rigorous econometric methods such as Difference-in-Differences (DID) and multi-period multi-entity DID to empirically analyze the effects of the "Broadband China" demonstration city creation policy on employee allocation efficiency. The results of our study reveal that the demonstration cities significantly contribute to reducing redundant staff and improving employee allocation efficiency in enterprises. The mechanism lies in the demonstration city pilot program stimulating entrepreneurial activity and promoting digital transformation in enterprises. Further research has revealed that the effectiveness of the demonstration city policy varies based on the location and wage level within cities, as well as the ownership nature and growth stage of enterprises. Additionally, the enhanced employee allocation efficiency resulting from the demonstration cities leads to favorable economic consequences in terms of total factor productivity for enterprises. In conclusion, this study provides valuable insights into the impact of the digital economy policy on optimizing human resource structures in enterprises. It highlights the significance of promoting digital transformation within enterprises to achieve efficient talent allocation and improve production efficiency.
Keywords: Digital economy, Employee allocation efficiency, Multi-time point DID, Broadband China

I. Introduction

China is presently undergoing a crucial period of transition aimed at achieving high-quality economic development, with a deep focus on integrating the digital economy with the real economy. Facilitating high-quality economic development has emerged as a signif-

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icant objective for governments at all levels in China. The digital economy, characterized by the advancement and utilization of digital technologies, encompasses various sectors such as information technology, big data, and the internet. It is recognized as a pivotal catalyst in China's transition from traditional to modern economic drivers. According to data from the China Academy of Information and Communications Technology (CAICT), the scale of China's digital economy in 2021 reached 7.1 trillion USD, accounting for 39.8% of GDP and playing a significant role in supporting the country's economic development. The rapid growth of China's digital economy can be attributed, in part, to the implementation of the "Broadband China" strategy and the establishment of demonstration cities by the government. This policy aims to enhance the independent innovation capabilities of the information industry, improve the coverage and application level of information network infrastructure, and enhance the consumption level of information services. As of 2021, China has made remarkable strides in network infrastructure development through the implementation of the "Broadband China" policy. The country has reached 498 million households with fixed broadband users and a mobile phone user base of 1.643 billion households. Notably, the number of 4G and 5G users has reached 1.069 billion and 355 million, respectively. [1] The extensive deployment of network infrastructure has injected robust vitality into the growth of China's digital economy while also fostering increased employment opportunities (Atasoy, 2013), thereby showcasing the positive impact of the digital economy on the real economy. Strengthening the influence of the digital economy on optimizing the talent structure of enterprises has emerged as a crucial consideration in achieving deep integration between the digital and real economy.

China's digital economy development has played a significant role in driving labor employment. According to research data from the CAICT, the digital economy sector in China generated 191 million job positions in 2018, accounting for 24.6% of total employment that year. The digital economy has become an important tool for ensuring employment stability. Consequently, the demonstration city policy, as a crucial initiative to promote digital economy development, has not only stimulated employment growth but also provided enterprises with improved network infrastructure, facilitating the optimization of internal human resources management strategies. According to data from iResearch Consulting Group, in 2021, flexible employment accounted for 51.8% of total enterprise scale in China, a significant increase compared to 29.3% in 2020. This rise can be attributed to the application of digital platforms, enabling enterprises to maintain organizational flexibility through flexible human resource arrangements. This study aims to comprehensively analyze how the demonstration city policy promotes the reduction of redundant employees in enterprises and enhances employee allocation efficiency, thereby investigating the impact of digital economy development on optimizing human resources management. To achieve this, we will utilize the demonstration city policy as a quasi-natural experiment.

Existing studies have extensively investigated the impact of the digital economy on both macro-level employment structure and micro-level labor employment quality. At the macro level, the digital economy has a significant influence on employment structure by facilitat-

[1] Data Source: 2021 China Communications Industry Statistics Bulletin

ing industrial restructuring. Wu and Yang (2022) find that the digital economy drives the transition of labor from the secondary to the tertiary sector. Dauth et al. (2017) analyze German manufacturing data and reveal a negative effect of the digital economy on the manufacturing sector. They report that approximately 275,000 manufacturing jobs in Germany were replaced by robots between 1994 and 2014, but overall employment levels remained largely unaffected. Parschau and Hauge (2020) show that the adoption of automation technologies in the South African garment industry did not lead to substantial job losses but instead resulted in increased productivity and employment growth. Moreover, Koch, Manuylov and Smolka (2021) find that Spanish manufacturing firms utilizing robots have experienced an annual job growth rate of 10%. This positive effect is attributed to the substantial output growth resulting from robot technology, which outweighs the reduction in labor costs. These studies collectively highlight the favorable role of digital technologies in promoting industrial restructuring and enhancing productivity, contributing to a comprehensive understanding of the impact of the digital economy on the labor market.

At the micro level, the influence of the digital economy on labor employment quality primarily manifests in terms of job matching. Gürtzgen et al. (2021) demonstrate that online recruitment accelerates the search process and enhances matching efficiency between employers and workers. Additionally, Mang (2012) using data from the German Socio-Economic Panel (SOEP), finds that online job seekers have better opportunities to leverage their skills, leading to significantly increased chances of promotion and job satisfaction. More research is needed to investigate the impact of digital technologies on existing employee matching, as previous studies have mainly focused on the influence of the digital economy on job matching quality.

Our research contributes to the existing literature in several significant ways. Firstly, we deviate from previous studies that primarily examine the alignment between the digital economy and prospective employees. Instead, our study focuses on the impact of the digital economy on the efficiency of human resource allocation within established enterprises. This perspective offers insights into how enterprises can optimize their human resource management and enhance internal operational efficiency. Secondly, We conducted an in-depth analysis of the impact of demonstration city policies on the efficiency of enterprise employee allocation, revealing the macro and micro internal mechanisms between the development of the digital economy and the improvement of enterprise employee allocation efficiency. Thirdly, our empirical findings are robust and hold important implications for policymakers. The research underscores the role of digital economic development in optimizing the existing talent structure within enterprises. This suggests that enterprises should proactively embrace digital economic trends to enhance their management efficiency. Additionally, government authorities should tailor their policies to specifically target eastern cities, cities with higher wage levels, non-state-owned enterprises, and non-emerging enterprises, in order to fully leverage the positive effects of the policy.

The subsequent sections of our study are structured as follows: Section II provides an overview of the policy context surrounding the demonstration city strategy and presents our research hypotheses. Section III outlines our research design. Section IV presents the empirical results pertaining to the impact of the demonstration city policy on employee allocation efficiency within enterprises. Section V conducts a mechanism analysis. Section VI offers an exploratory analysis. Finally, Section VII presents our research conclusions and discussion.

II. Policy Background and Research Hypotheses

A. Policy Background

To address issues related to slow internet speed and inadequate coverage, the Chinese government introduced the "Broadband China" strategy and implementation plan in 2013. This policy aimed to promote the development of network infrastructure and was implemented in multiple phases. The initial phase of the policy was initiated in 2014 and involved the selection of 39 cities (or city clusters) as demonstration areas for the demonstration city initiative. The second and third phases of the policy were introduced in 2015 and 2016, respectively. The policy was designed to be implemented over a three-year period.

The demonstration city policy can indeed be considered representative of China's digital economic development. From the perspective of the digital economy's essence, which revolves around utilizing knowledge, information, and information and communication technologies to enhance efficiency and optimize economic structures, the policy aligns with these objectives. Its primary focus is on improving broadband infrastructure, harnessing network infrastructure externalities, and fostering the development of the digital economy. The policy outlines specific measures to achieve its objectives. Firstly, it aims to expand and deepen the application of broadband in production and operations, facilitating enterprise broadband connectivity, and promoting network-based process reengineering and business innovation. By leveraging information technology to transform and enhance traditional industries, the policy seeks to achieve networked, intelligent, intensive, and environmentally friendly development, thereby promoting industry optimization and upgrading (i.e., industrial digitization). Secondly, the policy emphasizes the cultivation of innovative broadband application models, the fostering of new markets and business forms, and the promotion of new-generation information technology industries such as cloud computing, the Internet of Things (IoT), mobile internet, and smart terminals (i.e., digital industrialization). Considering these factors, it is evident that the demonstration city policy serves as a significant driving force behind China's digital economic development.

B. Research Hypotheses

Digital technology advancements enable businesses to enhance internal organizational flexibility and reduce redundancies, thereby improving employee allocation efficiency. Automation and AI technologies boost productivity, reduce labor costs, and replace routine and low-skilled tasks (Brynjolfsson and McAfee, 2014). This necessitates businesses to optimize their talent structures by focusing on innovative capabilities and high-level skills while eliminating excess labor. Digital platforms provide remote workspaces and flexible employment arrangements, allowing businesses to adjust workforce size and working hours based on market fluctuations (Bloom et al., 2015; Autor, 2015). Digital technology also facilitates faster matching with outsourcing partners, enabling businesses to transfer non-core functions and reduce internal labor costs (Oshri, Kotlarsky and Gerbasi, 2015; Sobinska and Willcocks, 2016). Additionally, digital tools like big data analysis, online recruitment platforms, and professional networks enhance labor market transparency and speed up employee-employer matching (Autor, 2009), reducing labor costs for businesses and improving overall employment efficiency.

The demonstration city policy, implemented through the creation of demonstration cities, aims to enhance broadband infrastructure and support the development of the digital economy. This policy is expected to drive digital transformation in businesses and improve employee allocation efficiency. In conclusion, digital technology plays a vital role in optimizing internal talent structures and enhancing employee allocation efficiency in businesses. Therefore, we propose the following hypothesis:

H1: Demonstration cities as a supportive policy for digital economic development, effectively promotes the improvement of employee allocation efficiency in businesses.

The development of ICT has made the entrepreneurial process more convenient and lowered entry barriers. For example, digital technologies like cloud computing, big data, and the Internet of Things have provided entrepreneurs with digital platforms that facilitate resource acquisition, market analysis, and business process optimization (Varadarajan and Yadav, 2009; Hilbig, Etsiwah and Hecht, 2018; Ferri, Spanò and Tomo, 2020). Additionally, digital marketing and social media have enabled entrepreneurs to effectively promote their products and services, expanding their market share (Kaplan and Haenlein, 2010).

As a result, the digital economy, through its technological advancements and platform support, has played a crucial role in inspiring entrepreneurial enthusiasm among both businesses and individuals. The rise in entrepreneurial activity in cities boosts both entrepreneurial vitality and employment prospects for working individuals. Moreover, cities with high entrepreneurial activity often possess favorable innovation and entrepreneurship ecosystems, including incubators, venture capital, and government support (Mason and Brown, 2014). This ecosystem offers entrepreneurial businesses enhanced access to resources and external support, while simultaneously providing employees with a favorable work environment and increased employment options. Consequently, the digital economy's influence on entrepreneurial activity in cities benefits not only entrepreneurs but also employees, as it creates a more favorable job market environment and opportunities for personal development and career growth.

The creation of demonstration cities policy has fostered the robust development of network infrastructure, resulting in enhanced network coverage and service quality. This policy has played a pivotal role in bolstering entrepreneurial activity in urban areas and stimulating the creation of additional employment opportunities that align with the skills of workers. Therefore, we propose research hypothesis H2a.

H2a: The demonstration city policy, through the establishment of demonstration cities, stimulates entrepreneurial activity and enhances employee allocation efficiency by creating more job positions that align with employees' skills and qualifications.

In the context of seeking productivity transformation and upgrading, the digital economy promotes the development of intelligent automation technology, aiding in task automation and optimized decision-making (Agrawal, Gans and Goldfarb, 2018). Additionally, companies reshape organizational structures with external partners using digital technologies, enabling collaborative innovation of products and services (Yoo et al., 2012), and enhancing operational efficiency through platform strategies for resource sharing and transaction matching (Hagiu and Wright, 2015). Building upon the digital economy's foundation, companies utilize digital tools for employee training and performance evaluation optimization (Bondarouk and Ruël, 2013), and expand recruitment channels through social media (Kaplan and Haenlein, 2010), thereby enhancing talent matching from external sources. Within the company's internal organization, digital transformation promotes organizational structure optimization and reshaping. For example, creating shared information platforms improves communication efficiency among employees and transparency in internal social networks (Leonardi, 2014), reducing unnecessary job positions. Moreover, ICT technology streamlines hierarchical structures, facilitating flat information flow (Spanos, Prastacos and Poulymenakou, 2002). A flattened organizational structure enhances human resource management effectiveness by reducing levels and improving overall efficiency.

The demonstration city policy, through macro-level support, facilitates cost reduction in network fees by internet service providers. This enables businesses to access high-speed internet at a lower cost and promotes their digital transformation. In response to digital transformation, companies are compelled to enhance internal organizational management and adopt flatter structures, thereby improving employee efficiency and maintaining competitiveness in the digital era. Based on this analysis, we propose research hypothesis H2b.

H2b: The policy of creating demonstration cities contributes to promoting the digital transformation of enterprises, leading to a reduction in labor redundancy and an improvement in employee allocation efficiency.

III. Methodology

A. Model

Based on the preceding analysis, we can exploit the demonstration city policy as an exogenous shock that effectively captures the development of the digital economy. This enables us to employ the Difference-in-Difference (DID) approach, which is a robust empirical method, to investigate the causal effect of digital economy development on employee allocation efficiency. The empirical model is as follows.

$$\text{Ex\_employee}_{it} = \alpha_0 + \beta(D_{c(i)} \times T_t) + \lambda \ \text{Control}'_{ihct} + \theta_h + \omega_t + \varepsilon_{ihct} \tag{1}$$

Our primary focus lies in estimating the coefficients β and $\left(D_{c(i)} \times T_t\right)$ in model (1), which represent the DID term. The variable $D_{c(i)}$ indicates whether enterprise i in city c

is designated as a demonstration city. It takes a value of 1 if it is a demonstration city and 0 otherwise. The variable T_t represents the implementation of the demonstration city creation policy in city c during year t. $Ex\_employee_{it}$ denotes the employee allocation efficiency of enterprise i in year t. $Control'_{ihct}$ represents a set of control variables at the enterprise, industry, and city levels. The parameter θ_h captures industry fixed effects, ω_t captures year fixed effects, ε_{ihct} represents the error term, and standard errors are clustered at the enterprise level using robust standard errors.

B. Variables

Independent variable

The core explanatory variable is constructed based on the model setting in the previous text, creating a DID term that reflects the changes in enterprise employee allocation efficiency before and after the implementation of the demonstration city policy.

Dependent variable

The dependent variable. Companies need to employ a sufficient number of employees to achieve their predetermined production goals. However, redundant employees increase production costs and decrease corporate profits (Li and Liang, 1998; DeWenter and Malatesta, 2001).Therefore, the degree of employee redundancy directly reflects the efficiency of employee allocation in the company. In this study, we adopt the method proposed by Bai, Lu and Tao (2006) to measure the degree of employee redundancy using the concept of excess employee ratio. The excess employee ratio is employed as an indicator of employee allocation efficiency, and the specific calculation formula is provided below:

$$\text{Ex\_employee}_{it} = \left(\text{Employee}_{it} - \text{Sale}_{it} \times \frac{\text{Ind\_employee}_{iht}}{\text{Ind\_sale}_{\text{iht}}} \right) / \text{Employee}_{it} \tag{2}$$

In Model (2), $Ex\_employee_{it}$ represents the number of employees in firm i during year t, $Sale_{it}$ represents the sales revenue of firm i during year t, $Ind\_employee_{iht}$ represents the average number of employees in the industry where firm i operates during year t, and Ind_sale_{iht} represents the average sales revenue in the industry where firm i operates during year t.

Control variables

We select a series of indicators at the firm, industry, and city levels as control variables. Firstly, for the firm-level control variables, we include firm size (Size), represented by the natural logarithm of total assets; firm age (Age), measured as the difference between the observation year and the year of IPO; employee wages (Wage), represented by the ratio of employee compensation and cash paid to employees to pre-tax profits; return on assets

(ROA), calculated as the ratio of net profits to total assets; leverage ratio (Lev), represented by the ratio of liabilities to assets, reflecting the level of leverage in the firm; operating cash flow (Cash), represented by the ratio of net cash flow from operating activities to total assets; and revenue growth rate (Growth), reflecting the firm's growth potential. Secondly, for the industry-level control variables, we include Lerner index (Lerner),[2] which reflects the monopoly power in the industry; and Tobin's Q value (TobinQ), calculated as the ratio of industry total market value to industry total assets, indicating the industry's development prospects. Finally, for the city-level control variables, we include per capita gross domestic product (PerGDP), reflecting the level of economic development in the city; and employment population scale (Pop), represented by the ratio of the year-end employed population to the total population of the city.

C. Data

Data Sources and Sample Selection.The data for listed companies and industry information mainly come from the CSMAR database, while the city-level data is obtained from the China City Statistical Yearbook. The study covers the period from 2011 to 2019. Regarding the listed companies and industry data, we implemented the following procedures: First, we excluded samples from the financial and real estate sectors. Second, we removed samples of companies labeled as ST, ST*, and those that were delisted during the observation period. Third, we excluded samples of companies with less than 200 employees. Fourth, we removed industry samples with fewer than 10 companies. Fifth, we winsorized all continuous variables used in the regression analysis at the 1st and 99th percentiles to mitigate the influence of extreme values. Additionally, considering that the industry is an important factor influencing employee hiring, we classified industries according to the China Securities Regulatory Commission's 2012 and 2001 classification standards. Except for the manufacturing industry, which was further subdivided into two-digit code industries, other industries were classified at the one-digit code level. Following these adjustments, we obtained a sample of 2,225 firms, comprising a total of 10,420 firm-year observations.

Processing of City-Level Data.Considering that the administrative units of the city samples in this study are prefecture-level cities, to ensure consistency in statistical definitions, we excluded the sample of Haidong City, which was converted from a county to a prefecture-level city in 2013. The list of cities was manually compiled from government websites such as the Ministry of Industry and Information Technology. Given that the demonstration city program was implemented in three phases and there were cases of policy's exit, it is not appropriate to simply classify the observation samples into treatment and control groups. Using a two-way fixed effects model with multiple time points for DID estimation in the presence of policy policy's exit can lead to serious bias (Goodman-Bacon, 2021; Callaway and Sant'Anna, 2021). To overcome the influence of policy's exit on the classification of treatment and control groups, we excluded the samples of the first batch of demonstration cities from 2018-2019 and the samples of the second batch of demonstration cities

[2] Lerner index = (firm revenue/total industry revenue) * individual firm Lerner index, where individual firm Lerner index = (revenue - operating costs - selling expenses - management expenses) / revenue.

from 2019. Through these procedures, we obtained a sample of 231 prefecture-level city observations.

The main descriptive statistics of the variables in this study are presented in Table 1. The mean of the excess employee rate *Ex_employee* is 0.48, indicating a relatively high level of redundancy among the observed sample of companies. This suggests that there is room for improvement in terms of employee allocation efficiency.

TABLE 1—VARIABLE STATISTICS

Variable	Observations	Mean	Standard Deviation	Minimum	Maximum
Ex_employee	10420	0.48	0.22	0.01	0.90
D×T	10420	0.30	0.46	0.00	1.00
Size	10420	21.93	1.10	18.65	26.10
Age	10420	9.30	6.74	1.00	26.00
Inwage	10420	0.00	0.02	-0.18	1.41
Roa	10420	0.04	0.06	-0.48	0.22
Lev	10420	0.39	0.20	0.04	0.92
Cash	10420	0.04	0.06	-0.17	0.26
Growth	10420	0.16	0.39	-0.52	4.07
Lerner	10420	0.11	0.07	-0.03	0.49
TobinQ	10420	2.22	1.12	0.35	7.83
Pergdp	10420	9.29	5.69	1.66	46.77
Pop	10420	0.33	0.30	0.02	1.47

IV. Empirical results

A. *Baseline Regression*

Based on the research hypothesis and model specification, we employed Model (1) to examine the impact of the demonstration city creation policy on enterprise employee configuration efficiency. The estimation results of the benchmark regression with different combinations of control variables are presented in Columns (1)-(4) of Table 2. Even after including control variables at the firm, industry, and city levels, the estimated coefficient of the DID term remained negative. The most comprehensive estimation results (Column 4) indicate that demonstration city enterprises experienced a 2.05% improvement in employee configuration efficiency compared to non-demonstration city enterprises, suggesting a significant enhancement in employee configuration efficiency due to the demonstration city policy. To assess the robustness of the findings, we conducted regression analyses using samples that included both positive and negative excess employee rates (Column 5) and samples that only included negative excess employee rates (Column 6). The results show that the coefficient of DID term was significantly negative in Column 5, while it was not statistically significant in Column 6. This implies that, on one hand, the impact of the demonstration city policy on enterprises with excess employees was more pronounced, indicating a greater need for improving employee configuration efficiency in such firms. On the other hand, the exclusion of listed companies, which are characterized by their larger size and favorable reputation, from the sample of employee shortage enterprises did not introduce significant estimation bias since they exhibited less evident employee shortage issues. Thus, these findings further confirm that using excess employees as a measure of employee configuration efficiency is a more precise proxy variable, thereby validating hypothesis H1.

B. Preference Score Matching (PSM)

To address the potential endogeneity issue resulting from systematic differences in changing trends between the control group and the treatment group relative to the sample of demonstration cities, we employ the propensity score matching method to identify non-demonstration cities with similar characteristics to the demonstration cities. Regarding the matching approach, we conduct a 1:1 nearest neighbor matching between the control and treatment groups, and the results are presented in column (1) of Table 3. The estimated coefficient of the DID term is negative but statistically insignificant, possibly due to the larger sample size in the treatment group, which increases the sample variance. [3] To reduce variance and obtain more useful sample information, we explore matching ratios of 1:2, 1:3, and 1:4, as shown in columns (2)-(4) of Table 3. With different matching ratios, the estimated coefficients of the DID term consistently indicate a negative and significant effect at the 10% level. Therefore, even after considering the endogeneity issue arising from sample self-selection, the robust conclusion remains that the demonstration city policy significantly promotes the reduction of redundant employees and further enhances employee allocation efficiency.

C. Parallel trend test

The parallel trends assumption is a crucial prerequisite for employing the DID model. Given the context of the demonstration city program, this assumption implies that in the absence of policy impact, the treatment group and the control group would exhibit a shared trend. To test the validity of the parallel trends assumption, we employ the following model.

$$\text{Ex\_employee}_{it} = \alpha_0 + \sum_{j=-6}^{2} \beta \left(D_{c(i)} \times T_t\right)^j + \lambda \text{ Control }'_{icht} + \theta_h + \omega_t + \varepsilon_{icht} \tag{3}$$

Whereas $\left(D_{c(i)} \times T_t\right)^j$ represents the relative year policy variable generated with refer-

[3] In the benchmark regression sample, there are 6,994 treatment group observations and 3,426 control group observations at the "firm-city-year" level.

Table 2—Baseline regression results

	(1) Ex_employee > 0	(2) Ex_employee > 0	(3) Ex_employee > 0	(4) Ex_employee > 0	(5) Ex_employee $!= 0$	(6) Ex_employee < 0
D x T	-0.0265***	-0.0265***	-0.0250***	-0.0205**	-0.0603**	-0.0352
	(0.0084)	(0.0081)	(0.0081)	(0.0080)	(0.0289)	(0.0673)
Size		-0.0559***	-0.0564***	-0.0564***	-0.1969***	-0.0966***
		(0.0045)	(0.0045)	(0.0045)	(0.0184)	(0.0339)
Age		-0.0007	-0.0007	-0.0008	-0.0042	-0.0128**
		(0.0007)	(0.0007)	(0.0007)	(0.0029)	(0.0064)
lnwage		-0.1075	-0.0988	-0.0869	0.3898	40.7821
		(0.0780)	(0.0731)	(0.0740)	(0.2969)	(29.5766)
Roa		-0.4854***	-0.5001***	-0.4950***	-1.4241***	-0.6088
		(0.0598)	(0.0602)	(0.0601)	(0.2607)	(0.5670)
Lev		-0.0752***	-0.0779***	-0.0790***	-0.4763***	-0.5968**
		(0.0245)	(0.0243)	(0.0242)	(0.1023)	(0.2412)
Cash		-0.0687	-0.0765	-0.0710	0.6501***	0.8387**
		(0.0507)	(0.0504)	(0.0504)	(0.2062)	(0.3720)
Growth		-0.0274***	-0.0271***	-0.0272***	-0.2084***	-0.3415***
		(0.0059)	(0.0059)	(0.0059)	(0.0313)	(0.0593)
Lerner			0.4520***	0.4450***	1.4077***	0.9482
			(0.1066)	(0.1063)	(0.5227)	(0.9543)
TobinQ			−0.0069*	−0.0068*	−0.0480**	−0.0415
			(0.0042)	(0.0041)	(0.0187)	(0.0407)
Pergdp				−0.0038***	−0.0146***	−0.0136
				(0.0007)	(0.0035)	(0.0093)
Pop				0.0324**	0.0942	−0.1160
				(0.0164)	(0.0751)	(0.1937)
Constant	0.4830***	1.7699***	1.7495***	1.7756***	4.7659***	1.7960**
	(0.0050)	(0.0929)	(0.0938)	(0.0938)	(0.3941)	(0.7414)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
N	10420	10420	10420	10420	14912	4491
R-squared	0.105	0.205	0.210	0.214	0.209	0.159

Note: *, **, and *** represent significance levels of 10%, 5%, and 1%.The standard errors clustered at the firm level are shown in parentheses.

Table 3—PSM results

	(1) PSM 1: 1	(2) PSM 1: 2	(3) PSM 1: 3	(4) PSM 1: 3
$D \times T$	-0.0130	-0.0190^{**}	-0.0198^{**}	-0.0179^{**}
	(0.0103)	(0.0091)	(0.0088)	(0.0086)
Control variables	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
N	4101	5906	6976	7684
R-squared	0.207	0.209	0.209	0.209

Note: *, **, and *** represent significance levels of 10%, 5%, and 1% respectively. The values in parentheses are robust standard errors clustered at the firm level. The control variables remain consistent with Table 2.

ence to the year of demonstration city creation. Based on the implementation year of the demonstration city policy and the duration of our sample, we designate the year prior to the pilot program as the base year and aggregate all years before the sixth year with the second year onwards.

Based on Figure 1, the coefficients $\left(D_{c(i)} \times T_t\right)^j$ before the implementation of the policy pilot are statistically insignificant, suggesting no significant disparity in employee configuration efficiency between demonstration cities and non-demonstration cities. Following the initiation of the policy pilot, the policy effect becomes apparent with a significant reduction in redundant employees and an improvement in employee configuration efficiency. However, the average treatment effect experiences a rebound in the third year. This may be attributed to the three-year duration of the policy implementation, where firms, in the two years prior to policy implementation, respond not only to the policy's financial incentives but also anticipate the policy's exit, leading to adjustments in employee configuration in the final year to offset some of the policy effects. In general, the results provide support for the parallel trends assumption between the treatment and control groups prior to the establishment of the demonstration cities.

D. Placebo Test

Although this study controls for factors at the firm, industry, and city levels that may affect the estimation results of the impact of the demonstration city creation policy on firm's employee allocation efficiency, other unobservable factors may still influence the results. To address the issue of potential endogeneity in the estimated policy effects, and to ensure robustness of the estimates, we employ a placebo test. Based on the distribution of the policy variable $\left(D_{c(i)} \times T_t\right)$ as specified in Model (1), we randomly generate 1,000 samples of "pseudo policy variables" and re-estimate the results using these samples. We examine the coefficients and p-values of the "pseudo policy variables" to assess their distribution. From Figure 2, it can be observed that the mean estimate of the "pseudo policy variables"

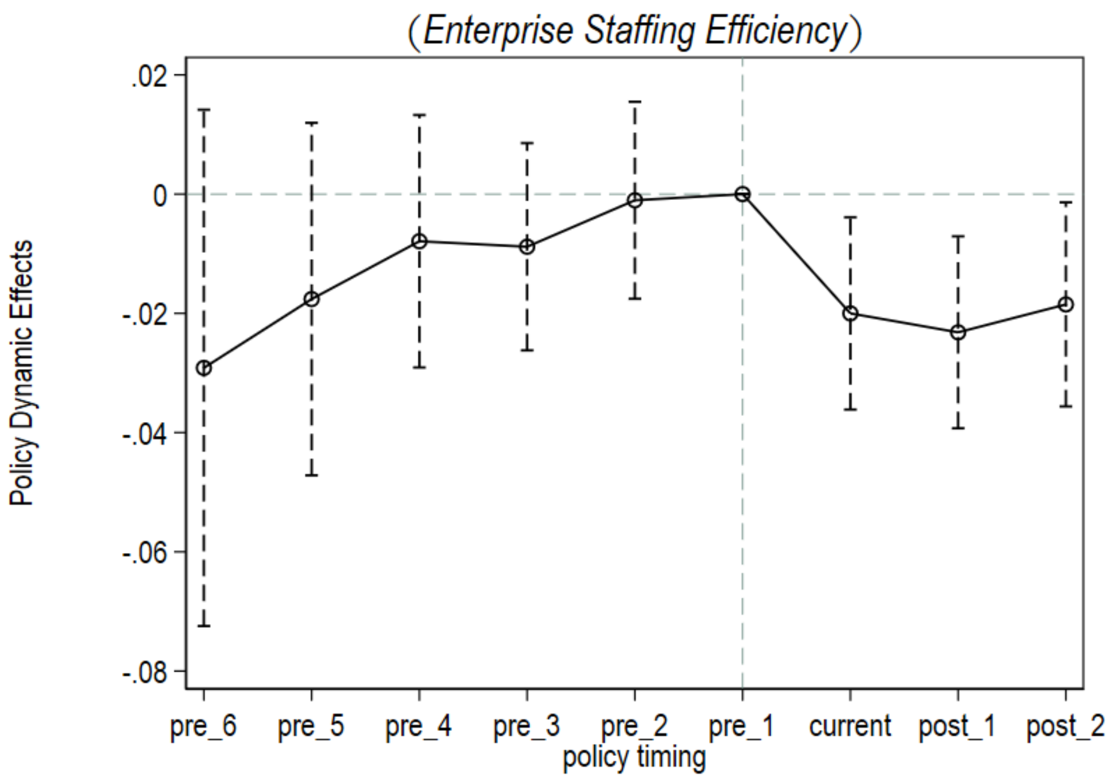

Figure 1. Graph of Parallel Trends Test

is close to zero, and significantly larger than the estimated policy effect of -0.0205 in the baseline regression. Moreover, most of the p-values are above 0.1, indicating that at a 10% significance level, we fail to reject the null hypothesis that the estimated coefficients of the "pseudo policy variables" are equal to zero. These placebo test results provide strong evidence that the conclusion of the positive impact of the demonstration city creation policy on firm's employee allocation efficiency is not a random occurrence, further confirming the robustness of the baseline regression results.

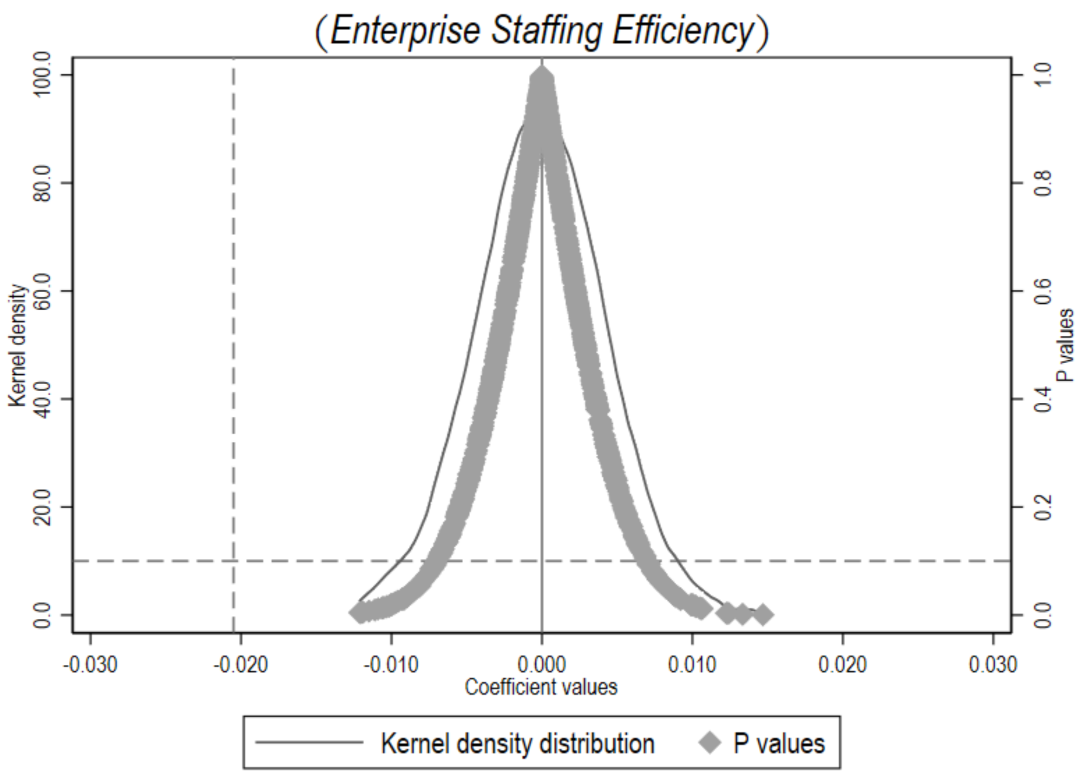

Figure 2. Placebo Test Results

E. Heterogeneity of Treatment Effects Test

we acknowledge the possibility that the average treatment effect could be negative when the policy effect varies over time. To address this concern, we adopt a methodology inspired by Sun and Abraham (2020); Borusyak, Jaravel and Spiess (2023), employing an event study framework that incorporates heterogeneous treatment effects. We re-estimate Model

(3) and extend the observation period from 2010 to 2020.

Figure 3 shows the impact of the demonstration city policy on firm's employee allocation efficiency, considering heterogeneous treatment effects. Before policy implementation, the average treatment effect is not statistically significant. After policy implementation, there is a significant reduction in employee redundancy and an improvement in employee allocation efficiency. Although the reduction rate of employee redundancy decreases as the policy is about to or has already exited, the policy treatment effect continues to promote the reduction of employee redundancy. Furthermore, using the multi-period multi-individual DID model and the corresponding estimator (DIDM) proposed by de Chaisemartin and D'Haultfœuille (2020), we test the proportion of negative weights. Based on 50 random samples, the proportion of negative weights in the baseline regression sample is 8.795%, and the sum of negative weights is -0.0212, which is close to zero. This suggests that the issue of negative weights in heterogeneous treatment effects does not significantly bias the coefficient estimation in Model (1).

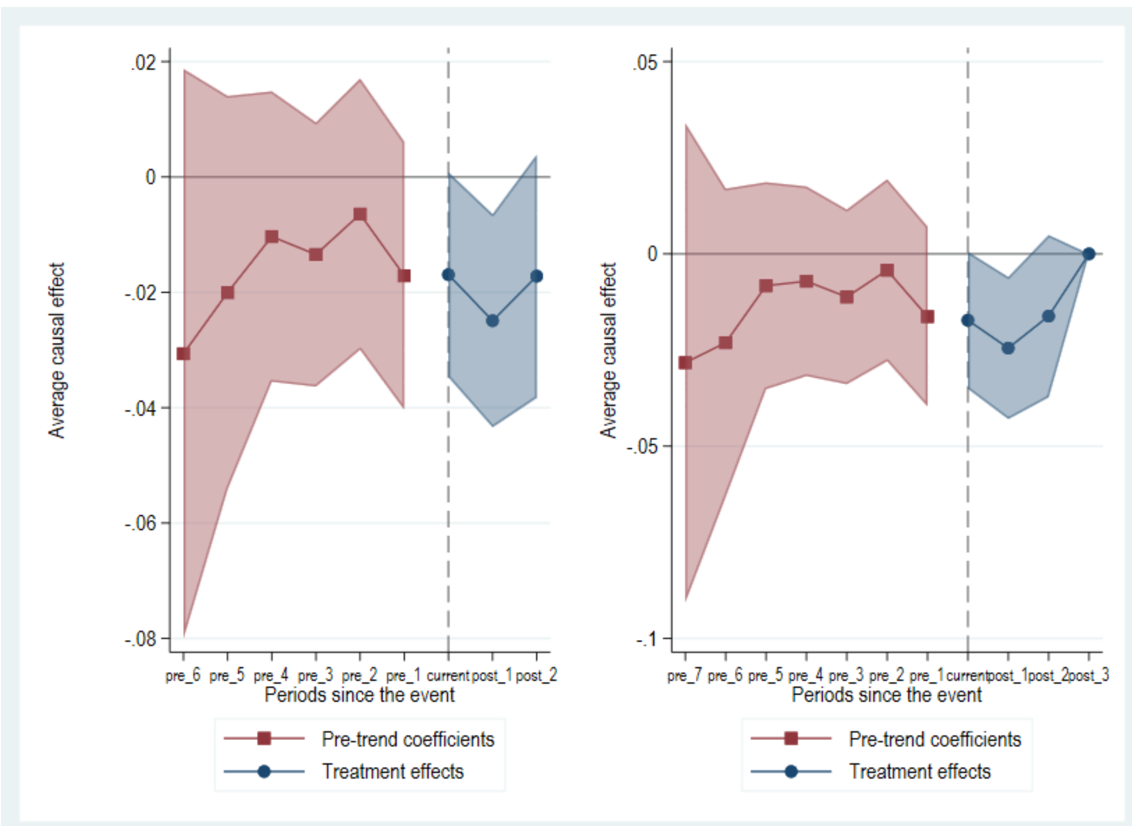

Figure 3. Event Study Graph of Heterogeneous Treatment Effects

F. Robustness Test

Firstly, we conducted robustness tests by replacing the dependent variable. In Model (1), we used the excess employee rate to measure the level of employee redundancy. To incorporate more factors in measuring employee redundancy, we referred to the approach proposed by Zeng and Chen (2006), which includes factors such as firm size, leverage ratio, capital intensity, firm growth, as well as industry and time characteristics. We estimated the model using Ordinary Least Squares (OLS) method, considering year and industry fixed effects. The specific model specification is as follows.

$$\begin{aligned}\text{Emp}_{it} &= \theta_0 + \theta_1\text{Size}_{it} + \theta_2\text{Lev}_{it} + \theta_3\text{Growth}_{it} + \theta_4\text{Roa}_{it} + \theta_5\text{Capital}_{it} \\ &+ \sum \theta_6\text{Industry}_j + \sum \theta_7\text{Year}_t + \varepsilon_{ijt}\end{aligned} \tag{4}$$

In the model, i, j, and t represent the firm, industry, and year, respectively. Emp_{it} represents the firm's employee scale, calculated as the number of employees divided by total assets and multiplied by 10,000. Growth_{it} captures firm growth and is measured by the growth rate of total operating income. Roa_{it} represents the firm's profitability. Capital_{it} represents the capital intensity, calculated as the fixed assets divided by total assets. Industry_j and Year_t represent unobservable factors at the industry and year levels, respectively. ε_{ijt} denotes the random error term. Employee redundancy is calculated by estimating the residuals from Model (4). If the residual is greater than 0, it indicates employee redundancy, while if the residual is less than 0, it indicates employee shortage in the firm.

We replaced the explained variable, excess employee rate, in Model (1) with the estimated residuals of employee redundancy and re-estimated the model. The regression results are shown in column (1) of Table 4. It can be observed that the demonstration city creation policy promotes the improvement of enterprise employee allocation efficiency still holds.

Secondly, we excluded the samples of firms in the computer, communication, and other electronic equipment manufacturing industry. The demonstration city creation policy primarily focuses on improving urban households' access to broadband with speeds of 20Mbps or higher, promoting fixed broadband penetration rate, and mobile phone penetration rate. This brings more business opportunities to firms in the computer, communication, and other electronic equipment manufacturing industry, leading to an increased demand for employees to expedite business operations and generate profits. The regression results indicate a statistically significant and negative coefficient for the DID term, which is consistent in magnitude with the baseline regression. This suggests that the inclusion of companies directly associated with digital economic development does not lead to estimation bias in the results.

Thirdly, considering the policy expectation effect, we incorporate lagged policy shock variables, $(D \times T)_{\text{lag1}}$ and $(D \times T)_{\text{lag2}}$, corresponding to different batches of the demonstration city, into model (1) for re-estimation. The estimated results indicate that even after controlling for the policy expectation effect, the coefficient of the DID term remains significantly negative. Additionally, the coefficients of both lagged one-period and lagged two-period expectation effects are not statistically significant. This suggests that the implementation of the demonstration city creation policy did not generate significant expectation effects for the companies, affirming the validity of the baseline regression model specification.

Fourthly, we control for concurrent policy effects. By consulting relevant policy documents and considering existing literature, we identify three potential pilot city policies that could influence the efficiency of employee allocation in firms: the Smart City pilot policy, National Innovation City pilot policy, and Low-carbon City pilot policy. After incorporating these policy dummy variables into the baseline regression model (1), the estimated coefficient of the DID term remains significantly negative, as indicated by the results in column (5) of Table 4. The magnitude of the coefficient is consistent with the estimates obtained from the baseline regression, confirming the robustness of the findings. This suggests that even after accounting for the simultaneous effects of other relevant policies, the baseline regression results remain robust.

Fifthly, we account for spillover effects. In the presence of intervention policies, the control group individuals may not remain unaffected and could be influenced by the treatment group, violating the stable unit treatment values assumption (SUTVA) of the DID method. To examine the potential bias arising from spillover effects, we adopt the approach proposed by Lu, Wang and Zhu (2019) to assess whether the creation of demonstration cities has led to improvements in employee allocation efficiency among firms within the same province. The specific model specification is as follows.

$$\begin{aligned} \text{Ex\_employee}_{it} &= \alpha_0 + \beta(D_{p(i)} \times D_{c(i)} \times T_t) + \rho(D_{p(i)} \times T_t) \\ &+ \lambda \text{Control}'_{\text{ihct}} + \theta_h + \omega_t + \varepsilon_{\text{ihct}} \end{aligned} \tag{5}$$

In model (5), all variables are set the same as in model (1), except for the variable $D_{p(i)}$. Here, $D_{p(i)}$ indicates whether the province where enterprise i is located has cities included in the demonstration city policy. The coefficient ρ estimates whether the creation of the demonstration cities has spillover effects within the same province, i.e., whether the policy has improved the employee allocation efficiency of other enterprises in the same province. The coefficient α represents the direct effect of the demonstration city creation policy.

From the results, it can be observed that the estimated coefficient of the spillover effect term $\left(D_{p(i)} \times T_t\right)$ is not statistically significant. On the other hand, the estimated coefficient of the direct effect term $\left(D_{p(i)} \times D_{c(i)} \times T_t\right)$ is significantly negative. The analysis reveals no significant spillover effects associated with the creation of demonstration cities policy, supporting the assumption of stable unit treatment values (SUTVA) in the DID framework.

Lastly, we employ the Logit and Probit models, replacing the model with the excess employee rate as a binary variable. The estimated coefficients of the DID term in columns (7) and (8) of Table 4 remain significant and negative, providing additional evidence for the robustness of the baseline regression results.

Table 4—Robustness test results

	(1) Replacing the dependent variable	(2) Excluding the electronics	(3) Anticipated effects: lagged by one	(4) Anticipated effects: lagged by two	(5) Excluding concurrent policies	(6) Spillover effects	(7) Logit	(8) Probit
$D \times T$	-0.0004^{**}	-0.0206^{**}	-0.0204^{**}	-0.0205^{**}	-0.0204^{**}		-0.1577^{**}	-0.0950^{**}
	(0.0002)	(0.0084)	(0.0083)	(0.0084)	(0.0080)		(0.0787)	(0.0468)
$(D \times T)\_\text{lag1}$			0.0015	0.0007				
			(0.0076)	(0.0083)				
$(D \times T)\_\text{lag2}$				-0.0052				
				(0.0075)				
Smart					-0.0088			
					(0.0065)			
Innovation					-0.0138			
					(0.0122)			
Carbon					-0.0128			
					(0.0091)			
$[D_{P(i)}] \times [D_{C(i)}] \times [T_t]$						-0.0263^{***}		
						(0.0093)		
$[D_{P(i)}] \times [T_t]$						-0.0054		
						(0.0118)		
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	14917	9240	10420	10420	10420	10420	14917	14917
R^2	0.027	0.217	0.214	0.214	0.215	0.215		
Pseudo-R^2							0.0869	0.0862

Note: *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. Standard errors clustered at the enterprise level are reported in parentheses. Control variables remain consistent with Table 2.

V. Mechanism Analysis

To explore the mechanisms through which the demonstration city creation policy promotes efficiency in enterprise employee allocation, we examine two potential mechanisms: entrepreneurial activity and digital transformation. Following the approach of Alesina and Zhuravskaya (2011), we construct the following model for analysis.

$$\text{Mechanism }_{\text{ihct}} = \alpha_0 + \beta \left(D_{c(i)} \times T_t \right) + \lambda \text{ Control }'_{\text{ihct}} + \theta_h + \omega_t + \varepsilon_{\text{ihct}} \tag{6}$$

In model (6), all variables remain consistent with model (1) except for the inclusion of $Mechanism_{ihct}$, which represents the mechanisms of entrepreneurial activity and digital transformation mentioned above.

A. Entrepreneurial Activity

Hence, the heightened entrepreneurial activity in the region amplifies the inclination of employees to "venture out", thereby facilitating a more optimized allocation of human resources within enterprises. To measure urban entrepreneurial activity, we refer to the research by Reynolds et al. (2005) and combine it with actual entrepreneurial data from China. We use the number of newly established private enterprises at the city level from the China Enterprise Credit Information Publicity System database to measure urban entrepreneurial activity ($Entrep$). By incorporating urban entrepreneurial activity ($Entrep$) into Model (6) for estimation, the results are presented in Column (1) of Table 5.

The estimated coefficient of the DID term is found to be statistically significant at the 1% level, indicating that the policy of demonstration cities has effectively promoted the increase in urban entrepreneurial activity. As a result, more employment options are available for employees within enterprises, leading to a significant improvement in employee allocation efficiency. This finding provides strong support for hypothesis H2a.

B. Digital transformation

Digital transformation enables businesses to efficiently transmit information through digital technologies and build efficient operational management systems to improve internal management efficiency. To measure business digital transformation, we refer to the research approach of Li et al. (2018) and combine it with information from annual reports of Chinese listed companies. we extract key words related to underlying technologies closely related to digital transformation, such as "artificial intelligence technology", "big data technology", "cloud computing technology" and "blockchain technology" from annual reports of companies. We then count the frequency of each keyword appearing in the annual reports for each company in the observation year. Finally, we sum up the frequencies of these keywords to obtain a total word frequency as a measure of the extent of digital transformation in the company. We incorporate the variable of business digital transformation into model (6) for estimation, and the results are shown in column (2) of Table 5.

Through the analysis of the results,we can see that the coefficient of the DID term on business digital transformation is significant at the 1% level. This indicates that the demonstration city creation policy helps cities improve their network infrastructure construction, allowing businesses to achieve digital transformation with the convenience of network infrastructure. As a result, internal management efficiency is strengthened, redundancies are reduced, and employee allocation efficiency is improved.Thus, hypothesis H2b is also supported by the evidence.

VI. Extension analysis

A. Heterogeneity analysis

Although previous analyses have provided comprehensive evidence of the positive impact of the demonstration city creation policy on employee allocation efficiency, it is important to examine whether the policy effects differ across various dimensions, including cities and firms. In this section, we conduct heterogeneity analysis to investigate whether there are differences in the effects of the policy intervention on different dimensions.

Table 5—Mechanism testing results

	(1) Entrep	(3) Transform
$D \times T$	1.0655***	0.1399***
	(0.0644)	(0.0352)
Control variables	Yes	Yes
Industry FE	Yes	Yes
Time FE	Yes	Yes
N	10386	10425
R^2	0.262	0.461

Note: *, **, and *** represent significance levels of 10%, 5%, and 1% respectively. The values in parentheses are robust standard errors clustered at the firm level. The control variables remain consistent with Table 2.

Heterogeneity in city characteristics

Regional heterogeneity. We perform subsample regression analysis by dividing the sample into Eastern cities and non-Eastern cities. The estimated results in columns (1) and (2) of Table 6 indicate that the DID term in Eastern cities has a significant negative coefficient at the 5% level, while non-Eastern cities is not statistically significant. This suggests that the demonstration city policy has a more pronounced impact on improving employee allocation efficiency in Eastern cities. It is likely due to the advanced economic infrastructure, industrial support, infrastructure development, and wider network coverage in the Eastern region. The broadband network construction and digital transformation better meet the demands of companies in Eastern cities, leading to enhanced production efficiency and managerial capabilities, thereby reducing excessive staffing.

Wage level heterogeneity. We divide the sample into high wage level and low wage level groups based on the average wage level of the cities and conduct separate regression analyses for each group. The estimated results in columns (3) and (4) of Table 6 indicate that the DID term in high-wage level cities has a significant negative coefficient at the 10% level, while low-wage level cities is not statistically significant. This suggests that companies in high-wage level cities are more likely to utilize digital technologies, such as broadband networks, to improve production efficiency and managerial capabilities, leading to a reduction in unnecessary labor costs. In contrast, companies in low-wage level cities face challenges related to infrastructure support and labor mobility, resulting in obstacles for the policy to enhance employee allocation efficiency.

Heterogeneity of Enterprise Characteristics

Heterogeneity of enterprise ownership. We partition the sample into state-owned and non-state-owned enterprises and conduct separate subsample regressions. The estimates in columns (1) and (2) of Table 7 indicate that the coefficient of the DID term is statistically

TABLE 6—HETEROGENEITY ANALYSIS OF CITY CHARACTERISTICS - TEST RESULTS

	(1) East Coast cities	(2) non-East Coast cities	(3) high-wage cities	(4) low-wage cities
$D \times T$	-0.0248**	-0.0098	-0.0346***	-0.0014
	(0.0102)	(0.0132)	(0.0129)	(0.0099)
Control variables	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
N	6662	3757	4176	6243
R^2	0.211	0.278	0.196	0.259

Note: *, **, and *** represent significance levels of 10%, 5%, and 1% respectively. The values in parentheses are robust standard errors clustered at the firm level. The control variables remain consistent with Table 2.

insignificant for state-owned enterprises, while it is significantly negative at the 5% level for non-state-owned enterprises. This suggests that state-owned enterprises face complexities in decision-making hierarchies and slower implementation, leading to limited flexibility in implementing measures to reduce excess employees. Conversely, non-state-owned enterprises respond rapidly to the demonstration city policy by optimizing internal structures and enhancing employee allocation efficiency, thereby catching up with the digital transformation trend.

Heterogeneity of enterprise growth characteristics. By employing text analysis of their primary business, we categorize the entire sample into three groups: emerging enterprises, bottleneck enterprises, and mature enterprises. [4] Subsequently, we conduct regressions on each subgroup. The estimation results in columns (3)-(5) of Table 7 indicate that the coefficient of the DID term for emerging enterprises is not statistically significant. However, for bottleneck enterprises and mature enterprises, the coefficients of the DID term are both significantly negative at the 5% level. This implies that the impact of the demonstration city policy on employee allocation efficiency in emerging enterprises is not evident. On the other hand, bottleneck enterprises and mature enterprises require optimization of their employee structure to align with the digital transformation trend, thereby reducing redundancies and improving employee allocation efficiency.

B. Economic Consequences Test

Based on the analysis conducted, it can be inferred that the demonstration city policy contributes to a reduction in labor redundancy within enterprises, leading to an improve-

[4]Based on the Chinese government's plan, enterprises engaged in AI, big data, IoT, Internet Plus, new energy, new materials, aviation, aerospace, high-speed rail, marine engineering, biology, and energy conservation and environmental protection are classified as emerging enterprises. Enterprises involved in steel, cement, electrolytic aluminum, flat glass, and ships are categorized as bottleneck enterprises. All other enterprises are classified as mature enterprises.

Table 7—Heterogeneity in Firm Characteristics Test Results

	(1) State-owned enterprises	(2) Non-state-owned enterprises	(3) Emerging enterprises	(4) Bottleneck enterprises	(5) Mature enterprises
$D \times T$	-0.0213	-0.0203**	-0.0656	-0.1185**	-0.0174**
	(0.0137)	(0.0098)	(0.0455)	(0.0566)	(0.0083)
Control variables	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes
N	3837	6387	456	159	9804
R^2	0.269	0.200	0.270	0.615	0.217

Note: *, **, and *** represent significance levels of 10%, 5%, and 1% respectively. The values in parentheses are robust standard errors clustered at the firm level. The control variables remain consistent with Table 2.

ment in employee allocation efficiency. To further investigate the economic implications of digital economic development on firms, we employ total factor productivity (TFP) indicators to examine whether the improvement in employee allocation efficiency can boost firm productivity. Specifically, we utilize the LP method (Levinsohn and Petrin, 2003) and OP method (Olley and Pakes, 1992) to estimate firm-level TFP. Our choice of variables for TFP includes the natural logarithm of main business revenue as a measure of total output, the natural logarithm of employee count as a measure of labor input, the natural logarithm of net fixed assets as a measure of capital stock, and the natural logarithm of capital expenditures minus the disposal of fixed assets, intangible assets, and other long-term assets as a measure of intermediate inputs. Building upon this framework, we construct a model to assess the economic consequences of the demonstration city policy.

$$TFP_{it} = \alpha_0 + \beta Ex\_\text{employee}_{\ it} + \lambda \text{ Control}'_{\text{ihct}} + \theta_h + \omega_t + \varepsilon_{ihct} \tag{7}$$

$$\begin{aligned} TFP_{it} = \alpha_0 &+ \beta_1 (D_{c(i)} \times T_t) + \beta_2 Ex\_\text{employee}_{\ it} + \beta_3 (D_{c(i)} \times T_t \times Ex\_\text{employee}_{\ it}) \\ &+ \lambda \text{Control}'_{\text{ihct}} + \theta_h + \omega_t + \varepsilon_{\text{ihct}} \end{aligned} \tag{8}$$

Equation (7) is employed to examine the relationship between labor redundancy and total factor productivity (TFP), while our primary interest lies in the estimated coefficient in Equation (8), which indicates how the demonstration city policy affects TFP through the reduction of labor redundancy. The estimation results from Table 8 indicate that regardless of using the LP method or the OP method, the estimated effect of labor redundancy on TFP is significantly negative at the 1% level. This suggests that labor redundancy negatively impacts employee allocation efficiency, leading to a decline in firm productivity. Moreover, both the interaction term between labor redundancy and the DID variable ($D \times T \times Ex_$employee) are significantly negative at the 5% level, implying that the reduction of labor redundancy can further enhance TFP following the implementation of the demonstration city policy. These findings highlight that enterprises utilizing the policy to promote digital management and automate production can reduce excess human resources, improve employee work efficiency, and ultimately enhance labor productivity.

Table 8—Economic Consequences Inspection Results

	(1) TFP_LP	(2) TFP_LP	(3) TFP_OP	(4) TFP_OP
$Ex_$employee	-0.2736***	-0.2442***	-0.2737***	-0.2443***
	(0.0294)	(0.0332)	(0.0294)	(0.0332)
$D \times T$		0.0672***		0.0672***
		(0.0243)		(0.0243)
$D \times T \times Ex_$employee		-0.0931**		-0.0932**
		(0.0445)		(0.0445)
Industry FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
N	9778	9778	9778	9778
R^2	0.838	0.838	0.837	0.838

Note: *, **, and *** represent significance levels of 10%, 5%, and 1% respectively. The values in parentheses are robust standard errors clustered at the firm level. The control variables remain consistent with Table 2.

VII. Conclusion and critical discussion

Based on our analysis, the demonstration city policy in "Broadband China" has significant strategic implications for enhancing enterprise employee allocation efficiency and core competitiveness in China, a country with a large and digitally transforming enterprise sector. The results of this study demonstrate that the policy effectively reduces labor redundancy and improves employee allocation efficiency in enterprises. These findings are supported by robustness tests including propensity score matching, parallel trends analysis, heterogeneity treatment effects, and placebo tests. Moreover, the policy is found to stimulate regional entrepreneurship activity and facilitate digital transformation in enterprises, providing mechanisms and channels for enhancing employee allocation efficiency. It is important to note that the policy effects exhibit heterogeneity across different regions, ownership types, and growth stages of enterprises. Furthermore, the demonstration city policy significantly enhances overall factor productivity and strengthens core competitiveness after improving employee allocation efficiency. This study provides valuable policy recommendations for the government to drive digital economic development and offers empirical research support for maintaining enterprise vitality and enhancing core competitiveness. Based on the comprehensive analysis of our research findings, we propose the following discussion.

To enhance employee allocation efficiency and core competitiveness, it is recommended to leverage digital economic policies to stimulate entrepreneurial activity and drive digital transformation. Policies should be utilized to support the entrepreneurial ecosystem and encourage enterprises to innovate using broadband networks. This can be achieved by establishing digital innovation incubation platforms that provide technical support, policy guidance, and financial assistance to enterprises, thereby fostering entrepreneurial activity in cities. Additionally, promoting digital transformation within enterprises through initiatives such as remote work, online training, and human resources big data analysis can optimize talent structures. Encouraging collaborations between enterprises, other businesses, universities, and research institutions can facilitate the sharing of high-quality talent resources, thereby maximizing employee allocation efficiency.

In the implementation of policies, it is important to ensure their sustained and coherent effectiveness. Furthermore, a shift from comprehensive deployment to a targeted approach is recommended. Consideration should be given to factors such as the location of enterprises, wage levels, ownership types, and growth stages, enabling the design of tailored broadband service policies. For example, high-speed broadband services can be provided to enterprises in high-wage cities in the eastern regions, promoting the use of digital tools and technologies to improve employee allocation efficiency. Similarly, low-cost broadband services can be offered to enterprises in non-eastern cities with lower wage levels. Special emphasis should be placed on implementing digital economic policies for non-state-owned enterprises in advanced growth stages, aiming to optimize human capital structures and stimulate enterprise vitality.

In conclusion, it is essential to design and implement precise policies based on the specific circumstances of enterprises, with the goal of enhancing employee allocation efficiency and core competitiveness. In our empirical analysis, due to data limitations, we are unable to determine the employment destinations of redundant employees after they leave the company, which prevents us from fully reflecting that the promotion of enterprise employee allocation efficiency by the digital economy does not affect the overall employment rate in society. In future research, we will continue to collect data on workers' employment destinations and match it with enterprise employee data to further analyze the impact of digital economy policies on workers' job changes after employment shifts.

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