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The Impact of Labor Misallocation on Carbon Emissions in China: Whether Digital Space Matters

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Abstract: Digital networks have brought about more frequent economic interaction. Labor misallocation influences regional green development through digital channels. Constructing a digital divide matrix among 30 Chinese provinces, a spatial Durbin model was applied in this paper to address the digital spillover of labor misallocation on carbon emission. We obtained the following research findings: (1) The digital divide in China tends to spread from east to west between 2006 and 2021. (2) Labor misallocation impacts carbon emissions through digital spillover. Specifically, labor misallocation increases local carbon emissions, as well as carbon emissions in digital adjacent regions. (3) The widening digital divide exacerbates the digital spillover effects of labor misallocation. The result's plausibility was further verified by generalized spatial two-stage least squares. (4) Labor misallocation increases carbon emissions when the digital divide exceeds a threshold. The results provide an effectual reference for digital governance in Chinese carbon emissions.

Keywords: labor misallocation; carbon emission; digital spillover; digital divide; spatial Durbin model

1. Introduction

Global warming is an urgent environmental crisis, and sustainable economic growth will be optional to reduce greenhouse gas emissions. Given its position as the world's second-largest economy, China has a priority to participate in the global governance process [1]. As a positive response to the United Nations' Sustainable Development Goals (SDG), the Chinese government drew up achievable goals to limit carbon emissions in the future, including reaching its peak carbon emissions by 2030 and becoming carbon neutral by 2060 [2]. Digitization is a competent path to allow China to shift from severe pollution to sustainable economic growth. Reducing carbon emissions through the digital economy not only allows China to positively implement its responsibilities and obligations to the international community in terms of environmental protection, but also is an inevitable choice for the Chinese economy to optimize labor allocation [3].

Labor misallocation has older origins in China's economic development and is persistently affecting its sustainable transformation. According to the assumption of free mobility of productive resources in the market, labor is efficiently allocated when labor resources are Pareto-optimal across regions, firms, and industries. Conversely, when there is a deviation from Pareto optimality, there is a labor misallocation [4]. The policy of "distribution according to work" has greatly liberated labor enthusiasm after the reform and opening up of China. It also resulted in majority labor crowding in the high-return sectors including finance and monopolies [5]. High-tech industries, represented by computers, struggle to promote sustainable economic transformation due to a shortage of high-quality labor, ultimately causing large carbon emissions.

Since the 21st century, the Chinese government has built thousands of kilometers of fiber optic networks between regions. An online space was created by a vast digital facility for economic interactions between regions. Spatial econometrics gave a clear definition of spillover effects [6], which can be viewed as the economic effect of local production behavior on neighboring regions in geographic space. This paper has drawn from the

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concept that economic effects transmitted through digital connectivity between regions are defined as digital spillovers. Digital facilities provide access to digital spillovers. However, the unequal distribution of facilities also raises social issues regarding the digital divide between regions, populations, industries, and rural and urban areas [7]. The divide represents inequality, and the current digital divide mainly consists of two inequality issues [8]: one is the unequal distribution of digital facilities and the unequal application of digital technologies; the other one is social inequalities caused by digitization, such as salary differences due to digital skill gaps, or employment opportunity differences due to digital information disparity. The digital economy reduces pollution emissions by optimizing the labor market, but the digital divide may disorder labor allocation and thereby increase carbon emissions. It can be noted that the digital infrastructure creates both spillovers and inequalities. The influence on sustainable economic development of these two properties deserves further research by scholars.

In summary, the Internet has provided digital channels for labor mobility, while having to be influenced by the digital divide. Moreover, there is a spillover effect of labor misallocation under geographic space, which creates additional carbon emissions. This paper will research the following questions. First, do labor misallocations have a digital spillover? Digital networks are also involved in labor regulation to some degree [9]; therefore, spillovers may occur within the digital space as well. Second, if digital spillovers from labor misallocation exist, do they affect carbon emissions? Digital technology reduces the obstacles to labor mobility across regions, which in turn facilitates a low-carbon transition in production [10]. Third, what are the trends in carbon emissions affected by digital spillovers from labor misallocation in dynamic digital divides? Statistics on digital facilities will support this paper in further quantifying the dynamic "digital divide" and its economic effects. Beginning with the above questions, panel data from 30 provinces in China was adopted to support our research. After proven diagnostic testing, the spatial Durbin model (SDM) was applied to capture digital spillovers of labor misallocation on carbon emissions and the dynamic trends of digital spillovers. The threshold effect of labor misallocation on carbon emissions provides more robust empirical support for a clear comprehension of the relationship.

The paper contains the following innovative contributions. Firstly, it explores the potential impact of labor misallocation on carbon emissions within the expanding digital divide, providing insights into the sustainable economic transformation in the digital era. Secondly, our research identified an online pathway between labor misallocation and carbon emissions. It provides a new strategy of digital governance for achieving emission reductions. Thirdly, we verified temporal heterogeneity, as well as the threshold effect, between labor misallocation and carbon emissions. This expands existing research from the dynamic perspective of the digital divide, providing valuable references for green development in China.

The remaining sections of this paper are as follows. Relevant research literature and shortcomings of existing research are presented in the "Literature Review" section. The "Methodology and Data" section contains the construction of the digital divide, the empirical model of the paper, and the data sources. The "Empirical Results" section provides empirical results, robustness tests, and extended research. The last section summarizes the research conclusions, policy recommendations, and research limitations.

2. Literature Review

There is a practical significance in assessing digital spillovers of labor misallocation on carbon emissions towards achieving SDG. Our work is related to the following literature.

Firstly, the literature's theme is about the impact of labor misallocation on carbon emissions. The resource misallocation theory based on productivity dispersion suggests that production factors will aggregate from low-productivity to high-productivity firms [11]. Insufficient production efficiency is also a critical contributor to excessive pollution emissions [12–14]. Hao et al. [15] found that labor misallocation reduces local energy efficiency

using Chinese provincial panel data, thereby increasing carbon emissions, but there is no spatial spillover between them. Combes et al. [16] constructed a nested model of selection and agglomeration, empirically exposing major drivers of labor agglomeration, including the accessibility of infrastructure, labor market intensity, and skill spillovers. Additionally, labor misallocation tends to occur less frequently in employment-intensive areas. Bian et al. [17] found that a major ingredient of resource misallocation is Chinese market segmentation across provinces, which, in turn, increases pollution emissions. Han et al. [18] concluded that labor marketization could diminish carbon emissions caused by labor misallocation. Misallocation of land resources due to government land policies can weaken labor agglomeration, further hindering sustainable development and ultimately leading to additional carbon emissions. Producer service aggregation can be viewed as a labor allocation; this aggregation can contain carbon emissions through technological upgrading and scale economies. The allocation of productive resources with government intervention also has a nonlinear effect on carbon emission reduction [19]. Ji's [20] regression results revealed there is a positive correlation between market factor distortions and industrial pollution. The implementation of public ownership policies alleviates pollution emissions arising from distortions. It will emit pollution because government intervention in factor allocation prevents enterprises from technological upgrading [21], and enterprises will have to be more energy-dependent to gain profits.

Secondly, the literature is about the digital divide. The digital divide shouldn't be a cramped technological issue. It is most probably a reflection of social inclusion as well as social inequality [22]. Gradually, the government has tended to construct internet facilities for vulnerable groups to minimize their negative stereotypes [23]. Luan et al. [8] constructed a digital divide index at a household level and empirically identified that the digital divide deprives household energy welfare, especially for low-income and rural families. While digital finance lessens inequality in renewable energy innovation, it has been negatively mediated by the digital divide between Chinese provinces [24]. Digital economy has a significant dampening effect on carbon intensity. This includes both local and spillover effects [25].

Dynamic digital divides have potential implications for labor misallocation. Liao et al. [26] found that there is a dynamic process of digital divide using key-route main path analysis. The whole process can be broadly divided into three stages, including information and communications technology (ICT) connectivity, ICT usability, and ICT accessibility. It is critical for managers to make non-static policies to bridge the digital divide between various groups. The widening digital divide could cause young people to be excluded from the labor market, and because they are missing out on digital business education opportunities, it will affect national sustainable development [27]. Digital participation presents an unequal trend, and digital technologies provide the unemployed with a gig economy, which exacerbates labor distortions [28]. Digital skills have increased the probability of employment for some people, but the digital divide has led to a declining employment status for disadvantaged people such as women and the elderly [29]. The popularization of digital technology has narrowed the digital divide between the young and the elderly, further reducing income inequality across age groups [30].

After consideration of the above literature, it is clear that labor misallocation and digital divide issues still exist in Chinese sustainable transformation. Labor misallocation was not only affected by issues such as market segmentation, wage differentials, and government intervention, but it was also affected by the dynamic digital divide. Existing research highlights digital technologies as essential tools for improving green productivity. Advancement in ICT has brought along the digital divide among populations, while few researches have focused on the relationship between the digital divide and pollution emissions. In addition, production factors no longer rely on regular transportation facilities for movement. The Internet has become the primary driver for employment information dissemination. As a result, labor misallocation has been greatly impacted by the digital divide. What role does the digital divide play in the relationship between labor misallocation and

carbon emissions? Credible results are not given by academics, so it is a meaningful topic to research. Drawing on existing research, this paper incorporated the quantified digital divide into an empirical model, identifying the digital spillovers of labor misallocation on carbon emissions.

3. Methodology and Data

3.1. Quantification of the Digital Divide

Network facilities distribution differences result in a digital divide between geography, urban and rural areas, and industries. So, the broadband access ports per capita are treated as a proxy variable for regional digitization in this paper. The digital accessibility gap between the two regions was innovatively abstracted as a quantifiable digital divide by us. This approach was useful for substituting the digital divide into econometric models. Just as spatial spillover between regions was measured by a spatial matrix with geographic distance, a digital spatial matrix constructed from disparities in digital amenities assists us in recognizing digital spillovers of CO_2. The digital divide between Chinese provinces is indicated by W_{ij}^{INTER}, and the calculation formula is shown in Equation (1):

$$W_{ij}^{INTER} = \begin{cases} \frac{1}{|N_i - N_j|} & i \neq j \\ 0 & i = j \end{cases} \quad (1)$$

N_i denotes the broadband access ports per capita in province i. To ensure the sum of row elements is 1 for the difference matrix, we normalized the matrix, with the normalized matrix denoted as W_{Inter}. On the one hand, we would like to identify digital spillovers from resource misallocation on carbon emissions. On the other hand, we would need to capture the dynamics of this spillover for the selected digital divide. Thus, we calculated the digital matrix for the three selected years individually. They are the beginning, middle, and end years of the sample observation period, respectively, denoted as W_{2006}, W_{2014}, and W_{2021}.

3.2. Digital Spatial Autocorrelation

The Moran index is a suitable measurement to test digital spatial autocorrelation of variables, as shown in Equation (2):

$$I = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} W_{ij}\left(X_i - \overline{X}\right)\left(X_j - \overline{X}\right)}{S^2 \sum_{i=1}^{n}\sum_{j=1}^{n} W_{ij}} \quad (2)$$

S^2 is the sample variance calculated by $\frac{\sum_{i=1}^{n}(x_i - \overline{x})^2}{n}$. W_{ij} is the element of the spatial weight matrix. $\sum_{i=1}^{n}\sum_{j=1}^{n} W_{ij}$ denotes the sum of all spatial weights. The global Moran index ranges from -1 to 1. A value higher than zero indicates a positive autocorrelation, while a value less than zero indicates a negative autocorrelation.

3.3. Construction of the Spatial Econometric Model

Classical linear regression models fail to identify digital spatial spillovers of variables [31]. The quantized digital spatial matrix was introduced into our spatial econometric model. Spatial econometric models are categorized as spatial error models, spatial autoregressive models, and spatial Durbin models. A series of tests determined the selection of spatial econometric models. Those diagnostic test results are presented in Table 1.

Table 1. Results of the diagnostic test.

Test Items	Value	*p*-Value
LM-error	26.75	0.000
Robust LM-error	39.51	0.000
LM-lag	3.36	0.004
Robust LM-lag	16.12	0.000
Hausman test	47.63	0.000
LR-SDM-SAR	67.92	0.000
LR-SDM-SEM	64.21	0.000
LR-both-ind	84.67	0.000
LR-both-time	1434.65	0.000
Wald Test for SAR	72.91	0.000
Wald Test for SEM	67.91	0.000

The Lagrange multiplier (LM) test, including the LM-error and LM-lag statistics of both the spatial error model (SEM) and spatial autoregression (SAR) under the W^d and W^e matrices, pass the 1% significance test, so the SDM model can be selected. The Hausman test was used to determine whether to use a fixed-effects model or a random-effects model, and the W^d matrix and W^e matrix significantly passed the Hausman test, thus the fixed-effects SDM model was chosen. Further, the Wald tests by both W^d and W^e matrices were significant at the 1% level, so the original hypothesis of SDM degradation to SAR and SEM models was rejected, and the SDM model was accepted. In the end, each spatial matrix model passed the likelihood-ratio (LR) test at the 1% level, and the LR-SDM-SAR and LR-SDM-SEM tests showed that SDM could not be degraded to SAR and SEM models, and the LR-both-ind and LR-both-time tests showed that the SDM model with time-space dual fixation was superior, and was therefore chosen.

W_{Inter} is employed by us to identify digital spillovers of labor misallocation on carbon emissions in the SDM. The regression model is depicted in Equation (3):

$$CAR_{it} = \alpha + \rho W_{Inter} \times CAR_{it} + \theta_1 W_{Inter} \times LFM_{it} + \beta_1 LFM_{it} + \theta_2 W_{Inter} \times X_{it} + \beta_2 X_{it} + \mu_i + \delta_t + \varepsilon_{it} \quad (3)$$

W_{2006}, W_{2014}, and W_{2021} were substituted into the SDM model, respectively, to observe dynamic trends in digital spillovers. The model is shown in models (4), (5), and (6), respectively:

$$CAR_{it} = \alpha + \rho W_{2006} \times CAR_{it} + \theta_1 W_{2006} \times LFM_{it} + \beta_1 LFM_{it} + \theta_2 W_{2006} \times X_{it} + \beta_2 X_{it} + \mu_i + \delta_t + \varepsilon_{it} \quad (4)$$

$$CAR_{it} = \alpha + \rho W_{2014} \times CAR_{it} + \theta_1 W_{2014} \times LFM_{it} + \beta_1 LFM_{it} + \theta_2 W_{2014} \times X_{it} + \beta_2 X_{it} + \mu_i + \delta_t + \varepsilon_{it} \quad (5)$$

$$CAR_{it} = \alpha + \rho W_{2021} \times CAR_{it} + \theta_1 W_{2021} \times LFM_{it} + \beta_1 LFM_{it} + \theta_2 W_{2021} \times X_{it} + \beta_2 X_{it} + \mu_i + \delta_t + \varepsilon_{it} \quad (6)$$

CAR_{it} denotes the carbon emissions of province i in year t. LFM stands for labor misallocation index. X represents a series of provincial-level control variables. ρ is the spatial autoregressive coefficient, indicating the spillover effect based on digital space in this paper. θ is the spatial regression coefficient of the independent variable. It is the most topical because it denotes the digital spillover of independent variables to the dependent variable in this paper. β is the regression coefficient of the independent variable. μ_i controls individual fixed effects. δ_t controls time-fixed effects. ε_{it} denotes the random error term.

The coefficient θ, regressed by SDM, not only involves spatial spillovers from local explanatory variables to local provinces' explanatory variables, but also covers spatial spillovers of local explanatory variables to explanatory variables in neighboring provinces. Thus, these spatial effects regressions are inaccurate. Pace et al. [32] proposed an idea for

calculating partial derivatives. They decompose the spatial spillover effect of cross-sectional data into direct, indirect, and total effects. Elhorst et al. [33] further applied the method to panel data. So, the above model can be rewritten in the format of Equation (7):

$$Y_{it} = (I - \rho W)^{-1}(X_{it}\beta + \theta W X_{it} + \phi_i + \delta_t + \varepsilon_{it}) \tag{7}$$

Easily verified: $(I - \rho W)^{-1} = I + \rho W + \rho^2 W^2 + \rho^3 W^3 + \cdots$. Applying the partial derivation to the independent variables of the above equation gives the direct effect:

$$\frac{\partial y_i}{\partial x_{ir}} = (I - \rho W)^{-1}(I\beta_r + (W)_{ii}\theta_r) \tag{8}$$

and indirect effect:

$$\frac{\partial y_i}{\partial x_{jr}} = (I - \rho W)^{-1}\left(I\beta_r + (W)_{ij}\theta_r\right) \tag{9}$$

$$\frac{\partial y_i}{\partial x_{ir}} + \frac{\partial y_i}{\partial x_{jr}} \tag{10}$$

I is an $N \times 1$ identity matrix, and N is the number of regions. β_r is the regression coefficient of the rth explanatory variable. θ_r is the spatial lag coefficient of the rth explanatory variable. In our model, the direct effect is resource misallocation on local carbon emissions and the indirect effect is also known as a digital spatial effect, which is the impact of resource distortions in digital adjacency regions on local carbon emissions. The total effect can be regarded as the sum of direct and indirect effects.

3.4. Variables and Data Sources

Chinese provincial panel data for 2006–2021 were selected. In this paper, data from the Tibet, Hong Kong, Macao, and Taiwan regions were excluded to ensure the robustness of regression conclusions. The total number of provincial equilibrium panel observations is finally obtained for 30 provinces, with a total of 480 observations.

3.4.1. Measurement of the Labor Misallocation

We measure regional labor misallocation according to the theory of Hsieh et al. [11]. This paper assumes a competitive market with factor misallocation that is captured by factor input prices. The absolute labor misallocation coefficient γ_{Li} is as in Equation (11):

$$\gamma_{Li} = \frac{1}{1 + \tau_{Li}} \tag{11}$$

where τ_{Li} represents the labor misallocation that already exists in region i. For instance, when $\tau_{Li} = 0$ and $\gamma_{Li} = 1$, then there is no labor misallocation in the region at all. $\tau_{Ki} \neq 0$ indicates that wages are above or below the normal value, causing labor misallocation. Absolute misallocation coefficients indicate the absence of misallocation of factor prices in area i. However, absolute misallocation coefficients cannot be measured by actual data. Under optimal production conditions of perfectly competitive markets, absolute factor distortions cause factor prices to rise by the same percentage, but the relative prices of factors remain unchanged, so relative factor price is decisive for factor allocation, not absolute price.

Therefore, we employ the relative coefficient $\hat{\gamma}$ to express the factor misallocation in region i; it reflects relative information on factor cost, and the relative coefficients can be evaluated by the actual observed data. The calculation is shown in Equation (12):

$$\hat{\gamma}_{Li} = \left(\frac{L_i}{L}\right) \Big/ \left(\frac{s_i \beta_{Li}}{\beta_L}\right) \tag{12}$$

$s_i = \frac{p_i y_i}{Y}$ denotes the proportion in area i to overall output Y. According to Euler's theorem, $Y = \sum_{i=1}^{N} p_i y_i$, the final social product is the denominated matter in the economy, $p_i = 1$. $\beta_L = \sum_{i=1}^{N} s_i \beta_{Li}$ denotes labor output weights, $\frac{L_i}{L}$ denotes the actual proportion of the labor in area i to the total labor, and $\frac{s_i \beta_{Li}}{\beta_L}$ can be further interpreted as the proportion of labor in region i. When $\hat{\gamma}_{Li} > 1$, production in region i overinvests in labor factors; conversely, when $\hat{\gamma}_{Li} < 1$, the region underutilizes labor factors.

Before calculating $\hat{\gamma}_{Li}$, we still need to estimate the factor output elasticities β_K and β_L for capital and labor, respectively. In this paper, we used the Solow residual method, giving an assumption that each region has a Cobb-Douglas production function with constant returns to scale, referring to Equation (13):

$$Y_{it} = A K_{it}^{\beta_{Ki}} L_{it}^{1-\beta_{Ki}} \tag{13}$$

$$ln(Y_{it}/L_{it}) = lnA + \beta_{Ki} ln(K_{it}/L_{it}) + \mu_i + \lambda_t + \varepsilon_{it} \tag{14}$$

Y_{it} denotes the output of region i in year t, when the gross domestic product (GDP) was eliminated by inflation, using 2006 as the base period. Labor input L_{it} is given in terms of regional employment. Capital input K_{it} is given in terms of the annual fixed capital stock of each region. We construed the regression model (14) that introduces individual dummy variables and interaction terms between dummy variables and explanatory variables with variable coefficients. This approach avoids intergroup correlation problems. Moreover, regression estimation was performed using the least-squares dummy variable method. After obtaining β_{Ki} and β_{Li} for each province, the labor misallocation index for each province was calculated by Equation (12).

3.4.2. Measurement of Carbon Emission

Chinese provinces lack a regional statistical system on carbon emissions. The Intergovernmental Panel on Climate Change (IPCC) has given a series of conversion factors to measure CO_2 emissions for mainstream energy consumption. This set of factors was multiplied by the consumption of seven dominant fossil energy sources such as crude, coal, gas, etc. The regional carbon emission is the sum of carbon emissions from the seven energy sources.

3.4.3. Control Variables

A total of five control variables were introduced into our regression model:

Economic development $(Pergdp)$—This variable, represented by GDP per capita, serves as a proxy for economic development. Given that nearly all economically productive activities emit carbon dioxide, GDP per capita is employed to reflect the level of economic advancement within a region.

Environmental governance intensity (Env)—denoted by investment in environmental governance, it plays a crucial role in curbing carbon emissions, given the current focus on reducing carbon emissions as a primary environmental goal [34]. This variable is selected as a proxy for the intensity of environmental governance efforts, with higher investments indicative of stronger governance measures aimed at reducing carbon emissions.

Industrial structural upgrading (Ind)—industrial structural upgrading signifies the transition from energy-intensive production methods to knowledge-intensive production processes, thereby contributing to a reduction in carbon emissions [35]. This variable is operationalized using the ratio of the secondary to tertiary sector's added value, where a higher ratio indicates a more advanced industrial structure with reduced carbon intensity.

Technological innovation (Ino), as measured by the number of patents for inventions, is vital for enhancing productivity, a key factor in reducing carbon emissions [36]. This variable serves as a proxy for the level of technological innovation within a region, with higher patent numbers indicating greater innovation potential and, consequently, enhanced capabilities for carbon emission reduction.

Foreign trade development (*Open*), represented by the total value of imported and exported goods, influences local energy consumption through trade interactions, thereby impacting carbon emissions. This variable captures the extent of foreign trade activities within a region, with higher trade volumes indicating greater integration into global markets and potential for emissions reduction through trade-related mechanisms.

Descriptive statistics results are presented in Table 2.

Table 2. Descriptive statistical results.

Variable	Obs.	Mean	Std.	Min	Max
CAR	480	10.08	0.794	7.429	12.20
LFM	480	0.42	0.441	0.005	3.30
Pergdp	480	12,216	7838	3371	48,075
Env	480	152.70	142.8	3.510	1263
Ind	480	7.59	0.782	5.624	8.86
Ino	480	9.07	1.614	4.369	12.40
Open	480	0.29	0.345	0.008	1.72

3.4.4. Multiple Collinearity and Correlation Tests

The selected variables' variance inflation factor and the multiple covariance test results are shown in Table 3. The significance of correlations between variables is basically less than 0.001, and the variance inflation factor is much less than 10. This indicates that the correlation of variables can be ignored, and the correlation between control variables will not bias the regression results.

Table 3. Results of the multiple collinearity and correlation tests.

	VIF	CAR	LFM	Pergdp	Env	Ind	Ino	Open
CAR		1						
LFM	3.39	−0.22 ***	1					
Pergdp	5.64	−0.09 **	0.76 ***	1				
Env	1.94	0.47 ***	−0.02	0.28 ***	1			
Ind	2.49	0.69 ***	−0.16 ***	−0.11 **	0.48 ***	1		
Ino	3.35	0.46 ***	0.24 ***	0.49 ***	0.64 ***	0.59 ***	1	
Open	4.18	−0.08 *	0.79 ***	0.82 ***	0.16 ***	0.03	0.43 ***	1
Mean VIF	3.50							

Note: *, **, and *** represent the significance at 10%, 5%, and 1% levels, respectively.

4. Empirical Results

4.1. Evolution of the Digital Divide

The digital facilities gap between regions was abstracted as a quantifiable digital divide. Building on this idea, it could be called a digital adjacency province, in that two provinces have similar levels of digital facilities. Figures 1–3 shows the digital divide of selected years. The pixel points in the heatmap represent the difference in the number of broadband ports per capita between the two locations. So, the broader the spread of digital facilities between different regions, the darker the color of the pixel dots will be. The 30 provinces from east to west have been ordered geographically, so it is intuitive to watch the spatial characteristics of the digital divide.

In 2006, there was a very clear digital divide between Beijing, Shanghai, and the rest of the provinces. The digitization of each province was in a state of underdevelopment. Tianjin, Zhejiang, and Jiangsu pixels are almost gray; this suggests an ambiguous digital divide between these three provinces and others, which could stem from the spillover of the digital divide, because Tianjin borders Beijing, and Shanghai borders Zhejiang and Jiangsu, respectively.

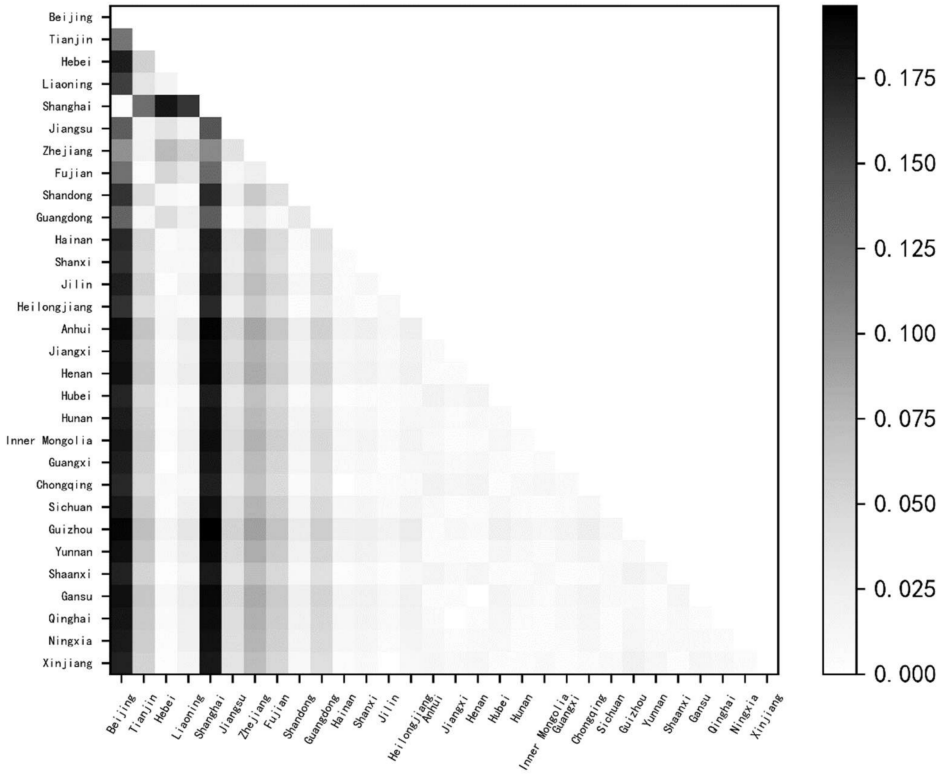


Figure 1. The digital divide in 2006.

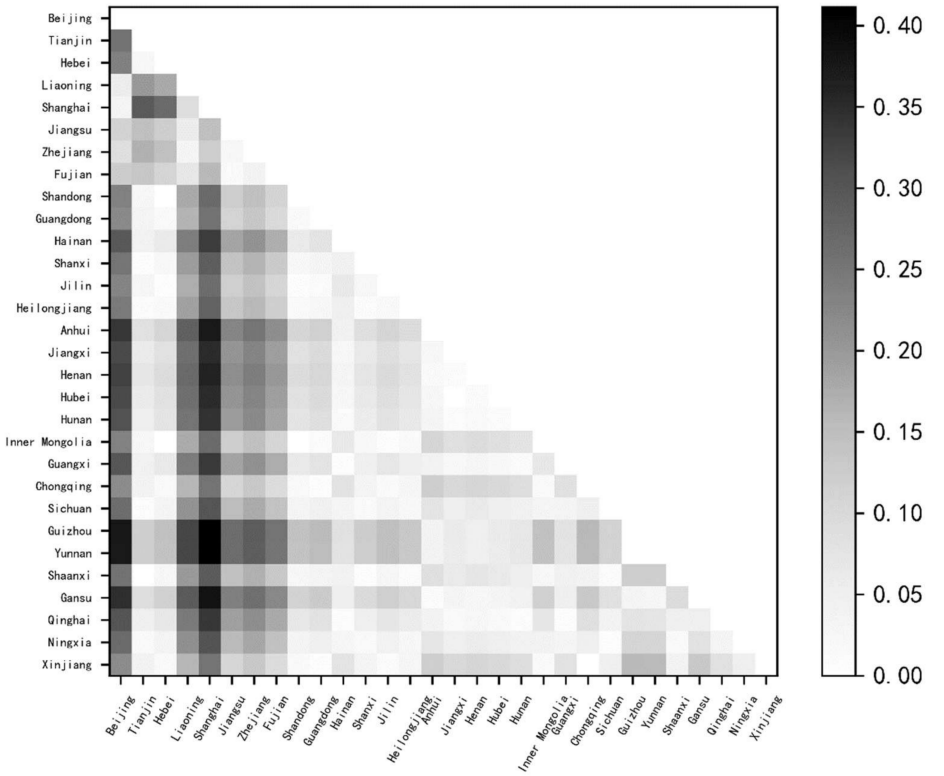


Figure 2. The digital divide in 2014.

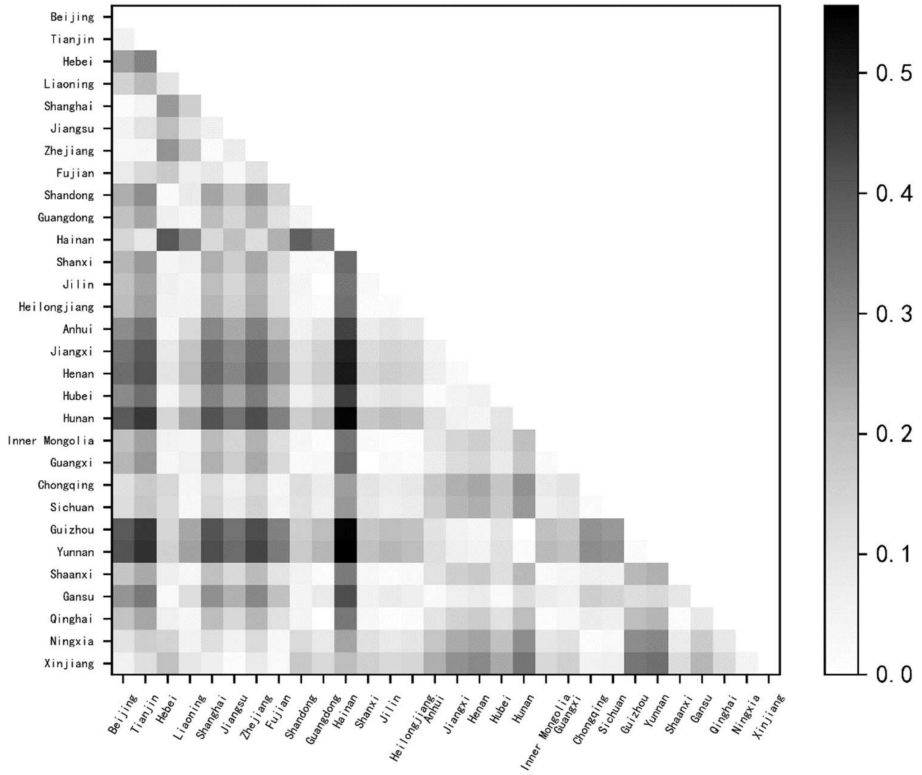


Figure 3. The digital divide in 2021.

By 2014, there is still a digital divide between Beijing, Shanghai, and other provinces, but extreme black pixels are reduced. There are significantly more gray pixels in Liaoning, Jiangsu, Zhejiang, and Fujian, because they are largely neighboring Beijing and Shanghai, which further suggests that there are some spatial spillovers across the digital divide. The pixels in the western provinces also change from basic white to large areas of gray, but these provinces are largely located in the southwest region of China.

In 2021, extremely black pixels no longer exist in the graph. More noticeable is the presence of many different concentrations of gray pixels in the figure. Moreover, the digitization of southwestern provinces such as Guangxi, Guizhou, Sichuan, and Chongqing is significantly more similar to that of eastern provinces. To our surprise, there is a digital divide between Hainan and most of the provinces. This could be due to Hainan's low population but high tourism industry, while digital facilities are well-developed.

From 2006 to 2021, there is a trend of the digital divide in China spreading from the east to the west. It cannot be denied that China has made progress in building its digital facilities, but the digital divide has indeed been a problem in the development of Chinese digitization. We further hypothesize that factors contributing to the digital divide not only include physical conditions such as geography and space, but also social conditions such as economics and policy. Thus, it is imperative to incorporate the digital divide into econometric modeling when analyzing carbon emissions.

4.2. Autocorrelation of Carbon Emission

Calculated by Equation (2), the digital spatial autocorrelation of carbon emissions and labor misallocation is shown in Table 4. The Moran index of carbon emissions has basically remained around 0.3 during the sample period, and the significance levels are mostly below 1%. This proves that carbon emissions have a significant digital spatial correlation. Besides, labor misallocation has significant digital spatial autocorrelation, and its Moran index was maintained at around 0.2 during the sample period.

Table 4. Global Moran indexes of carbon emissions and labor misallocation.

Moran'I Year	Carbon Emission	Labor Misallocation
2006	0.302 ***	0.169 ***
2007	0.277 ***	0.186 ***
2008	0.319 ***	0.189 ***
2009	0.334 ***	0.188 ***
2010	0.338 ***	0.184 ***
2011	0.348 ***	0.179 ***
2012	0.355 ***	0.178 ***
2013	0.345 ***	0.202 ***
2014	0.335 ***	0.203 ***
2015	0.330 ***	0.203 ***
2016	0.322 ***	0.199 ***
2017	0.295 ***	0.196 ***
2018	0.310 ***	0.190 ***
2019	0.298 ***	0.179 ***
2020	0.147 *	0.144 **
2021	0.102 *	0.141 **

Note: *, **, and *** represent the significance at 10%, 5%, and 1% levels, respectively.

4.3. Spatial Benchmark Regression Results

Benchmark regression results are presented in Table 5. The time-individual double-fixed effects regression results in column (1) point out that labor misallocation can significantly increase carbon emissions without considering spatial and digital spillovers. Labor misallocation directly results in research and development (R&D) workforce distortions and reduced consumer desire, which in turn hinders productivity improvements and ultimately leads to additional carbon emissions [37]. Using the geographic distance matrix, spatial Durbin model regression results are presented in column (2). The regression coefficients and spatial coefficients of its labor misallocation are both significantly positive, which suggests that carbon emissions suffer not only from the positive effects of labor misallocation in local areas, but also from the positive spatial spillover of labor misallocation. Labor has mobility itself, and distorted labor causes misallocation of production, innovation, and energy consumption in other regions, hindering green production [38]. In column (3), the direct and digital spatial effects of labor misallocation on carbon emissions are both significantly positive. This suggests that labor misallocation significantly increases local carbon emissions in the digital divide. In addition, there is an online spillover mechanism for labor misallocation, which significantly increases carbon emissions in the digital adjacency regions.

Table 5. Results of benchmark regression.

Variable: CAR	(1)	(2)	(3)
LFM	0.375 *** (0.05)	0.417 *** (0.08)	0.344 *** (0.07)
Pergdp	−7.430 (0.68)	−0.112 (0.12)	−0.069 (0.18)
Env	−0.251 ** (0.18)	−0.023 (0.21)	−0.012 (0.11)
Ind	0.830 *** (0.15)	0.852 ** (0.33)	0.842 *** (0.31)
Ino	0.083 *** (0.02)	0.081 ** (0.03)	0.078 ** (0.03)
Open	0.170 ** (0.08)	0.090 (0.16)	0.146 (0.15)

Table 5. *Cont.*

Variable: CAR	(1)	(2)	(3)
_cons	2.955 ***		
	(1.14)		
W×LFM		1.176 **	0.850 ***
		(0.52)	(0.30)
ρ		−0.071	−0.346 **
		(0.15)	(0.14)
Ind. fixed effect	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes
R^2	0.975	0.392	0.340
Obs.	480	480	480

Note: The *t*-statistics or z-statistics are reported in parentheses; *, **, and *** represent the significance at 10%, 5%, and 1% levels, respectively.

4.4. Regression Results for the Selected Digital Divide

In the selected year's digital divide matrix, the result of SDM regressions is presented in Table 6. The regression coefficient of labor misallocation on local carbon emissions is significantly positive. In the three digital divide matrices, local labor misallocation rises by one standard deviation, and local regions' carbon emissions were upgraded by 32.5%, 33.6%, and 34.2%, respectively. In the digital divide in 2006, observation column (1), the digital spatial coefficients of labor misallocation on local carbon emissions in digital adjacency provinces does not pass the significance test. This indicates that local carbon emissions at this time will not be affected by digital spillovers from labor misallocation. With the digital divides in 2014 and 2021, respectively, labor misallocation in digital adjacent provinces can significantly increase local carbon emissions, as displayed in columns (2) and (3). On the one hand, the significance becomes stronger. On the other hand, the regression coefficients become higher. With a wider digital divide, labor misallocation in digital adjacent provinces has an increasing impact on local carbon emissions. The estimation results for the geographic matrix are similar to the results using the digital matrix. This is reflected in the main results, and spatial effects were both significantly positive.

Table 6. Regression results with selected year's digital divide matrix.

Variable: CAR	(1)	(2)	(3)
	W_{2006}	W_{2014}	W_{2021}
LFM	0.325 ***	0.336 ***	0.342 ***
	(3.639)	(3.912)	(4.515)
Pergdp	−0.189	−0.358	−0.297
	(−0.143)	(−0.294)	(−0.260)
Env	−0.232	−0.023	−0.231
	(−1.458)	(−1.579)	(−1.444)
Ind	0.781 **	0.829 **	0.871 ***
	(2.463)	(2.571)	(2.698)
Ino	0.068 *	0.070 *	0.067 *
	(1.813)	(1.906)	(1.841)
Open	0.142	0.188	0.120
	(0.934)	(1.354)	(0.672)
W×LFM	0.361	0.593 *	0.603 ***
	(0.231)	(0.321)	(0.209)
_cons	0.361	0.593 *	0.603 ***
	(1.561)	(1.845)	(2.879)
ρ	−0.211 *	−0.322 ***	−0.101
	(−1.929)	(−2.964)	(−0.905)

Table 6. *Cont.*

Variable: CAR	(1)	(2)	(3)
	W_{2006}	W_{2014}	W_{2021}
Ind. fixed effect	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes
R^2	0.344	0.324	0.343
Obs.	480	480	480

Note: The z-statistics are reported in parentheses; *, **, and *** represent the significance at 10%, 5%, and 1% levels, respectively.

The findings could be interpreted as follows. Internet technology breaks traditional geospatial boundaries and improves the ability to integrate resources [39]. Economically developed Chinese provinces usually have a well-developed Internet infrastructure. Geographical distribution is approximate to Internet facilities distribution, so there is a similarity between the effect of labor misallocation on carbon emissions under the two matrices. Although the SDM regression results suggest that carbon emissions would be subject to spillovers from digital adjacent regions as described above, its accuracy is still limited by the model itself. The SDM regression coefficients incorporate spatial spillovers from the dependent variable. We further decompose the effect of labor misallocation on carbon emissions into indirect effect, direct effect, and total effect.

From the row of direct effects in Table 7, labor misallocation expresses a prominently positive effect on local carbon emission, and each standard deviation increase in labor misallocation will add about 30% to local carbon emissions. There was no significant fluctuation in the direct effect of the labor misallocation within the row of indirect effects in Table 7. Not only did the scale of these three coefficients appear to increase, but so did the significance level of the indirect effect. These differences derive from the fact that we altered the digital space matrices in the three regression models.

Table 7. Decomposition of digital spillovers.

Dependent Variable: CAR	(1)	(2)	(3)
	W_{2006}	W_{2014}	W_{2021}
Direct effect	0.315 ***	0.304 ***	0.336 ***
	(4.802)	(4.518)	(5.964)
Indirect effect	0.248 *	0.395 **	0.521 ***
	(1.908)	(2.095)	(4.001)
Total effect	0.563 ***	0.699 ***	0.857 ***
	(5.302)	(4.449)	(6.711)
Control variable	Yes	Yes	Yes
Time effect fixed	Yes	Yes	Yes
Ind. effect fixed	Yes	Yes	Yes
R^2	0.344	0.324	0.343
Obs.	480	480	480

Note: The z-statistics are reported in parentheses; *, **, and *** represent the significance at 10%, 5%, and 1% levels, respectively.

Accordingly, this paper contends that the deepening digital divide has increased labor misallocation spillovers in digital adjacent regions, further expanding local carbon emissions. The digital economy improves carbon efficiency by reducing labor misallocation [40]. Labor misallocation led to an external flow of innovative capacity, and this distortionary effect was amplified by the growing digital divide. This prevents the local transition from energy-intensive to knowledge-intensive economic growth, which subsequently results in higher carbon emissions. The total effect of digital spatial matrices was 0.563, 0.699, and 0.857 for 2006, 2014, and 2021, respectively, all of which passed significance tests. However, the digital economy also has a nonlinear effect on carbon reduction. At the same time, the

suppression effect of digital economy on carbon emissions was affected by the "digital divide" in the labor market [41]. The digital divide diminishes the restraining effect of digital economy on carbon emissions [42]. By decomposing the total effect, we attribute the amplifying effect of labor misallocation on local carbon emissions to the deepening of the digital divide.

4.5. Robustness Analyses

4.5.1. Replacement of the Dependent Variable

The original core explanatory variable, the labor misallocation index, is substituted with the labor distortion coefficient, thus completing the initial robustness test. The price signal is an essential reference for market participants to allocate resources. When factor allocation is distorted, the referential value of market prices is weakened, and the actual payoff of labor deviates relative to the ideal payoff. Accordingly, price deviations in labor factor compensation can reflect labor misallocation to some degree. This paper draws on Brandt et al. [43], and the core computational process is shown in Equation (15):

$$dist_L = \beta_{Li} \frac{p_i y_i}{w_i L_i} - 1 \tag{15}$$

$p_i y_i$ is the gross product of the ith province, which this paper quantifies with regional GDP. w_i is the regional labor price, interpreted as wage level. This paper quantifies this with statistics on the average wage of urban employed persons. β_{Li} is the production elasticity of labor. L_i is the regional labor level, which this paper quantifies with the number of people employed in cities. $dist_L$ denotes the coefficient of labor distortion. When it equals 0, the factor payoff of labor is equal to the marginal output of the factor and the expected payoff, optimizing resource allocation theoretically. If it deviates relative to zero, it indicates a distortion is present in factor allocation.

The regression results after replacing the explanatory variables are shown in Table 8. The main effect of labor distortions on carbon emissions remains significantly positive, and the value remains stable. Labor distortions also have a significant positive effect on carbon emissions, and the trend is widening as the digital divide deepens. The process above illustrates the robustness of our benchmark regression results to some extent.

Table 8. Regression results of replacing labor misallocation.

Variable: *CAR*	**(1)**	**(2)**	**(3)**	**(4)**
	W_{Inter}	W_{2006}	W_{2014}	W_{2021}
LFM_sub	1.342 **	1.362 ***	1.449 ***	1.332 ***
	(2.082)	(5.227)	(5.544)	(4.983)
Pergdp	−0.887	−0.895	−0.102 *	−0.725
	(−0.731)	(−1.599)	(−1.823)	(−1.268)
Env	−0.025	−0.021 ***	−0.024 ***	−0.025 ***
	(−1.520)	(−3.100)	(−3.504)	(−3.634)
Ind	0.686 **	0.639 ***	0.622 ***	0.772 ***
	(2.423)	(6.733)	(6.421)	(7.248)
Ino	0.091 **	0.084 ***	0.107 ***	0.093 ***
	(2.165)	(3.790)	(4.821)	(4.095)
Open	0.146	−0.002	0.192 **	0.150 *
	(0.730)	(−0.023)	(2.278)	(1.763)
W×LFM_sub	1.608 **	2.218 ***	−1.571 ***	1.491 **
	(2.209)	(4.063)	(−2.890)	(2.129)
ρ	−0.204	−0.223 ***	−0.195 ***	0.046
	(−1.420)	(−2.832)	(−2.882)	(0.555)

Table 8. *Cont.*

Variable: *CAR*	(1)	(2)	(3)	(4)
	W_{Inter}	W_{2006}	W_{2014}	W_{2021}
Ind. fixed effect	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes
R^2	0.429	0.398	0.392	0.414
Obs.	480	480	480	480

Note: The z-statistics are reported in parentheses; *, **, and *** represent the significance at 10%, 5%, and 1% levels, respectively.

4.5.2. Alleviation of Endogenous

Because carbon emissions are a result of economic production, carbon emissions do not inversely interfere with resource allocation in the economic market. While there is no obvious reverse causation problem in logic, this article cannot exclude a correlation between the core explanatory variables and the error term. We speculate that there are two main reasons that reduce the accuracy of benchmark regression results. First, there are still unobservable factors interfering with the effect of labor misallocation on carbon emissions. For example, the province's talent introduction policy affects not only the allocation of labor markets, but also the carbon emissions of production upgrading resulting from labor aggregation. This omitted policy variable biases the estimates. Second, statistical errors and omissions are inherent in the data used to measure labor misallocation, including GDP, fixed assets, and employment numbers. Referring to Wang et al. [44], the generalized spatial two-stage least squares (GS2SLS) model is chosen to mitigate the endogeneity, as well as heteroskedasticity problems, in spatial econometric models.

Instrumental variables remain the GS2SLS model's central solution to SDM endogeneity. Unlike the instrumental variables of two-stage least squares (IV2SLS), when using GS2SLS for parameter estimation in spatial panel regression, normally the multistage spatial lag terms of explanatory variables are selected as instrumental variables for the dependent variable; as the matrix of instrumental variables $[X, WX, W^2X, \cdots, W^\gamma X]$, γ refers to the spatial lag order. The first-order spatial lag terms of the explanatory variables are already present on the right side of the SDM model selected for this paper, so the instrumental variable order is identified as 3 to avoid the weak instrumental variable problem. GS2SLS estimation results with the selected 3-year digital matrix are shown in Table 9. The main effect of labor misallocation on carbon emissions remains significant, further supporting the robustness of the benchmark regression.

Table 9. Results of GS2SLS.

Variable: CAR	(1)	(2)	(3)	(4)
	W_{Inter}	W_{2006}	W_{2014}	W_{2021}
LFM	0.284 ***	0.327 ***	0.330 ***	0.314 ***
	(0.061)	(0.061)	(0.061)	(0.060)
ρ	−0.204 **	−0.223 ***	−0.195 ***	0.046 **
	(0.144)	(0.079)	(0.068)	(0.083)
Ind. fixed effect	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes
R^2	0.535	0.113	0.321	0.130
Obs.	480	480	480	480

Note: The z-statistics are reported in parentheses; *, **, and *** represent the significance at 10%, 5%, and 1% levels, respectively.

4.6. The Threshold Effect of the Digital Divide

Though we identify a positive digital spatial spillover effect of labor misallocation on carbon emissions, it is not a recommendation to shut down the Internet connection; there is a certain positive impact of Internet infrastructure development on the transformation of

economic growth. Previously, in the dynamic digital divide regression results, the impact of labor misallocation on carbon emissions is exacerbated by a deepening digital divide. While the digital divide is inevitably emerging in digital transformation, it is necessary for identification of digital divide thresholds to mitigate carbon emissions due to labor misallocation. The threshold model can help us identify the severity of the digital divide, but it also fails to import digital divides between regions. To overcome this shortcoming, this paper calculated the deviation of the number of broadband access ports per capita in each province. This deviation reflects each province's degree of gap from the national average for digital facilities. It can be further recognized as the digital divide between the provinces and the national average. Larger deviation values reflect a wider gap between the digitization of a province and the national average, which means a more severe digital divide. We constructed threshold models to estimate the above problems. Refer to model (16) for details:

$$CAR_{it} = \pi_0 + \pi_1 LM_{it} * I(Diggap \leq \xi) + \pi_2 LM_{it} * I(Diggap > \xi) + \pi_3 X_{it} + \varepsilon_{it} \quad (16)$$

CAR_{it} denotes regional carbon emission. LM_{it} is labor misallocation. I denotes the schematic function. Dig_{gap} denotes the digital divide. The deviation is calculated as the ratio of the number of Internet broadband access ports per capita in each province to the national average for the current period. Table 10 demonstrates the results of the diagnostic tests for single and double thresholds, and there is a significant single-threshold effect for the digital divide, with a corresponding threshold of 0.6122, whereas the double-threshold results, with thresholds of 0.5760 and 0.7337, respectively, did not pass the significance test. Ultimately, we conclude that there is a single-threshold effect due to the digital divide between carbon emissions and labor misallocation by a series of LR statistic tests. This threshold and the regression coefficients passed the significance test. The test results are shown in Table 10 and Figure 4.

Table 10. Results of the threshold effect test.

Threshold Variable:		**Diggap**	
Thresholds Numbers	Threshold Value	F Statistic	*p*-Value
Single threshold	0.6122	66.79	0.000
Double threshold	0.5760 0.7337	31.05	0.102

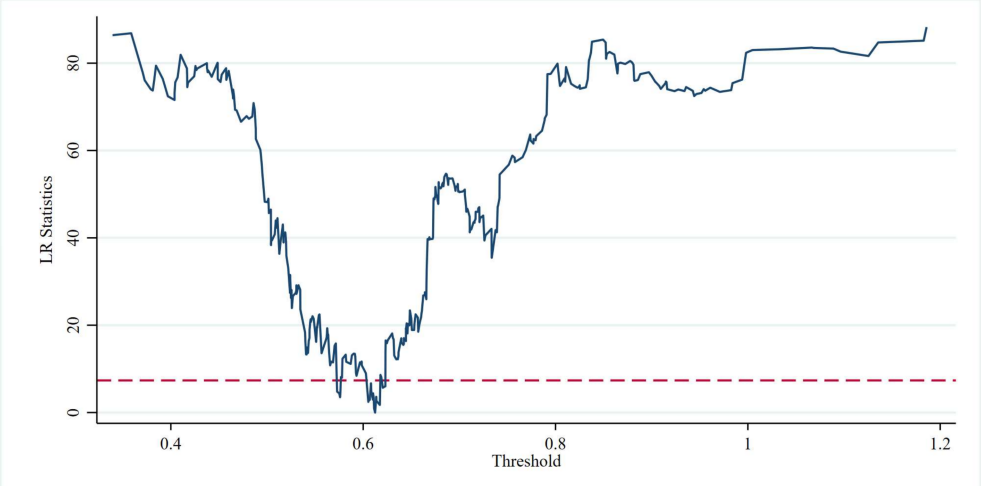


Figure 4. The LR graph of the threshold within the 95% confidence interval.

Table 11 presents regression results for the threshold effect. The regression coefficient of labor misallocation on carbon emissions is −0.357 at a digital divide index less

than the threshold (ξ = 0.6122). The labor misallocation coefficient is 0.421 when the digital divide index is greater than the threshold value. Both coefficients are significant at the 1% level, suggesting a nonlinear effect between labor misallocation and carbon emissions. When a clear digital divide has occurred, labor misallocation has exacerbated local carbon emissions.

Table 11. Estimated results of the threshold effect between CAR and LFM.

Dependent Variable: CAR	Estimation Results	Confidence Interval
LFM×I (Diggap ≤ x)	−0.357 *** (−3.52)	[−0.557, −0.158]
LFM×I (Diggap > x)	0.421 *** (6.12)	[0.286, 0.557]

Note: The *t*-statistics are reported in parentheses; *, **, and *** represent the significance at 10%, 5%, and 1% levels, respectively.

When the digital divide intensifies, the knowledge and consumption flows, which were originally undertaken by traditional media and transportation facilities, are confined to regions with advanced networks [45]. Meanwhile, high-quality labor presents a significant agglomeration effect [46]. This prevents the digital transformation of production in lagging regions, making traditional resource-concentrated economic growth exacerbate carbon emissions. Combined with the heat map, there is still a digital divide between most provinces and developed regions, which also occurs in the mid-western provinces that are slow to digital transformation.

5. Conclusions and Implications

We have collected Chinese panel data for 30 provinces from 2006 to 2021, which have been employed in this paper to analyze the trend of digital divide evolution in Chinese provinces and the digital spatial correlation of labor misallocation. The digital spillover effect of labor misallocation on carbon emissions was verified by SDM regression results. Further, we also have examined the threshold effect between the above two variables. Our research conclusions are as follows.

Firstly, according to quantified digital divide matrices, the digital divide has become broader among provinces in selected years, tending to spread from eastern to western provinces. With standardized digital divide matrices, the Moran test indicates a significant digital spatial correlation of labor misallocation.

Secondly, labor misallocation significantly amplifies local areas' carbon emissions and also enlarges the carbon emissions of digital adjacent provinces. The quantified digital divide between provinces was brought into our spatial Durbin model. After switching the selected digital divide matrices, the digital spillovers appear to have an increasing time trend. The previous results are still significant after the robustness test and endogeneity test.

Thirdly, there was a single-threshold effect of labor misallocation on carbon emissions. The digital divide is designated as a threshold variable for labor misallocation affecting carbon emissions. Labor misallocation will increase carbon emissions when the digital divide exceeds a threshold value.

The following policy recommendations in government governance and sustainable development can be derived from the above conclusions.

Firstly, provincial digital resources should be allocated rationally to narrow the digital divide. It can avoid inequitable development caused by the digital divide. It is an essential driver of sustainable economic growth to integrate real economy and digital technology. Local governments should prioritize the improvement of digital infrastructure in rural, underdeveloped areas. Implementing an inclusive training program in digital technology contributed to improving various social groups' capacity in the perception and application of digital technology, leveraging digital facilities' shared capabilities to promote equalization of opportunities offered by digitization.

Secondly, regional managers should guide labor mobility across regions and industries, taking into account market demand, and weakening the impact of digital transformation on low-income groups through digital skills training. Policymakers ought to guide the widespread application of digital technologies across all groups, thereby creating more employment opportunities in the digital sphere, perfecting digital industrial zones to assure digital transformation. Industries should foster cooperation with educational institutions, ensuring education systems better meet the market demand for digital skills.

Finally, as carbon emissions in Chinese provinces are cyber-spatially correlated, online platforms can be set up to manage pollutant emissions across regions. Regulators should encourage firms to adopt low-carbon technologies and innovations through mechanisms such as online markets. Relevant policies ought to incline towards sustainable business operations, supporting development in areas such as renewable energy, clean technology, and environmental services.

Although this paper has demonstrated that there is a digital spillover effect of labor misallocation on carbon emissions, there are still some limitations in the conclusions, which may also be a direction for future research. Firstly, the generalization of the methodology for quantifying the digital divide could be further improved. The digital divide could be categorized by population categories in more detail, for instance, the total population or the labor population. Secondly, digital interactions between countries represent a new carbon spillover pathway. This will provide new thoughts on global green governance. Finally, using city-level labor force data: The digital connection between labor misallocation and carbon emissions could be more accurate due to the increased sample size.

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