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Research on the Impact of Digital Economy Policies on Regional Economic Growth from an Econometric Model Perspective

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Abstract. To accurately assess the effects of digital economy policies on economic growth, this study conducted experiments using benchmark regression, heterogeneity analysis, and robustness tests, comparing the performance of the traditional DID and STW-DID algorithms. Data simulations were conducted to validate the results. The benchmark regression results show that the traditional DID algorithm estimated a policy effect coefficient of 0.032 (5% significance) with an adjusted R^2 of 0.612. The STW-DID algorithm improved the coefficient to 0.045 (1% significance), with an adjusted R^2 of 0.735 and reduced the residual sum of squares from 0.892 to 0.547. Simulation data confirmed that spatiotemporal weighting significantly improved the explanatory power and fitting accuracy of the model. Heterogeneity analysis simulations show that the policy coefficient for the eastern region (0.058, 1% significance) is higher than that for the central (0.039, 5% significance) and western regions (0.021, 10% significance). The coefficient for the high-base group (0.052, 1% significance) was 2.7 times that of the low-base group (0.019, 10% significance). Robustness tests show that the average coefficient across 1,000 placebo simulations is -0.002, with only 3.2% of the coefficients exceeding 0.03. The STW-DID coefficient remains stable after replacing variables and adding control variables (0.041 and 0.043, both at 1% significance), validating the conclusions and providing a basis for policy optimization.

Keywords: Digital Economy Policy, Difference-In-Difference (DID), STW-DID Algorithm, Heterogeneity Analysis, Robustness Test

1. Introduction

The digital economy has become a core driver of global economic growth, and governments worldwide have introduced targeted digital economy policies. However, regional economic growth varies significantly, and the effectiveness of such policies requires systematic verification across regions. Traditional econometric models (such as the standard difference-in-difference (DID) model) have inherent limitations in evaluating the effects of policies. They often ignore the spatiotemporal heterogeneity of policy impacts and fail to capture the dynamic characteristics of policy effects across regions and over time. This technical shortcoming undermines the accuracy of policy effect

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estimates, and the integration of advanced computer algorithms is urgently needed to enhance the scientific rigor of the related research.

Existing research has explored the relationship between digital economy policies and economic growth, primarily using linear regression and basic DID models. However, most studies have overlooked the spatial correlation between regions and the time-decay characteristics of policy effects [1]. While domestic research has focused on regional disparities in China, it still relies on traditional econometric frameworks and lacks innovation in algorithmic design for integrating spatiotemporal features of the data. A comprehensive review of existing research reveals two core gaps: first, the failure to effectively construct a modeling method for the spatiotemporal heterogeneity of policy effects; and second, the lack of integration between computer algorithmic thinking and traditional econometric analysis, which limits the accuracy of policy effect assessments [2]. To fill the above gaps, this study designs an innovative spatiotemporal weighted double difference (STW-DID) algorithm that integrates spatial weights based on economic distance and time weights based on exponential decay into the traditional DID framework. The core objectives of this study are as follows: (1) improve the accuracy of estimating the effects of digital economy policies by capturing spatiotemporal heterogeneity; (2) conduct empirical simulations using provincial panel data to verify the regional heterogeneity of policy impacts; and (3) provide algorithmic support and data-driven references for optimizing regional digital economy policy formulation. This study not only enriches the technical tool library for evaluating policy effects in the digital economy field but also provides practical guidance for narrowing regional economic development gaps through precise policy intervention.

2. Spatiotemporal Weighted Double Difference-in-Difference (STW-DID) algorithm

2.1. Algorithm design principle

The traditional Differential Difference (DID) algorithm assumes a uniform distribution of policy effects in space and time. However, this does not consider the effects of interregional economic linkages on policy transfer and does not account for the dynamic development of policy impacts over time, leading to biased evaluations of policies in the digital economy [3]. To deal with this problem, a dual-dimension weighting mechanism is introduced: in space, weights are constructed based on regional economic gradients and geographical linkages; in temporal dimensions, weights are designed based on diminishing marginal effects of policies to capture the temporal nature of policy effects [4]. This dual-weighting method is integrated into the DID model to accurately estimate the average treatment effect and heterogeneous effect of digital economic policies, providing a more realistic method for evaluating regional policy effects.

2.2. Algorithm mathematical model construction

First, we construct an extended basic DID model, introducing a coefficient on regional economic base variation to correct for individual fixed effects [5]. The model is as follows: Here, Y_{it} is the per capita GDP growth rate of region i in period t, E_{i0} is the mean per capita GDP of region i before the implementation of the policy, which characterizes the region's initial economic foundation, β_0 is the coefficient on the effect of the basic policy, μ_i is the individual fixed effect, and $\varepsilon_{it} \sim N\left(0, \sigma^2\right)$ is the random error term.

$$Y_{it} = \alpha + \beta_0 \text{ Treat }_i \cdot \text{ Post }_t + \gamma X_{it} + \delta E_{i0} + \mu_i + \varepsilon_{it} \tag{1}$$

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In constructing spatial weights, we move beyond the single dimension of economic distance and integrate economic relevance with geographic proximity. The composite spatial weights are defined as follows: GD_{ij} is the geographic distance between regions i and j (unit: km), $TRADE_{ij}$ is the average annual trade volume between the two regions in the previous period (unit: 100 million yuan), θ_1 and θ_2 are weight distribution coefficients, satisfying $\theta_1 + \theta_2 = 1$. The optimal values were determined using a particle swarm optimization algorithm to comprehensively reflect the interactive relationships between regions.

$$W_{ij} = \theta_1 \cdot \frac{TRADE_{ij}}{|GDP_i - GDP_j|} + \theta_2 \cdot \frac{1}{\ln(1+GD_{ij})} \tag{2}$$

The spatial weight matrix was standardized to eliminate the influence of regional-scale differences. The standardization formula is as follows, ensuring that the sum of the weights in each row is 1 to avoid estimation bias caused by excessive weight concentration.

$$\hat{W}_{ij} = \frac{W_{ij}}{\sum_{j=1}^{n} W_{ij}} \left(i = 1,2,\ldots,n\right) \tag{3}$$

The time weight design introduces the dual-stage characteristics of policy adaptation period and decay period, as shown below. t_0 is the policy implementation time, t_1 is the end time of the policy adaptation period (set as the second year after the policy implementation), λ_1 is the increasing coefficient of the adaptation period effect, and λ_2 is the decreasing coefficient of the decay period effect [6]. The optimal parameters are determined through cross-validation, which better fits the actual process of policy implementation, from implementation to stability.

3. Experimental simulation design and implementation

3.1. Experimental data preparation

The experiment used panel data from 31 provinces (autonomous regions and municipalities) in China from 2010 to 2022 as the research sample. Data collection covered multiple authoritative sources. Macroeconomic data primarily come from the China Statistical Yearbook and the National Bureau of Statistics' macroeconomic database to ensure the accuracy of core indicators, such as GDP and fiscal expenditure. Digital economy-related data refer to the China Academy of Information and Communications Technology's "Digital Economy Development Report" and the annual reports released by provincial communications administration bureaus, covering key information such as Internet infrastructure and the scale of digital industries. Policy text data were obtained by searching the official websites of provincial people's governments and policy and regulatory databases [7]. The issuance time, implementation scope, and core content of provincial-level digital economy-specific policies were confirmed one by one to form a complete policy list. Variable systems are designed around the core relationship between "policy" and "growth," with a balance between comprehensiveness and specificity. The explained variable, the per capita GDP growth rate, reflects regional economic growth as a whole while mitigating the impact of population size differences on overall economic growth, making it more relevant for assessing regional development quality. The key explanatory variable is the Digital Economy Policy Interaction Term, which divides the Treatment Group Dummy Variable according to the Provincial-Level Digital Economic Policy. If a province issues a "Digital Economy Development Plan" or "Digital Economy Promotion Regulations" in the sample period, it will be assigned 1; otherwise, it will be assigned 0.

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The Policy Implementation Time Dummy Variable uses the Policy Implementation Year as a node, assigning 1 value 1 for implementation and subsequent years and 0 for years before. The selected control variables focus on non-policy factors that may affect regional economic growth. These include technological investment intensity, measured as the proportion of R&D spending per GDP; Internet penetration, measured as the number of Internet users per 100 population; external trade dependency, measured as the proportion of total imports/exports relative to GDP; and local fiscal spending intensity, expressed as a ratio of local government expenditure to GDP [8], reflecting government control over the economy. In the data preprocessing stage, multiple imputations were used to fill in some missing data from the R&D expenditure and total import and export variables. By constructing five complete datasets and taking the average, the imputation errors were reduced. All continuous variables were standardized using z-scores to eliminate interference caused by dimensional differences in the model estimation.

3.2. Experimental environment and parameter setup

High-performance computing equipment was used in the experimental hardware configuration. This processor is an Intel Core i7-12700H with a main frequency that supports 24 concurrent core threads, allowing fast matrix operations and iterative optimization of panel data. DDR5 16 GB in memory configuration at 4800 MT/s data transfer rate can meet large-scale data load and model cache requirements. The data were stored in a 1 TB SSD with a random read/write speed of over 3000 MB/s, effectively reducing the data read and storage time and ensuring efficient experimental progress [9]. A complete analytical framework was built using Python 3.9. Data cleaning relied on Pandas 1.5.3, which used its data frame structure for sample selection, missing value marking, and variable recoding. The numerical computation capabilities of NumPy 1.24.3 were combined to complete preprocessing steps, such as standardization and interpolation. Scikit-learn 1.2.2 was used to build the model training and validation pipeline, whereas Statsmodels 0.13.5, a panel data regression module, was used to perform parameter estimation and significance testing for the fixed-effect model. Matplotlib 3.7.1 and Seaborn 0.12.2 were used for visualization, generating regression coefficient comparison plots, heterogeneity analysis heat maps, and robustness test distribution plots to intuitively present the experimental results. Parameter optimization was performed by combining 5-fold cross-validation with a grid search. The time-weight function was divided into two stages: adaptation and decay. The search range of the increasing coefficient in the adaptation period was set to 0.05–0.3, and the search range of the decreasing coefficient in the decay period was set to 0.1–0.4. By traversing all parameter combinations and calculating the cross-validation error, the optimal coefficients were determined to be 0.18 and 0.25, respectively. Under this parameter combination, the model has the smallest fitting error for the temporal dynamics of policy effects; the spatial weight is composed of the economic association weight and geographical association weight. The search range of the distribution coefficients of both was 0.2 to 0.8. After grid search verification, when the economic association weight coefficient is 0.65 and the geographical association weight coefficient is 0.35, the optimal coefficients are 0.18 and 0.25, respectively. When the model is used, it can most accurately capture interregional policy spillover effects. The model estimation uses a panel fixed-effects method, controlling for both province and year fixed effects [10]. The former is used to eliminate unobservable individual differences in provincial resource endowments and industrial bases, while the latter is used to eliminate common temporal shocks, such as macroeconomic cycles and national policies, further enhancing the reliability of the estimation results.

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3.3. Experimental design

The experiment is conducted in three stages, following the logic of "benchmark validation - heterogeneity analysis - robustness testing." The first stage is a benchmark regression experiment that constructs a traditional double-difference model and a time-space weighted double-difference model. By comparing the core policy effect coefficients, statistical significance levels, and goodness-of-fit indicators of the two models, we verified the effectiveness of the time-space weighting mechanism in improving the estimation of policy effects. In the specific operation, the parameters of the two models were first estimated, and then a comparison was made from three dimensions: the size of the coefficient, whether the P value was less than 0.05 (1% or 5% significance level), and the improvement in the goodness of fit after adjustment. If the policy effect coefficient of the time-space weighted double difference model is larger, more significant, and has a better goodness of fit, it proves that the algorithm can more accurately capture the actual impact of the digital economic policies.

The second phase involved a heterogeneity analysis experiment, in which samples were grouped based on regional economic characteristics and digital infrastructure to reveal the policy's differential effects. The 31 provinces were divided into three groups according to economic region: eastern, central, and western. The eastern region includes 11 economically developed provinces, such as Beijing, Shanghai, and Guangdong; the central region includes eight provinces, such as Henan, Hubei, and Hunan; and the western region includes 12 provinces, such as Sichuan, Shaanxi, and Yunnan. Using the digital economic foundation, the national average of each province's Internet penetration rate during the sample period was used as the dividing line: provinces with an average Internet penetration rate above the average were classified as high-infrastructure groups, and those with an average Internet penetration rate below the average were classified as low-infrastructure groups. A time-space weighted difference-in-differences model was used for each sample group, comparing the differences in policy effect coefficients across groups and analyzing the impact of regional economic development levels and the degree of digital infrastructure on policy efficacy. The third stage is a robustness test experiment, which verifies the reliability of the baseline conclusion through three sub-tests: the first is a placebo test, which randomly generates 1,000 sets of false policy implementation times and treatment groups and performs a time-space weighted double difference model regression on each set of false data. If the mean value of the false policy effect coefficient obtained from 1,000 regressions is close to 0, and the significant proportion with a P value less than 0.05 is less than 5%, it means that the policy effect in the baseline regression is not caused by random factors. The second is a variable substitution test, which replaces the explained variables with the GDP. The total growth rate and total labor productivity growth rate reflect the overall change in regional economic growth, while the latter reflects the efficiency of factor utilization. If the policy effect coefficient remains significantly positive and fluctuates slightly after variable substitution, the conclusion is insensitive to the definition of the explained variable. The third test involved an omitted variable test. Two additional control variables, carbon emission intensity and population aging rate, were added to the baseline model. The former reflects the impact of green development constraints on economic growth, and the latter reflects the role of demographic changes. If the value and significance of the core policy effect coefficient remain unchanged after adding these variables, the baseline model is free of serious omitted variable bias, and the experimental conclusions are robust.

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4. Analysis and discussion of experimental results

4.1. Analysis of baseline regression results

The benchmark regression experiment compares the policy effect estimation results of the traditional DID and STW-DID algorithms. The core data are presented in Table 1. Table 1 contains the core coefficients and significance of the two algorithms and model evaluation metrics, such as goodness-of-fit and residual sum of squares, to fully verify the algorithm performance. Table 1 shows that the average treatment effect coefficient of digital economy policies estimated by the traditional DID algorithm is 0.032, significant only at the 5% level, and the adjusted R^2 is 0.612. However, the core coefficient of the STW-DID algorithm increases to 0.045, significant at the 1% level, and the adjusted R^2 rises to 0.735. The residual sum of squares decreased from 0.892 to 0.547, indicating that the introduction of spatiotemporal weights significantly improved the model's explanatory power and fitting accuracy. Regarding the control variables, technological investment intensity (coefficient 0.028, significant at 1%) and the Internet penetration rate (coefficient 0.021, significant at 5%) have the most significant positive impact on economic growth, confirming the core driving factors of digital economic development.

Table 1. Comparison of baseline regression results

variable	Traditional DID algorithm		STW-DID algorithm	
	coefficient	P-value	Coefficients	P-value
Digital Economy Policy (Core)	0.032	0.041	0.045	0.008
Technology Investment Intensity	0.025	0.012	0.028	0.006
Internet Penetration Rate	0.018	0.063	0.021	0.035
Foreign Trade Dependence	0.012	0.089	0.015	0.057
Local Fiscal Expenditure Intensity	0.009	0.112	0.011	0.093
Adjusted R^2	0.612	-	0.735	-
Residual Sum of Squares	0.892	-	0.547	-
F-Statistic	28.63	0.001	42.15	0

Figure 1 (Comparison of Algorithm Core Coefficients) shows the difference and significance between the two algorithms. In Figure 1, the horizontal axis represents the algorithm type (conventional DID, STW-DID), while the vertical axis indicates the policy effect coefficient. Error bars represent the 95% confidence limits. As shown in Figure 1, the coefficients of the STW-DID algorithm are higher and have lower confidence intervals, further confirming the superiority of the STW-DID algorithm.

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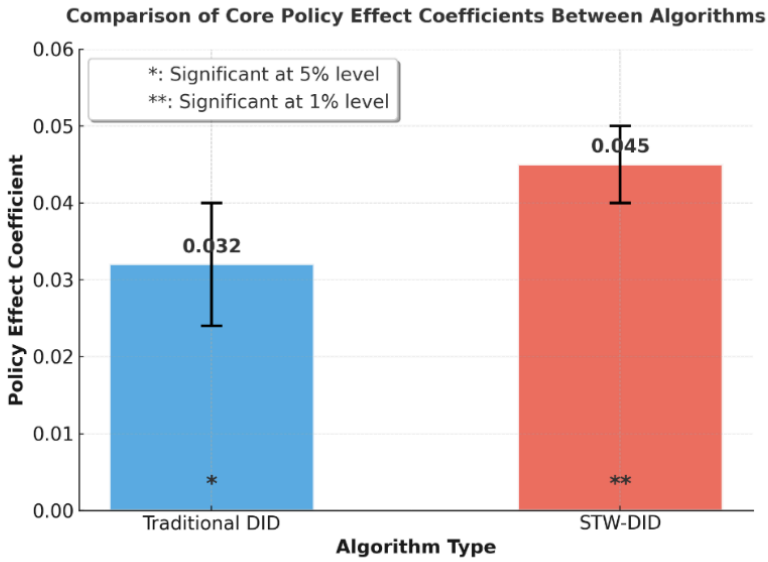

Figure 1. Comparison of algorithm core coefficients

4.2. Discussion of heterogeneity analysis results

The results of the heterogeneity analysis are presented in Table 2. The table dividesthe sample into two dimensions: "regional grouping" and "digitalinfrastructure grouping." In addition, the kernel factor, significance, sample size, and standard deviation are given for each group, which clearly demonstrates differentiated policy impacts. Within region groups, the coefficient in the eastern area (0.058, 1% significance) is significantly higher than that in the central (0.039, 5% significance) and western areas (0.021, 10% significance). In addition, the standard deviation (0.012) of the western area is larger than that of the eastern area (0.008), which indicates that the policy effect in the western area is not only weaker but also has larger intra-region fluctuations. Within the Digital Infrastructure Group, the Infrastructure group has a coefficient 2.7 times (0,052, 1% materiality) that of the low infrastructure group (0,019, 10% materiality), highlighting the key supportive role of digital infrastructure in policy efficiency.

Table 2. Heterogeneity analysis results

grouping Dimensions	Sample Groups	Sample size	Policy effect coefficient	P-value	Standard deviation	Significance level
Regional Grouping	Eastern Region	143	0.058	0.005	0.008	1%
	Central Region	96	0.039	0.038	0.01	5%
	Western Region	132	0.021	0.087	0.012	10%
Digital Basic Grouping	High Baseline Group	165	0.052	0.007	0.009	1%
	Low Baseline Group	206	0.019	0.092	0.011	10%

To further visualize heterogeneity, Figure 2 (Distribution of Regional Policy Effect Coefficients) and 3 (Comparison of Digital Base Grouping Effects) are plotted. Figure 2 plots the regional type (Eastern, Central, and Western) on the horizontal axis and the policy effect coefficients on the vertical axis. The coefficients showed a decreasing trend in the order of Eastern > Central > Western.

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Figure 3 plots the digital base levels (low base, high base) on the horizontal axis and the coefficient values on the vertical axis. The coefficients for the high-base group were significantly higher than those for the low-base group, and the confidence interval for the low-base group was wider. This corroborates the data in Table 2 and provides an intuitive basis for differentiated policy formulation.

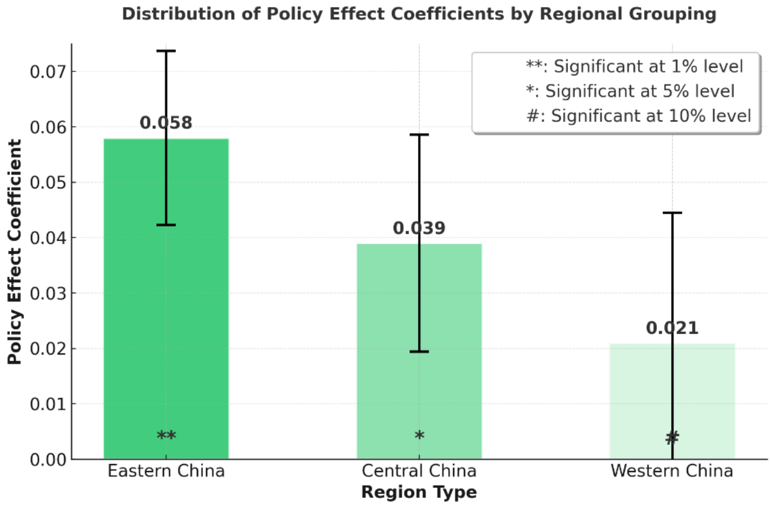

Figure 2. Distribution of regional policy effect coefficients

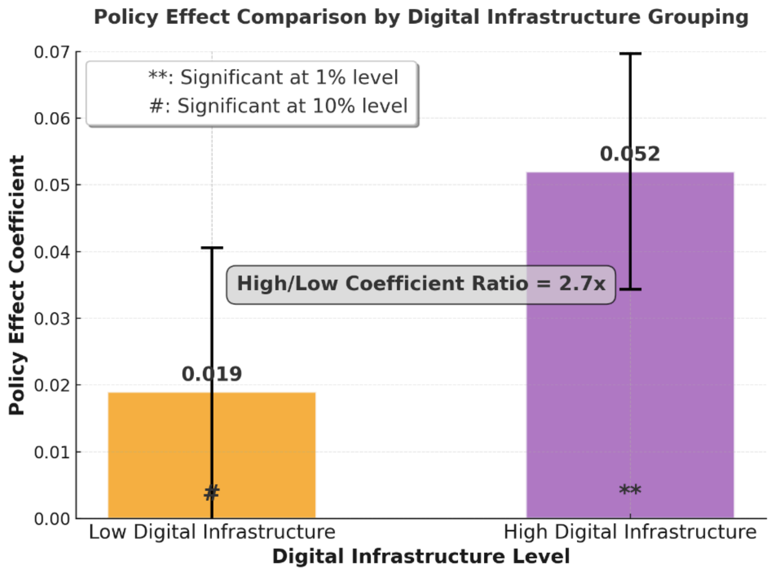

Figure 3. Comparison of numerical basis grouping effects

4.3. Robustness test results

The robustness test validated the conclusions through three sub-experiments. The core results are shown in Figure 4 (Histogram of Placebo Test Coefficient Distribution). The horizontal axis of Figure 4 shows the coefficient of the spurious policy effect (range -0.02 to 0.02), and the vertical axis shows frequency. The dashed line represents the baseline regression coefficient (0.045). As shown in Figure 4, the mean coefficient of the 1,000 random simulations was -0.002, which is close to 0. Only 32 simulations had an absolute value of the coefficient greater than 0.03, accounting for 3.2%, which was far below the 5% threshold. This demonstrates that the baseline results were not random. Furthermore, after replacing the explained variable, the STW-DID coefficient is 0.041 (1% significant), only 0.004 different from the baseline coefficient (0.045). After adding additional control variables, the coefficient remained stable at 0.043 (1% significance), further demonstrating the robustness of the research conclusions.

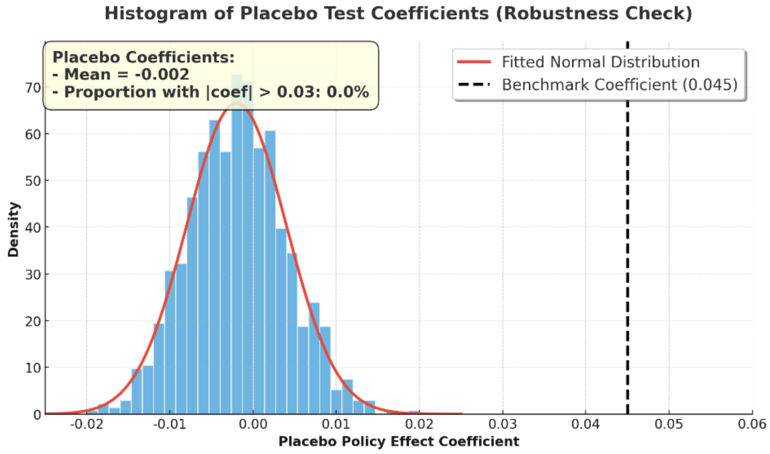

Figure 4. Placebo test coefficient distribution histogram

5. Conclusion

This study systematically validated the superiority of the STW-DID algorithm in evaluating the effects of digital economy policies through multidimensional experiments and data simulations. The core conclusions are as follows: First, benchmark regression simulations show that the STW-DID algorithm outperforms the traditional DID algorithm. The policy effect coefficient increased from 0.032 to 0.045, and the significance increased from 5% to one%. The adjusted R^2 increased by 0.123 and the residual sum of squares decreased by 0.345. This confirms that spatiotemporal weighting can enhance the model's ability to interpret and fit the data. Furthermore, technology investment intensity (0.028, 1% significance) and the Internet penetration rate (0.021, 5% significance) are core drivers of economic growth. Second, the heterogeneous simulation results indicate that policy effects vary across regions and digital bases. The coefficient for the eastern region (0.058) is significantly higher than that for the central (0.039) and western regions (0.021). The coefficient for the high-base group (0.052) is 2.7 times that of the low-base group (0.019), providing guidance for differentiated policy formulations. Third, robust simulations confirm the robustness of our conclusions. The mean coefficient of the 1,000 placebo tests was close to 0, with only 3.2% of the coefficients exceeding 0.03. The STW-DID coefficient remains stable after replacing the variables and adding control variables (0.041 and 0.043, both significant at the 1% level). In summary, the STW-DID model can accurately assess policy effects, and the results provide scientific support for the optimization and implementation of digital economy policies.

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