Analysis on the Next Generation of Artificial Intelligence Development Plan and Digital Financial Inclusion: Evidence From China

Aili Zhang[1] and Xinyu Sun[1]

Abstract

In 2017, the State Council of China released the Next Generation Artificial Intelligence Development Plan in order to seize the opportunity to develop artificial intelligence. Based on a panel dataset from 31 regions in China from 2014-2019, this study utilizes a difference-in-difference model to examine the impact of the release of the Next Generation of Artificial Intelligence Development Plan on the development of digital financial inclusion, and then utilizes a spatial difference-in-difference model to examine the spatial spillover effect of the release of the plan. In this study, results demonstrate that the release of the Next Generation of Artificial Intelligence Development Plan had a significant impact on the promotion of the development of digital financial inclusion, as indicated predominantly by the depth of its use and digitalization. Additionally, the spatial difference-in-difference analysis shows that the impact of this plan has a significant spatial spillover effect, which promotes the development of digital financial inclusion in the region, as well as increases the level of digital financial inclusion in the surrounding areas. The development of digital financial inclusion has been accompanied by a spatial agglomeration.

JEL classification numbers: O25, O33, R58.
Keywords: Artificial Intelligence, Digital Financial Inclusion, Difference-in-Difference Model, Spatial Difference-in-Difference Model, Spatial Spillover Effect

[1]School of Economics & Management, Beijing University of Technology, Beijing 100124, China.

1. Introduction

Artificial intelligence (AI) is one of the most significant technologies of today and tomorrow, which is transforming how we live and how we work. As such, AI contributes significantly to economic growth. The major developed countries have incorporated artificial intelligence into their national development strategies in order to maintain their dominance in the new round of international competition in science and technology. In 2017, the Next Generation of Artificial Intelligence Development Plan was released in China, aimed at capturing the strategic opportunity presented by science and technology and ensuring a competitive advantage in AI development, as well as achieving a high level of technological self-reliance. The design of public policy and the promotion of social capital are promoting the development of intelligence in all sectors of the economy and society through the overall promotion of the next generation of artificial intelligence. Furthermore, the Organisation for Economic Co-operation and Development (OECD) has identified the Next Generation Artificial Intelligence Development Plan as an important national strategy to promote the development of AI and to maximize its economic and social benefits (OECD, 2019).

At present, the next generation of artificial intelligence has been applied in a wide range of fields including finance, education, healthcare, and other aspects of people's everyday life at multiple levels, providing people with convenient and effective intelligent services. As a new application of artificial intelligence in the financial sector, digital financial inclusion changes the traditional logic of financial inclusion with human capital at its core, enabling customer access to more comprehensive and personalized financial services. In addition, AI is a form of general purpose technology (GPT), which displays the spillover characteristic of infrastructure (Brynjolfsson et al., 2017). As a result, a division of labor and a cooperative approach are enabled in the process of intelligent upgrading in the dominant industries in each region, resulting in the creation of a spatial agglomeration in the development of digital financial inclusion.

2. Literature Review

Recent years have seen a proliferation of academic research related to AI and its applications due to the deep development of AI. As part of the theoretical study of AI, existing literature mainly focuses on the impact and mechanism of AI applications on economic growth (Aghion et al., 2017; Chen et al., 2019), employment of the labor force (Acemoglu & Restrepo, 2018) and total factor productivity (Sun & Hou, 2021) through the development of theoretical models. Due to the limited availability of research data, existing empirical tests have focused on the economic effects of the implementation of industrial robots. The application of industrial robots contributes to productivity in both long and short term (Kromann et al., 2011). There is, however, research that indicates that the increased density of applications of industrial robots leads to lower marginal benefits (Graetz & Michaels, 2015). On the other hand, the application of industrial robots is associated with decreases in employment and wages (Acemoglu & Restrepo, 2018; Jeffrey et al., 2015), and changes the structure of employment to a certain degree (Sun & Hou, 2019).

In existing research on AI policy, both the evaluation of policies and their economic consequences have been discussed. The literature on policies evaluation analyzes and evaluates the content of policies primarily by using textual analysis and quantitative analysis. Considering the perspective of textual analysis, Cath et al. (2018), Tang et al. (2019) and Chen et al. (2021) conducted comparative studies of different countries' AI policies and provided relevant optimization suggestions for the further development of AI policies. A study conducted by Shan et al. (2021) developed a "policy attributes-policy structure" framework for comparing AI industrial policies in different regions of China. David et al. (2020) developed a Dynamic Public Policy Cycle (DPPC) model to analyze the benefits and possible pitfalls of applying artificial intelligence based on agenda setting and policy evaluation, providing a perspective on the evaluation of AI policies. In terms of quantitative evaluation, Hu et al. (2020) analysed the strengths and weaknesses of China's AI industrial policy by means of a policy-modeling-consistency (PMC) index model. In the area of policy's economic impacts, existing literature only discusses AI policies' impact on the efficiency of the financial industry and manufacturing employment in China(Liang, 2021; Li et al., 2020).

In most existing literature on digital financial inclusion, attention has focused on the economic effects of financial inclusion, with very little analysis of its impact factors. In their study, Pan et al. (2015) explored a specific impact of mobile payments on Internet financial inclusion and suggested that the development of Internet financial inclusion should be aimed at controlling the risks posed by the technology. Wang et al. (2021) examined the role of traditional financial provision on digital financial inclusion based on regional institutional differences, and found that digital financial inclusion is more prevalent in regions with a more developed traditional financial sector.

The literature has conducted a wide range of research on the applications of artificial intelligence and related industrial policies, but economic evaluation of the effects of AI policies is still in its infancy. As a kind of general purpose technology (GPT), artificial intelligence is destined to penetrate a variety of industries, therefore having a significant impact on social production and life (Brynjolfsson et al., 2017). In China, digital financial inclusion has grown rapidly as AI technology has been applied in depth in the financial sector. Therefore, the implementation of AI policies will also have a profound impact on the development of digital financial inclusion by facilitating the development of AI. However, there is still a lack of research regarding the economic effects of AI policies in the area of finance. The industrial clustering effect caused by AI also indicates the state of spatial agglomeration in the development of financial inclusion. However, existing literature does not explore in detail the spatial correlation of digital financial inclusion.

This research considers the release of the Next Generation of Artificial Intelligence Development Plan as a quasi-natural experiment. Using the digital financial inclusion data of 31 Chinese regions from 2014 to 2019, the difference-in-difference (DID) model and the spatial difference-in-difference (SDID) model are employed to examine the impact of the release of this plan on the development of digital financial inclusion and its spatial spillover effect. This research may contribute as follows: First, the research uses DID model to investigate the impact of the release of the Next Generation of Artificial Intelligence Development Plan on the development of digital financial inclusion itself and its subdimensions. It does not only overcome the endogenous challenges of the model, but also complements the empirical research on the economic effects of existing AI policies and the factors that affect digital financial inclusion. Second, the research uses the SDID model to estimate and test the spatial spillover effect of the plan on the development of digital financial inclusion, as well as to demonstrate that the industrial clustering effect of AI development will result in spatial agglomeration of the development of digital financial inclusion.

3. Methods and Data

3.1 Methodology

3.1.1 Difference-in-Difference (DID) Model

To evaluate the development trend of digital financial inclusion under the framework of AI policy, our research considers the Next Generation of Artificial Intelligence Development Plan released by the State Council in 2017 as a quasi-natural experiment, and develops a difference-in-difference (DID) model with the following setup:

$$Dfi_{it} = \beta_0 + \beta_1 Treat_i \times Post_t + \gamma X_{it} + \tau_t + \varepsilon_{it} \quad (1)$$

where, i and t refer to region i and year t, respectively. Dfi is the digital financial inclusion index, which is also further tested in this paper using the breakdowns of digital financial inclusion, by breadth of coverage, depth of use and digitisation. $Treat$ is the treatment variable, the research uses the number of AI invention patent disclosures by region for grouping. $Post$ is the policy dummy variable that takes the value of 1 after the release of the Next Generation of Artificial Intelligence Development Plan (2017 and beyond) and 0 before the release. X is a matrix of control variables at the provincial level.

3.1.2 Spatial Difference-in-Difference (SDID) Model

The traditional Difference-in-Difference model complies strictly with the Stable Unit Treatment Value Assumption (SUTVA), that is, individuals must be independent of one another, assuming that no individual in the sample will be affected by whether or not another individual receives the treatment (Rubin, 1978). Furthermore, the release of the Next Generation Artificial Intelligence Development Plan will not only have a direct impact on the development of digital financial inclusion in the region, but regions with a high degree of AI development can also have a spillover effect on their surrounding regions, thereby promoting the development of digital financial inclusion in these regions as well. As spatial spillovers violate the SUTVA hypothesis, the traditional DID method is biased and a further extension of the DID model is necessary (Chagas et al., 2016). Based on the researches of Chagas et al. (2016) and Dubé et al. (2014), this study extends the baseline DID model by using a Spatial DID (SDID) model, which is the following:

$$Dfi_{it} = \beta_0 + \rho W Dfi_{it} + \beta_1 Treat_i \times Post_t + \beta W Treat_i \times Post_t + \gamma X_{it} + \delta W X_{it} + \tau_t + (I - \lambda W)\varepsilon_{it} \quad (2)$$

where W is the spatial weight matrix, and this paper uses the contiguity weight matrix and inverse-geographic distance spatial weight matrix for analysis respectively. ρ is the spatial autocorrelation coefficient of the explanatory variable Dfi. β is the spatial spillover effect of the release of the plan. δ is the spatial spillover effect of the control variables. λ is the spatial autocorrelation coefficient of ε. Also, depending on the values of the coefficient matrix, the SDID model can be further divided into SAR-DID ($\beta = \delta = \lambda = 0$) model, SEM-DID ($\rho = \beta = \delta = 0$) model and SDM-DID ($\lambda = 0$) model.

3.2 Data

3.2.1 Selection of Variables

In the case of the treatment variable $Treat$ the research divides the experimental and control groups on the basis of the number of AI invention patent disclosures in each region, with the experimental group taking a value of 1 and the control group taking a value of 0. As the Next Generation of Artificial Intelligence Development Plan is applicable to all regions in China, it is not possible to separate the experimental group from the control group directly. Therefore, the study refers to Vig (2013), Campello & Larrain (2016) and Liu & Cao (2018), and divides the regions according to their exposure to policy shocks, with regions that are more exposed to policy shocks being the experimental group, and those that are less exposed being the control group. First, we calculated the average value of AI invention patent disclosures in each region from 2014 to 2016 (three years before the release of the plan), and then compared the average values in each region with the overall average value of all regions. If the average value of AI patent disclosures in a region is higher than the overall average, the region is assigned to the experimental group; otherwise, it is assigned to the control group.

To confirm the rationality of AI patent disclosures as the grouping treatment variable, we examines the grouping time-varying trend of AI patent disclosures, as shown in Figure 1.

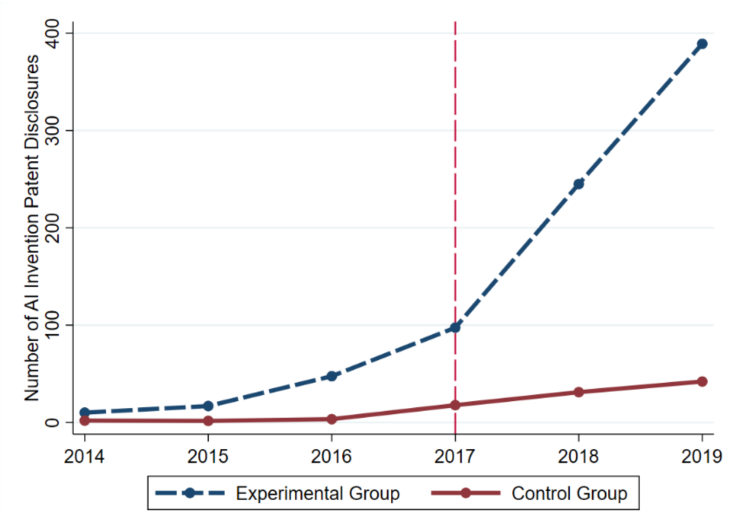

Figure 1: Time-varying trends in the grouping of AI inventions patent disclosures

Figure 1 demonstrates that the number of AI invention patent disclosures in the control group regions varied relatively little before and after the release of the plan, while the number in the experimental group regions continued to increase rapidly after its release. Consequently, the higher the number of AI invention patents, the higher the level of AI development in the region and the deeper the influence of the Next Generation of

Artificial Intelligence Development Plan. It confirms the reasonableness of our selection of the treatment variables in this paper.

In terms of control variables, Tec is measured using the logarithm of the amount of financial science and technology expenditure by region in China; Edu is measured using the logarithm of the amount of financial education expenditure by region in China; Fin is measured using the logarithm of the value added of the financial sector by region in China; Vol is measured using the logarithm of the capacity of mobile phone exchange by region in China.

3.2.2 Data Sources

In order to mitigate the interference of other exogenous events, this paper selects three years before and after the release of the Next Generation of Artificial Intelligence Development Plan (from 2014 to 2019) as a time window, and uses DID and SDID model to examine the impact of the plan on the development of digital financial inclusion based on the data of 31 regions in China. The data for the Digital Financial Inclusion Index is derived from the Peking University Digital Financial Inclusion Index published by Peking University's Digital Finance Research Centre. Data on AI invention patent disclosures was obtained from the PatentHub database and manually compiled by searching for invention patents containing the keyword "AI" in their title or abstract. All other data were obtained from the National Bureau of Statistics of China. For the purpose of minimizing confounding of the estimation results by outliers, all continuous variables are Winsorized at the upper and lower 1% levels. Table 1 provides descriptive statistics for each variable.

Table 1: Summary statistics of variables

Variable	Obs	Mean	Std.	Min	Max
Dfi	186	2.543	0.557	1.439	4.103
Dfi_cov	186	2.342	0.563	1.267	3.847
Dfi_dep	186	2.395	0.726	1.073	4.399
Dfi_dig	186	3.480	0.543	2.307	4.622
Treat	186	0.290	0.455	0.000	1.000
Post	186	0.500	0.501	0.000	1.000
Tec	186	4.348	1.106	1.486	7.064
Edu	186	6.594	0.673	4.810	8.074
Fin	186	7.157	0.989	3.993	9.078
Vol	186	8.702	0.754	5.974	10.078

Figure 2 shows the time-varying trend of the digital financial inclusion index for the experimental and control groups, which were divided based on the number of patent applications for AI inventions. The Figure 2 illustrates that the gap between the experimental and control group regions over time did not significantly change from 2014 to 2016. Since 2017, however, the gap has gradually widened. Furthermore, this confirms that the digital financial inclusion indices for both groups confirm the assumption of a parallel trend, which can be tested by using the DID model.

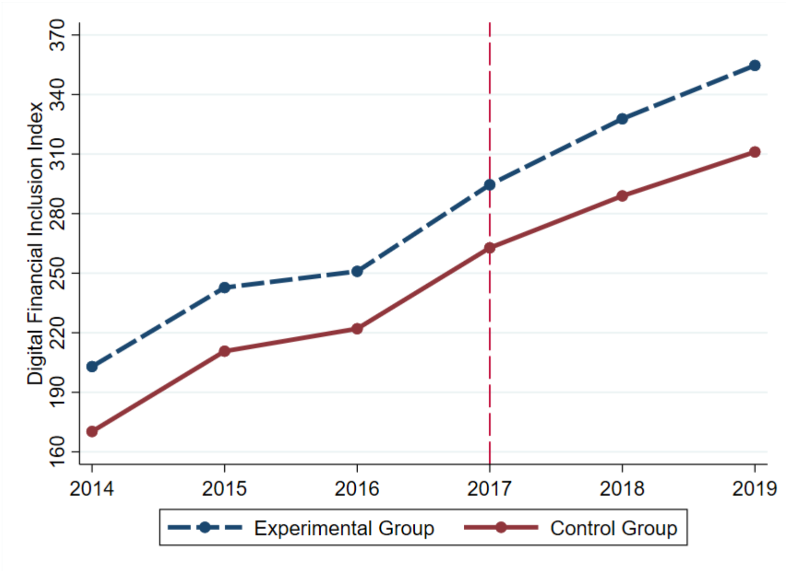

Figure 2: Time-varying trends in the grouping of digital financial inclusions

4. Results

4.1 The result of DID estimation

Table 2 reports the results of examining the impact of the release of the Next Generation of Artificial Intelligence Development Plan on the development of digital financial inclusion using DID model. In Table 2, column (1) is analyzed using the digital financial inclusion index as the explanatory variable, while columns (2) to (4) are analyzed further using the sub-indicators of breadth of coverage, depth of use, and digitization of digital financial inclusion, as explanatory variables. All regression models adjust for standard errors using district-level clustering and control for year-fixed effects.

In Table 2, it can be seen that the coefficient of the interaction term Did is significantly positive at the 1% level of significance when Dfi is used as an explanatory variable. It appears that the publication of the Next Generation of Artificial Intelligence Development Plan has facilitated the advancement of digital financial inclusion. This paper proposes three possible explanations for this phenomenon: First, because of the rapid development of artificial intelligence, Chinese financial institutions, represented by the four state-owned banks, are scrambling to establish strategic partnerships with technology companies to seek to digitally upgrade finance. Hence, the publication of the plan can effectively facilitate the transformation of AI fintech accomplishments, making AI technology widely applicable to diverse aspects of digital financial inclusion, such as payments and credit. Traditional financial inclusion can be accelerated by technological market development, effectively facilitating the development of digital financial inclusion on a deeper level through digital innovation and transformation. Secondly, financial institutions have massive amounts of data and complex data structures, therefore they require an intelligent infrastructure system that will provide them with the ability to model financial data via the advance of artificial intelligence and to carry out quantitative and qualitative analyses to advance the development of financial services. Third, the plan proposes to establish a national AI entrepreneurship base, which would provide entrepreneurial services in AI, based on areas with a high concentration of AI research, thereby facilitating the transformation and commercialization of scientific and technological achievements. Innovation entrepreneurship in high-tech fields will increase the level of technological innovation and provide more opportunities to apply AI in the financial sector, thereby promoting the development of digital financial inclusion.

Table 2: The Result of DID Estimation

Variable	(1)	(2)	(3)	(4)
	Dfi	Dfi_cov	Dfi_dep	Dfi_dig
Did	0.091*** (0.024)	-0.027 (0.018)	0.162*** (0.042)	0.339*** (0.084)
Tec	0.070** (0.033)	0.028 (0.017)	0.078 (0.051)	0.200 (0.121)
Edu	0.191** (0.087)	0.166** (0.064)	0.183 (0.160)	0.209 (0.247)
Fin	0.256*** (0.059)	0.177*** (0.053)	0.308** (0.119)	0.462** (0.201)
Vol	0.041* (0.021)	0.019 (0.018)	0.048* (0.025)	0.050 (0.084)
Constant term	-1.811** (0.681)	-0.854* (0.425)	-2.462** (0.985)	-3.155 (2.331)
Time fixed effect	YES	YES	YES	YES
N	186	186	186	186
R^2	0.727	0.791	0.767	0.290

Note: ***, **, and * are significant at 1%, 5%, and 10%, respectively.

According to columns (2) to (4) of Table 2, the coefficients of the interaction term Did are significantly positive at the 1% significance level when using Dfi_dep and Dfi_dig as the explanatory variables. However, the coefficient of interaction term Did was not significant when using Dfi_cov. According to the results, the release of the plan increases the depth of use and digitalization of digital financial inclusion, but it does not significantly expand its breadth. The following reasons may account for this phenomenon: First, the actual use of digital financial services by users, which includes payment services, money fund services, credit services, insurance services and investment services, shows the depth of digital financial inclusion. Accordingly, the release of the plan promotes innovation and entrepreneurship through the development of entrepreneurial bases, and enables the application and transformation of AI technological achievements. At the same time, digital financial inclusion can meet the capital needs of entrepreneurs and increase the volume of digital financial inclusion, thus positively impacting the depth of use of digital financial inclusion. Second, the digitalization of financial inclusion is mainly in the form of easy access of using mobile payments and consumer loans. With the implementation of this plan, artificial intelligence will be used more often in these scenarios, giving users increased convenience, resulting in the digitization of digital financial inclusion.

4.2 The result of dynamic effects analysis

This paper further employs a dynamic effects analysis for robustness testing. Based on Jacobson et al.'s (1993) research, this paper constructs interaction terms for treatment variables with annual dummy variables and uses 2016 as the base period for analysis of dynamic effects. The year-by-year interaction term coefficients and 95% confidence interval results are shown in Figure 3.

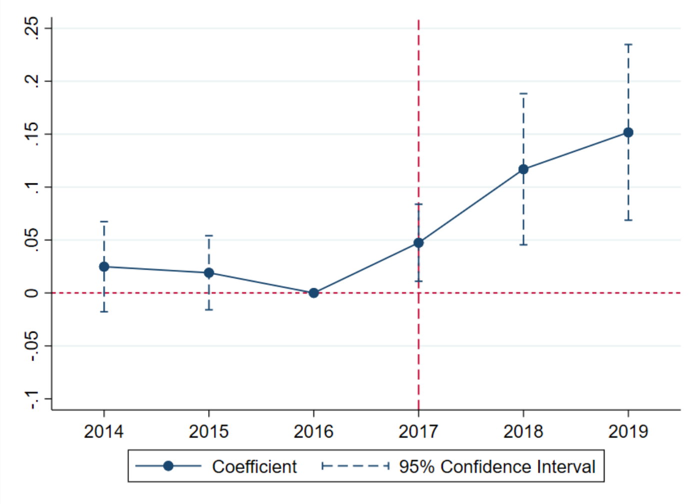

Figure 3: Dynamic effects analysis

According to Figure 3, the coefficients of the interaction term from 2014 to 2016 are not significantly different from zero and do not pass the significance test, while the coefficients from 2017 to 2019 are significantly positive, which indicates that there is no significant difference in the development of digital financial inclusion between the experimental group and the control group before the release of the plan, satisfying the parallel trend hypothesis. In addition, the publication of this plan has contributed to the development of digital financial inclusion in China, where the effect gains a year-over-year growth.

4.3 The result of placebo test

This paper further conducts a placebo test with the aim of evaluating whether the regression results of the DID model are not affected by omitted variables. The dummy policy treatment variables were constructed, and 500 random samples were taken from each of the 31 regions, with 9 randomly selected regions as a virtual experimental group, and the rest as a virtual control group. Figure 4 illustrates the kernel density curves of the estimated coefficients along with the distribution of p-values.

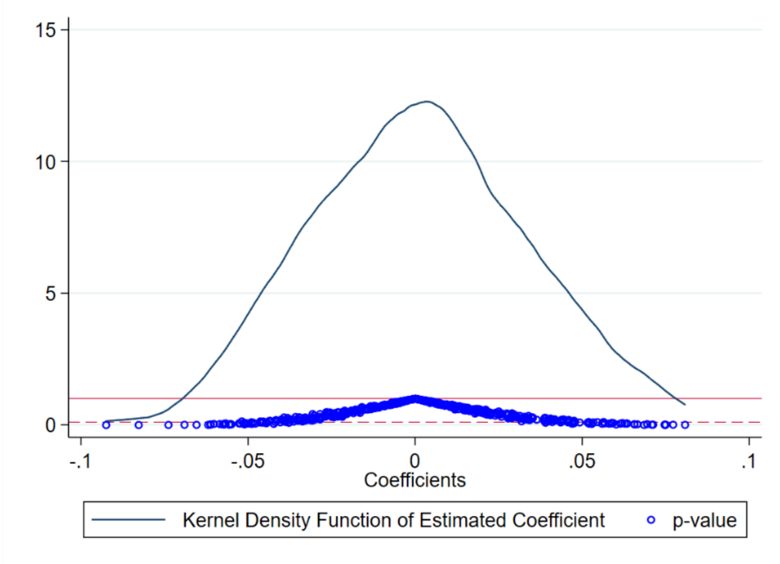

Figure 4: Placebo test

As shown in Figure 4, the estimated coefficients are concentrated around 0, and the vast majority of p-values are greater than 0.1. In addition, the true estimate of the interaction term in our baseline model is 0.091, which is significantly outside the kernel density function. The result of the placebo test suggests that the results of the DID model are not influenced by the omission of key variables from the estimates. It can be concluded that the empirical results are robust.

4.4 The result of SDID estimation

In order to estimate the SDID model, it is necessary to test the spatial relevance of Dfi. This paper measures the global Moran's I index of Dfi, and Table 3 reports the global Moran's I index for each year from 2014 to 2019. As shown in Table 3, all global Moran's I indices are significantly positive at the 1% level of significance, indicating that there is a significant positive spatial correlation in the development of digital financial inclusion across regions in China. Therefore, it is necessary to transform the traditional DID model into SDID model.

Table 3: Global Moran's I Indices of Dfi

Year	Moran's I	Z-value	Year	Moran's I	Z-value
2014	0.468	4.350	2017	0.508	4.728
2015	0.412	3.875	2018	0.548	5.041
2016	0.450	4.215	2019	0.556	5.101

Note: The Z-value greater than 2.56 indicates that Moran's I value is significant at the 1% level.

Table 4: The Result of SDID Estimation

	Contiguity weight matrix			Inverse-geographic distance weight matrix		
	(1)	(2)	(3)	(4)	(5)	(6)
	SDM-DID	SAR-DID	SEM-DID	SDM-DID	SAR-DID	SEM-DID
Did	0.042***	0.059***	0.039***	0.073***	0.081***	0.078***

	(0.012)	(0.013)	(0.013)	(0.013)	(0.013)	(0.014)
*W*Did	0.101*** (0.032)			0.401*** (0.096)		
ρ	0.476*** (0.085)	0.414*** (0.071)		0.366* (0.205)	0.690*** (0.115)	
λ			0.700*** (0.062)			0.567*** (0.162)
Wald Test	29.19***			39.33***		
LR Test	40.65***			54.42***		
Control variables	YES	YES	YES	YES	YES	YES
Time Fixed Effect	YES	YES	YES	YES	YES	YES
Spatial Fixed Effect	YES	YES	YES	YES	YES	YES
N	186	186	186	186	186	186
R^2	0.586	0.151	0.210	0.751	0.565	0.232

Columns (1) to (3) and (4) to (6) of Table 4 report the results of the SDID model based on the contiguity weight matrix and inverse-geographic distance spatial weight matrix, respectively. As shown in columns (1) and (4), the coefficients of ρ are significantly positive at the 1% and 10% significance levels respectively, indicating that there is a significant spatial spillover effect on the development of digital financial inclusion. Also, the coefficients of interaction term Did based on the SDM-DID, SAR-DID and SEM-DID models are all significantly positive at the 1% significance level, validating that the release of the plan has significantly contributed to the development of digital financial inclusion. The Wald test and LR test are further conducted in this paper to test whether the SDM model can be reduced to a SAR or SEM model. As can be seen from Table 4, both the Wald test and the LR test based on the two spatial weight matrices are significant at the 1% significance level. The results indicates that both the SAR and SEM model are rejected, SDM-DID model are further analyzed in this paper.

According the columns (1) and (4) of Table 4, both Did and WDid are significantly positive at the significance level of 1%, indicating that the release of the Next Generation of Artificial Intelligence Development Plan has significant positive spillover effects on the development of digital financial inclusion. This paper argues that there are two reasons for this phenomenon: First, the plan encourages regions to gather AI technology elements, enterprises and talents to build AI industry clusters, which leads to a high-high concentration of AI development between regions in China. The development of AI in the regions creates clustering effect, which leads to the synergistic development of digital financial inclusion, allowing for the existence of spatial clustering. Second, the development of technology has led to a transformation of AI achievements into replicable experiences for other regions, resulting in an interregional exchange of knowledge and technology, thus driving the development of AI and digital financial inclusion in neighboring regions and creating a spillover effect.

The release of the plan will therefore encourage the development of digital financial inclusion in regions with high levels of artificial intelligence development, as well as have a spillover effect on the development of digital financial inclusion in neighbouring regions via interregional knowledge exchange.

Table 5: The Direct and Indirect Effects Result of SDM-DID Estimation

	Contiguity weight matrix	Inverse-geographic distance weight matrix
	（1）	（2）
	Direct Effects	
Did	0.121*** (0.031)	0.087*** (0.018)
Tec	0.020 (0.045)	0.05099 (0.024)
Edu	0.556*** (0.148)	0.189*** (0.073)
Fin	0.729*** (0.117)	0.186*** (0.065)
Vol	0.045 (0.047)	0.069*** (0.027)
	Indirect Effects	
Did	0.307* (0.162)	0.745** (0.368)
Tec	-0.233 (0.195)	0.330 (0.377)
Edu	0.585 (0.669)	-0.159 (0.847)
Fin	0.848* (0.453)	1.546 (1.016)
Vol	0.148 (0.231)	0.687 (0.542)

Table 5 further shows the results of the direct and indirect effects of the SDM-DID model based on the two weight matrices. The direct and indirect effect values for the interaction term Did are significantly positive at the 1%, 5% and 10% significance levels. There is evidence that the release of the plan promotes the development of digital financial inclusion in regions with high artificial intelligence development as compared to regions with low artificial intelligence development. Moreover, the expansion of digital financial inclusion in high AI development regions has led to the development of digital financial inclusion in their neighbouring regions as well. A significant spatial spillover effect has been observed as a result of the release of the Next Generation of Artificial Intelligence Development Plan, leading to the development of digital financial inclusion.

5. Conclusions

Our paper contains the first analysis of this kind, which fills the existing research gap, particularly in the empirical and contextual areas. The paper uses panel data from 31 regions in China from 2014 to 2019 to test whether the Next Generation of Artificial Intelligence Development Plan has an impact on regional digital financial inclusion and its spatial spillover effects using the DID and SDID models. Our conclusions are as follows: First, the release of the Next Generation Artificial Intelligence Development Plan has contributed to the improvement of digital financial inclusion in the region, by promoting the development of technology markets for the transformation and application of AI innovations in the financial sector, optimizing the construction of intelligent information infrastructure to improve the data processing and computing capabilities of regional financial institutions, and encouraging AI innovation and entrepreneurship to achieve diversified application of AI technologies in the financial sector. Second, based on the SDID model, the release of the Next Generation Artificial Intelligence Development Plan has a positive spatial spillover effect on the development of digital financial inclusion. Regions with high AI development create AI industry clusters and build AI entrepreneurship bases to form regional AI synergistic development, thus driving the improvement of digital financial inclusion in the region and surrounding regions.

In this paper, we discuss only the impact and spillover effect of the Next Generation of Artificial Intelligence Development Plan on the financial sector, and do not investigate the effects on other sectors. As a kind of GPT, AI can be integrated and developed with all sectors of society. Consequently, the release of the plan will have a positive impact on many more areas, such as social governance and health care. We hope that this paper will stimulate the research interest of scholars in this field and lead to a more comprehensive analysis of the policy.

References

[1] Erik Brynjolfsson, Daniel Rock and Chad Syverson. (2018). Artificial Intelligence and the Modern Productivity Paradox: A Clash of Expectations and Statistics. NBER Chapters, 23-57.

[2] Philippe Aghion, Benjamin F. Jones and Charles I. Jones. (2018). Artificial Intelligence and Economic Growth. NBER Chapters, 237-282.

[3] Chen, Y. B., Lin, C. and Chen, X. L. (2019). Artificial Intelligence, Aging and Economic Growth. Economic Research Journal, 54(7):47-63.

[4] Acemoglu, Daron, and Pascual Restrepo. (2018). The Race between Man and Machine: Implications of Technology for Growth, Factor Shares, and Employment. American Economic Review, 108(6): 1488-1542.

[5] Sun, Z., Hou, Y. L. (2021). The Influence of Artificial Intelligence Development on Industrial Total Factor Productivity —— An empirical Research Based on Manufacturing Industries in China. Economists, (1):32-42.

[6] Lene Kromann, Nikolaj Malchow-Møller, Jan Rose Skaksen and Anders Sørensen. (2020). Automation and productivity—a cross-country, cross-industry comparison,

Industrial and Corporate Change. Oxford University Press, 29(2):265-287.
[7] Georg Graetz and Guy Michaels. (2015). Robots at work: the impact on productivity and jobs. CentrePiece - The magazine for economic performance 447, Centre for Economic Performance, LSE.
[8] Jeffrey D. Sachs, Seth G. Benzell and Guillermo LaGarda. (2015). Robots: Curse or Blessing? A Basic Framework. NBER Working Papers 21091.
[9] Sun, Z., Hou, Y. L. (2019). How Does Industrial Intelligence Reshape the Employment Structure of Chinese Labor Force. China Industrial Economics, (5):61-79.
[10] Cath, C., Wachter, S., Mittelstadt, B. et al. (2018). Artificial Intelligence and the ‘Good Society’: the US, EU, and UK approach. Sci Eng Ethics, 24:505–528.
[11] Tang, Z. W., Lei, H. Z. and Zhou, W. (2019). A Comparative Study of Artificial Intelligence Industry Policies in China and the United States: Content Analysis Based on Objectives, Tools and Implementation. Journal of Intelligence, 38(10):73-80.
[12] Chen, J. Y., Jiang, L. D. and Xue L. (2021). Artificial Intelligence (AI) Policy in a Cross-National Comparative Perspective: Goals, Concepts, and Paths. Science of Science and Management of S.& T., 42(03):87-100.
[13] Shan, X. H., He, Q., Liu, X. Y. and Yang, J. (2021). Regional Comparative Research on Artificial Intelligence Industry Policy under the Framework of "Policy Attributes-Policy Structure". Information Studies: Theory & Application, 44(03):194-202.
[14] Valle-Cruz, D., Criado, J.I., Sandoval-Almazán, R., & Gómez, E.A. (2020). Assessing the public policy-cycle framework in the age of artificial intelligence: From agenda-setting to policy evaluation. Gov. Inf. Q., 37, 101509.
[15] Hu, F., Qi, X. N. and Wang, X. Y. (2020). Quantitative Evaluation of Robot Industry Policies Based on PMC Index Model: Taking Eight Robot Industry Policies Intelligence as an Example. Journal of Intelligence, 39(01):121-129+161.
[16] Liang, L. (2021). The Impact of Artificial Intelligence Policies on the Efficiency of Financial Industry in China —— From the Perspective of the Efficiency of Resource Allocation in the Financial Industry. Taxation and Economy, (03):63-72.
[17] Li, X. E., He, Q., Li, X. Y. and Mu, H. L. (2020). Study on the Impact of Artificial Intelligence Policy on Manufacturing Employment Based on Policy Quantification. Science and Technology Management Research, 40(23):197-203.
[18] Yaqian Pan, Meng Yang, Shubing Li, Xinxin Chen. Shiqi Yu and Lijuan Yu. (2016). The Impact of Mobile Payments on the Internet Inclusive Finance, Journal of Management and Sustainability, 6(4):97-106.
[19] Wang, Z., Chen, Y. M. and Zhang, M. (2021). Traditional Financial Supply and Digital Finance Development: Supplement or Substitute? Based on the Perspective of Regional System Differences. Business and Management Journal, 43(05):5-23.
[20] Sandra Planes-Satorra and Caroline Paunov. (2019). The digital innovation policy landscape in 2019, OECD Science, Technology and Industry Policy Papers 71.
[21] Vikrant Vig. (2013). Access to Collateral and Corporate Debt Structure: Evidence from a Natural Experiment. Journal of Finance,68(3):881-928.

[22] Murillo Campello and Mauricio Larrain. (2016). Enlarging the Contracting Space: Collateral Menus, Access to Credit, and Economic Activity, Review of Financial Studies, 29(2):349-383.
[23] Liu, H. M. and Cao, T. Q. (2018). The Economic Impacts of Rollover Restrictions on Enterprises. Economic Research Journal, 53(04):108-121.
[24] Louis S. Jacobson, Robert J. LaLonde and Daniel G. Sullivan. (1993). Earnings Losses of Displaced Workers. The American Economic Review, 83(4): 685-709.
[25] Rubin, D. (1978) Bayesian Inference for Causal Effects: The Role of Randomization. The Annals of Statistics, 6:34-58.
[26] Chagas, André L.S., Azzoni, Carlos R. and Almeida, Alexandre N. (2016). A spatial difference-in-differences analysis of the impact of sugarcane production on respiratory diseases, Regional Science and Urban Economics, 59(C):24-36.
[27] Dubé, Jean, Legros, Diègo, Thériault, Marius and Des Rosiers, François. (2014). A spatial Difference-in-Differences estimator to evaluate the effect of change in public mass transit systems on house prices, Transportation Research Part B: Methodological, 64(C):24-40.