Using the Quantile Regression Model to Study the Impact of My Country's Big Data, Artificial Intelligence and Blockchain on the Real Economy

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Abstract. Based on the cross-sectional data of 162 cities in my country, this paper takes "Internet +" as the core explanatory variable, selects five control variables, and constructs a weighted least squares and quantile regression model to explore the impact on the real economy. The study found that the impact of "Internet +" on the real economy was significantly negative, and a "crowding-out effect" had occurred; under the conditions of different levels of the real economy, the "crowding-out effect" of "Internet +" was constant, but the degree of crowding out would vary. Marginal increase. Combined with the research results, relevant suggestions are put forward from the perspectives of how to develop the real economy in a healthy and effective manner and from the perspectives of big data, artificial intelligence, and blockchain serving the real economy, in order to promote better and faster development of the real economy. Fiscal and financial policies play a leading and safeguarding role in the real economy; give full play to the role of artificial intelligence's weakened geographic location on the flow of factors and industrial agglomeration, accurately support the intelligence of local traditional advantageous real industries, and realize the continuous transformation of new and old kinetic energy for industrial development.

Keywords: Artificial Intelligence · Real Economy · Internet+ Industry · Stata

1 Introduction

After the international financial crisis, the key to the transformation of the quality, efficiency and power of the real economy is "digital economic empowerment". "Promoting the deep integration of the Internet, big data, artificial intelligence and the real economy" is the new direction of economic development.

Some scholars believe that the excessive development of big data, artificial intelligence and blockchain has caused the funds that should have flowed into the real economy to flow into real estate and other fields, which has produced a "crowding out effect" on the real economy, thus hindering the development of the real economy. How to make big data, artificial intelligence and blockchain better serve the real economy in the context

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of the new era is one of the important topics for the development of my country's digital economy.

The rest of this paper is arranged as follows: the second part is the review of the literature; the third part is the model construction, variable selection and statistical analysis; The fourth part is the overall estimation results and analysis of the impact of big data, artificial intelligence, blockchain and other digital economies on the real economy, and finally the conclusions and policy recommendations.

2 Literature Review

First of all, the integration and transformation effects of digital economy such as big data, artificial intelligence, and blockchain need to be supported by preconditions, which are closely related to the level of industrialization, economic development stage, and global industrial division of labor. At the micro level, many real economy enterprises are less aware that the data resources generated during the business life cycle of enterprises can be used to improve production and operation efficiency and reduce production costs. In addition, some scholars believe that Internet finance can use big data, artificial intelligence and blockchain to reach "tail customers" more effectively, and promote the development of all aspects of the economy with faster speed, lower cost and wider coverage (Long 2017).

To sum up, scholars seldom explore the relationship between big data, artificial intelligence, blockchain and the real economy. There are also many problems in the actual development process of financial technology. Whether it promotes the development of the real economy and the extent to which it promotes the real economy are both important. Further confirmation and specification are required. In order to make up for the shortcomings of existing research, this paper uses quantile regression to evaluate the impact and characteristics of the current big data, artificial intelligence, and blockchain on the real economy and promote rational decision-making.

3 Research Design

3.1 Empirical Model

To answer scientific questions, an econometric model is established from two aspects. The first is to establish a benchmark model to evaluate the overall effect of Big data, artificial intelligence and blockchain on the real economy; the second is to use the quantile regression method to reveal the conditional characteristics of Big data, artificial intelligence and blockchain under the conditions of different levels of the real economy. The benchmark model is shown in formula (1), where i represents the region, t represents the time, RE is the development level of the real economy, DE is the development level of big data, artificial intelligence and blockchain, and CON is a series of control variables. Since the cross-sectional data is prone to heteroscedasticity, the benchmark model is estimated using the weighted least squares (WLS).

$$RE = a + b * DE + c * CON + u \tag{1}$$

The stimulation of the enabling effect of Big data, artificial intelligence and blockchain needs to be conditioned on the development level of the real economy. To this end, continue to use the quantile regression method proposed by Koenker and Bassett to estimate Eq. (1). The regression with the quantile of the development level of the real economy as the explanatory variable can reflect the variability of the impact of big data, artificial intelligence and blockchain under the conditions of different levels of the real economy.

3.2 Variable Description

Scholars have different opinions on the definition of the concept of real economy. In Professor Liu Zhibiao's view, those value-added activities based on the direct creation of social wealth are the real economy. Among them, industry is the leading force and the most important category of the real economy. Therefore, considering the availability of statistical data, this study uses the number of industrial enterprises above designated size to represent the level of the real economy.

Big data, artificial intelligence and blockchain are difficult to calculate. After comprehensively considering various factors, this paper uses the "Internet+" general index to express the development level of the digital economy. The index is obtained by the weighted average of four sub-indices of digital economy, digital government affairs, digital life and digital culture. Among them, wjj is the sub-index weight of digital economy, wzw is the sub-index weight of digital government affairs, wsh is the sub-index weight of digital life, and wwh is the sub-index weight of digital culture.

$$\begin{aligned} \mathrm{DE} \;=\; & \mathrm{wjj} * \text{digital economy} \;+\; \mathrm{wzw} * \text{digital government affairs} \\ & + \mathrm{wsh} * \text{digital life} \;+\; \mathrm{wwh} * \text{digital culture} \end{aligned} \tag{2}$$

In addition to being affected by Big data, artificial intelligence and blockchain, the development of the real economy is also affected by a series of other internal and external variables. The control variables selected in this paper mainly include five control variables, including financial development (FD), fiscal policy (FP), foreign direct investment (FDI), pollution control capability (PC), and location conditions (dq). Among them, financial development is measured by the loan balance of financial institutions at the end of each city (10,000 yuan); fiscal policy is measured by local budgetary expenditure (10,000 yuan); foreign direct investment is measured by the actual amount of foreign investment in each city (10,000 US dollars). Measurement; pollution control capacity is measured by the comprehensive utilization rate of industrial solid waste (%); location conditions are treated as dummy variables, if the city belongs to the eastern and northeastern regions, the value is 1; if it belongs to the central or western regions, the value is 0.

3.3 Data Sources and Descriptive Analysis and Correlation Coefficient Analysis

The data type is cross-sectional data of 162 cities in mainland China. At the same time, in order to maintain the consistency of caliber and dimension, the data involved in this paper are processed by taking the natural logarithm. Environmental governance capacity

Table 1. Descriptive statistics of variables.

Variable	Mean	Median	Max	Min	Standard Deviation
RE	1578.222	1166	9840	17	1573.862
DE	1.32049	0.6575	28.4297	0.2254	2.692509
FDI	119459.2	44207	2432909	5	249213.2
FD	4.46e+07	1,70e+07	6.34e+08	1577689	7.68e+07
FP	5507272	3741807	6.82e+07	753092	7668499
PC	0.8005969	0.8877	1	0.0024	0.2192334
dq	0.4814815	0	1	0	0.5012063

is not dealt with because it is a proportional indicator. The descriptive statistics of each index are shown in Table 1.

4 Empirical Results and Analysis

4.1 Evaluation of the Overall Effect of the Digital Economy on the Real Economy

Model (1) was estimated using weighted least squares (WLS). To avoid multicollinearity problems, stepwise regression is used. The specific operation process is: only one control variable is introduced at a time, and based on this, other control variables are gradually introduced. It can be seen that the higher the R^2 and F values, the stronger the interpretation ability of the results. Model (7) and the revised model (7) are the regression results after adding the multiplication term of the digital economy and location conditions. The influence direction and significance of each variable in models (1)–(4) have not changed, but in models (5)–(7), the sign of the digital economy becomes negative. After the heteroscedasticity test, it is found that the p value is 0.4935, and there is homoscedasticity. Finally, the results in the revised model (7) are used as the benchmark.

From the perspective of core variables, the impact of the Big data, artificial intelligence and blockchain on the real economy is negative, and it has already produced a certain "crowding out effect" on the real economy. The result reflects the reality that my country's big data, artificial intelligence and blockchain and the real economy are at a relatively low level of integration and development. Therefore, the current focus of work is to integrate existing policies, gradually reverse the phenomenon that the development of the Internet, big data, artificial intelligence and the real economy is out of sync, and effectively promote the deep integration of the Internet, big data, artificial intelligence and the real economy.

From the perspective of the multiplication term, the coefficient of DE in model (6) is −0.0027231, and the coefficient of DE in the revised model (7) is 0.1285056, indicating that location conditions have increased the impact of Big data, artificial intelligence and blockchain are difficult on the real economy. The "crowding-out effect" of Big data, artificial intelligence and blockchain are difficult on the real economy is greater in the eastern and northeastern regions than in the central and western regions.

From the perspective of control variables, the statistical results of some control variables are in line with expectations. For example, the impact of financial development on the real economy is positive, and financial development can promote the growth of the real economy. The impact of fiscal policy on the real economy has been significantly positive, and the focus of fiscal policy support has shifted to "three eliminations, one reduction and one supplement", and the operating costs of the real economy have been further reduced. The impact of environmental governance capacity on the real economy is significantly positive and flexible, which also reveals that environmental governance and real economic growth are not contradictory, providing effective support for the theory of "lucid waters and lush mountains are invaluable assets". In comparison, the two variables of fiscal policy and environmental governance capacity have a greater impact on the real economy, and the coefficients are both greater than 0.5. The effect of location conditions on the real economy is significantly positive, indicating that the growth of my country's real economy has significant spatial heterogeneity characteristics. The impact of foreign direct investment on the real economy is significantly positive. FDI can enhance export competitiveness and promote the growth of the real economy [7] (Table 2).

4.2 Using Quantile Regression to Analyse the Conditional Effect of Digital Economy at Different Levels of Real Economy

In view of the fact that there are large differences in the development level of Big data, artificial intelligence and blockchain at the city level, this paper divides the samples into three categories, and uses the quantile regression method to estimate the model. The 25%, 50%, and 75% quantiles were selected, corresponding to the low-level, medium-level, and high-level groups of the real economy, respectively. The results are shown in Table 3. In the three groups, the impact of the digital economy is negative, but in terms of the degree of impact, there is a marginal increase in the "crowding out effect".

From the perspective of control variables, the impact of financial development, fiscal policy, foreign direct investment, environmental governance capacity, and location conditions on the real economy is consistent with the overall analysis results, but the intensity is different under different level groups. For example, under different level groups of the real economy, the impact intensity of financial development increases marginally. This shows that the higher the level of the real economy, the stronger the financial demand. Therefore, the perfect digital capital market support is very important for the integration of the two. However, the impact strength of FDI under different real economy groups decreases marginally, and it is not significant in the high-level group.

4.3 DID Analysis and PSM-DID Analysis

After using the general two-difference method, it turns out that the p-value is 0.22. According to Duflo's idea, do double difference PSM on the data. The results show that the explanatory power of the dummy variables for the treatment variables is acceptable (quasi R^2 is 0.66) (Duflo 2003). The coefficient estimate for the mean treatment effect is 0.266, which is significant at the 5% level. When propensity score matching was used to test whether the distribution of variables between the treatment and control groups was

Table 2. Estimation results of regression.

Variable	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	Model (6)	Model (7)	Revised Model (1)
Constant term	7.124168 (0.0623754***)	5.307076 (1.098171***)	−8.969622 (2.506639***)	−7.202314 (2.330205**)	−7.844218 (2.322738**)	−7.823788 (2.351783**)	−7.389959 (2.335173**)	−7.89959 (3.708993**)
DE	0.8340437 (0.0722089***)	0.7638121 (0.0833885***)	0.0734368 (0.1343091)	0.0195352 (0.1240291)	−0.0052211 (0.1231484)	−0.0027231 (0.1295171)	−0.1285056 (0.1413175)	00.1285056 (0.1822401)
FD		0.1065099 (0.0642671*)	0.1162025 (0.0578452**)	0.0869308 (0.0535186)	0.0792702 (0.0530263)	0.0802914 (0.0555204)	0.085353 (0.0549662)	0.085353 (0.0699687)
FP			0.9188638 (0.1482675***)	0.7081701 (0.1418906***)	0.743604 (0.1412288***)	0.7414723 (0.1455149***)	0.7045441 (0.1449872***)	0.7045441 (0.2058604**)
FDI				0.1827884 (2.330205***)	0.1658132 (0.0342038***)	0.1655766 (0.0345106***)	0.1623522 (0.0341677***)	0.1623522 (0.0354758***)
PC					0.5061279 (0.2347186**)	0.5076564 (0.2366702**)	0.5221482 (0.2341852**)	0. 5221482 (0.2208221**)
dq						−0.0072312 (0.1125508	0.0536988 (0.1150124)	0.0536988 (0.1122654)
DE#dq							0.2657878 (0.1260874**)	0.2657878 (0.1563395*)
R2	0.4513	0.4572	0.5606	0.6277	0.6361	0.6338	0.6418	0.6361
F	133.41	68.81	68.47	68.86	57.30	47.44	42.20	57.30

Table 3. Quantile regression estimation results.

Variable	Model (8) low level group	Model (9) medium level group	Model (10) high level group
Constant term	−7. 376876 (3.069391**)	−10. 89045 (2. 160394***)	−4.217415 (3.440414)
DE	−0. 0538446 (0. 1690371)	−0. 2151822 (0. 118977*)	0. 0738718 (0.18947)
FD	0. 0266224 (0. 0724615)	0. 1063772 (0. 0510021**)	0. 0196394 (0.0812206)
FP	0. 7629913 (0. 1899164***)	0. 9083786 (0. 1336729***)	0. 5945316 (0.2128732*)
FDI	0. 1777504 (0. 0450409***)	0. 1715114 (0. 0317021***)	0.165926 (0.0504854**)
PC	0. 2313212 (0. 3088862)	0. 5113128 (0. 21741**)	0.2938787 (0.3462239)
Dq	−0.179261 (0.1468938)	0.0624141 (0.1033914)	0.4946641 (0.1646501**)
R2	0.4571	0.4576	0.4573

balanced, the results showed that only one covariate was significantly different between the treatment and control groups after matching.

5 Conclusion

(1) Fiscal policy emphasizes the use of financial technology to promote the healthy development of the real economy, implement the "Internet +" strategy, and give full play to the role of the big data, artificial intelligence and blockchain in reshaping and transforming the real economy. (2) Third, in view of the positive impact of financial development on the real economy, the financial support system for the integration of artificial intelligence and the real economy should be improved, and fiscal and financial policies should play a leading and guaranteeing role in the real economy. (3) Encourage the use of the Internet to build a technology sharing platform. The government should implement precise policies to accelerate the digital transformation of traditional industries in the region. It should vigorously promote the development of digital industries. At the same time, it should focus on the integration of new digital technologies and traditional manufacturing industries, and accurately support local entities with traditional advantages. The digitization and intelligence of the industry realize the continuous transformation of the new and old kinetic energy of industrial development. (4) In view of the significant spatial heterogeneity, the central and western regions should be encouraged to actively undertake industrial transfer from the eastern region, and new production factors such as artificial intelligence and big data should be used to promote balanced regional development.

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