Factor Market Distortions and Rural Information Inequality: Based on Empirical Analysis

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Abstract: Based on the 2018 China Household Tracking Survey data, the impact of factor market distortions on rural information inequality is examined in conjunction with macro data at the regional level. The research findings indicated that factor market distortions significantly increased rural information inequality based on indicators of the breadth and intensity of Internet use. Heterogeneity analysis shows that labor factor market distortions have a more significant impact. Introducing the e-commerce index as an indicator of information depth, the study finds that the contribution of factor market distortions to rural information inequality still holds, and this positive effect is more pronounced for the pioneer provinces. Heterogeneity analysis shows that focusing on capital factor market distortions has a stronger debilitating effect on alleviating rural information inequality. The above findings suggest that, in the context of the national implementation of the digital rural development strategy to inject new momentum into the successful implementation of the rural revitalisation strategy, the government should focus on different types of market distortions in addition to correcting the overall distortions in factor markets. Only by doing so can the "digital divide" in rural China be effectively broken.

1 INTRODUCTION

According to the 47th survey report released by China Internet Network Information Center (CNNIC), as of December 2020, the number of rural Internet users in China reached 309 million, an increase of 54.71 million from March 2020; the Internet penetration rate in rural areas was 55.9%, an increase of 9.7 percentage points from March 2020, and the gap between urban and rural Internet penetration rates shrank to 19.8 percentage points. The rapid penetration of the Internet has to a certain extent alleviated the information inequality in rural areas, but at the same time, problems such as the poor operation of Internet + finance and stagnant Internet + e-commerce projects need to be solved, and the problem of unbalanced and insufficient development of science and technology in China is still prominent. The "last mile" of network infrastructure in poor areas has not been completely bridged, and the "digital divide" still exists (Zhao, Zhou, 2019, Wang, Zhao, 2020). In 2018, the Opinions of the State Council of the Central Committee of the Communist Party of China on the Implementation of Rural Revitalization Strategy and the Strategic Plan for Rural Revitalization (2018-2022) stated the importance of implementing digital rural strategy and expanding digital agriculture construction. In May 2019, the General Office of the CPC Central Committee and the General Office of the State Council issued the Outline of the Digital Countryside Development Strategy, which clearly indicates that digital countryside will become a strategic direction for rural revitalization and accelerate the development of information technology to achieve the long-term goal of comprehensively promoting and facilitating the development of agriculture and rural modernization. In the 14th Five-Year Plan, the Party Central Committee clearly expressed the urgency of developing digital economy, promoting the deep integration of digital economy and real economy, scientifically laying out and promoting the construction of new infrastructure based on information network and driven by technological innovation, which is conducive to promoting stable growth, adjusting structure and benefiting people's livelihood. However, on a national scale, the level of

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development of China's digital economy in agriculture and rural areas, influenced by the level of economic development and the level of science and technology, shows a situation where the east is strong and the west is weak, the south is strong and the north is weak, and both suburban and regional development are unbalanced. The differential development of digital economy will lead to rural information inequality, which will have a negative impact on the rural revitalization strategy and the overall goal of the 14th Five-Year Plan. Therefore, in the era of technology where new technologies such as cloud computing and artificial intelligence are constantly iterating and evolving, it is of great theoretical value and practical significance to discuss how to alleviate information inequality in rural areas due to "tool exclusion" and "evaluation exclusion" caused by network technology. It is of practical significance.

Information inequality refers to the diverse information gaps between different types of subjects at the macro and micro levels of communication technologies and in the actual activities of availability and use of information resources (Wang, Zhang, Jia, 2019). It has been studied that the factors that influence information inequality are multidimensional. It can be encapsulated as natural, social and individual factors. Overall, geographical factors (Stornaiuolo, Thomas, 2017, Barnett, et al., 2017, Park, 2017). among natural factors, economic factors (Gagné, et al., 2018), resource factors (Courtois, Verdegem, 2016, Robinson, Wiborg, Schulz, 2018), and social class factors (Yu, Zhou, 2016, McNicol, Aillerie, 2017, Xu, 2017) among social factors, and educational factors (Liao, et al., 2016, Bol, Helberger, Weert, 2018), skill factors (Chen, Lee, Straubhaar, Spence, 2014, Katz, Gonzalez, 2016), psychological factors (Rashid 2016, Potnis 2016), and health factors among individual factors (Li, Yang, Li, 2016). Combined with previous studies, it can be seen that domestic and foreign scholars have a solid foundation for research on information inequality, but at the same time, there are three issues that deserve attention: first, most of the previous studies stay at the theoretical level, using micro databases, and empirical analysis to explore information inequality in rural areas is not common in the research literature. Second, previous scholars have not explored the extent of the impact of rural information inequality and the mechanistic paths using the factor market distortion perspective in the context of China's economic development, considering the reality that factor marketization varies across regions and factor market distortion (Yu, Wu, 2020, Zhang, Zhou, Li, 2011). Third, most of the literature focuses on information inequality in terms of computer and Internet applications, and does not conduct an in-depth analysis of information inequality in the context of frontier technology environment. In order to make up for the shortcomings of the above studies and further measure the impact related to factor market inputs on rural information inequality in the context of the new era, this study takes the following measures: first, for sample selection, the latest issue of CFPS 2018 micro data of farm households combined with the China Sub-Provincial Market Report Index (2018) and the China E-Commerce Development Index Report (2018) are used to establish a new panel data, a sample of 2508 farm households is selected for empirical analysis; second, considering the heterogeneity of factor market distortions, this article further extends to discuss the extent of the impact of different types of factor market distortions on rural information inequality. The rest of the article is structured as follows: the second part is mechanism analysis; the third part is data sources and model design; the fourth part is empirical analysis; and the fifth part is concluding remarks and recommendations.

2 MECHANISM ANALYSIS

In neoclassical economics, the production of firms seeking to maximize profits occurs at a position where the marginal cost of factors is equal to the marginal output. However, in the case of distorted factor market prices, it will lead to deviations between the actual prices of technology, capital, labor and other factors of production and equilibrium prices, making the use and allocation of factors by enterprises and other market players fail to achieve the Pareto optimal state, thus leading to efficiency losses, while the market segmentation blocks the free flow of factors such as R&D capital, significantly stalls the update and use of network technology, and ultimately exacerbates information inequality under the realistic conditions of inconsistent network technology market environment. This inequality is even more serious in rural areas where the network infrastructure is not perfect.

Factors of production such as technology, capital, and labor, as the lifeblood of economic development, play an important role in the allocation of information resources in rural areas (Liu, Liu, 2020) Technology market: (1) The disparity in the level of science and technology in rural areas of China makes the ability of information dissemination and audience access vary among regional farmers. The emergence of a series of high-tech industries, such as unmanned supermarkets and cashless cities, has led to the upgrading of the industrial structure in regions with these high-tech industries, which in turn has greatly contributed to enhancing the usefulness of Internet use among local rural residents. In contrast, the industrial structure in remote rural areas will be stagnant due to the distortion of the technology market, which will eventually lead to the lack of knowledge and ability to master new technologies and make farmers in these areas "disadvantaged", and the information gap between them and the "Internet-connected" groups will continue to widen. (2) Technology market distortion will also cause inequality in factor income shares and wages, which will further weaken the probability and possibility of accessing network technology in remote rural areas, including promoting the use of network activities such as shopping, entrepreneurship and social networking by farmers, resulting in negative effects and ultimately reducing the possibility of using network technology for productive activities by farmers in remote areas.

Labor factor market: (1) Along with the accelerated urbanization in China, the problem of urban-rural dual structured in China has become more obvious, concentrating on the lack of reform of the household registration system and the concentration of too many high-quality resources in big cities, in addition, the mechanism of labor mobility has not realized the freedom without security, thus exacerbating the distortion of the labor market. The unreasonable spatial distribution of technical talents as an important part of modern high quality labor force will lead to inconsistency in the efficiency of Internet technology in rural areas of various provinces and cities. (2) Under the dual constraints of fiscal decentralization and local governments' pursuit of GDP growth, governments at all levels will shrink enterprise costs, attract external investment, and promote economic growth and political performance by lowering labor prices, etc. Low labor prices will, on the one hand, lead enterprises to make more use of tangible factors and form path dependence, making them pay less attention to the innovative ability of Internet technology; on the other hand, it will also inhibit consumers' ability to purchase innovative products from local enterprises, thus forming a low-end vicious circle, resulting in the Internet penetration rate and Internet technology in remote rural areas not achieving simultaneous improvement, and ultimately exacerbating information inequality among rural areas.

Capital factor markets: (1) Theoretically, distortions in capital factor markets can increase rural information inequality by increasing the "credit constraint effect" and unproductive rent-seeking behavior. In the context of China's incomplete interest rate market reform, local governments tend to let financial institutions invest their credit funds in low-risk construction projects that can quickly achieve economic benefits in order to pursue GDP growth, while high-tech enterprises based on network technology generally have long investment cycles and high investment risks (Guo, Sun, 2019). (2) With local governments having a say in the pricing and allocation of capital factors, enterprises and other market players have sufficient incentives to use unproductive rent-seeking opportunities to pursue their own interests, which will result in a waste of resources in this game process, eventually making the beneficiary enterprises give up or delay their intention to introduce new network equipment and technologies, and discouraging other enterprises from using new technologies such as the Internet for production.

Given that the diffusion of network technologies is selective and innovative, the degree of local government intervention in the technology, capital, and labor markets in different regions will be heterogeneous, resulting in significant differences in the degree of distortion in the above three factor markets. The serious segmentation of factor markets will lead to the situation that factor prices are undervalued or highly differentiated, and the degree of resource skewing within regions will also lead to resource mismatch, and the degree of network technology development in rural areas will also show divergence, which will eventually lead to different barriers and costs of Internet access for farmers in different regions, thus affecting the reception and dissemination of information among farmers, and thus exacerbating rural information inequality.

3 DATA SOURCES AND MODEL DESIGN

3.1 Data Sources

The data are mainly from the China Household Tracking Survey (CFPS) 2018 data. CFPS data covers a wide range of provinces and a large survey sample, and is considered a national tracking survey data, which can better reflect the situation of rural households' internet use in the new era. In order to avoid outliers and missing values from biasing the experimental results, this paper treats the data as follows: (1) delete samples with missing income and income less than 0; (2) retain the labor force sample. The age of men is 16-60 years old and the age of women is 18-55 years old; (3) the missing values of core variables are removed. After these three steps, the final research sample of 2508 rural residents was obtained. In addition, this paper uses the China Sub-Provincial Market Report Index (2018) to measure the factor market distortion index, and introduces the China E-Commerce Development Index Report (2018) to further investigate the relationship between factor market distortion and rural information inequality in depth.

3.2 Variable Selection

Explanatory variable: rural information inequality. Most previous studies have used "Internet use" as an indicator to test individual use of the Internet, without taking into account the deeper information inequality. Therefore, in this paper, we use the Foster-Greer-Thorbecke (FGT) index (Foster, Greer & Thorbecke 2010) to establish an information distance indicator to measure rural information inequality based on previous studies. The information distance is measured as the ratio of the difference between the sample average Internet use and the Internet use of the farm households to the sample average Internet use. The specific measurement formula is as follows.

$$P_0 = \sum_{i=1}^{n} \frac{\bar{i} - i_i}{\bar{i}} \tag{1}$$

Where is the average Internet $\bar{i}$ usage and is the Internet usage of farm households. i_i If the distance from the average P_0 Internet usage is closer, it represents the smaller information inequality gap. In addition, considering that Internet usage is suitable for presenting the state of Internet usage breadth, but not describing the state of Internet usage intensity, this paper uses "online purchase amount" in CFPS questionnaire as an indicator of Internet usage intensity, and further tests the degree of influence of factor market distortion on rural information inequality on this basis. Finally, with the continuous improvement of network technology, the continuous promotion of innovative business models such as cross-border e-commerce and rural e-commerce in each region has a significant impact on the information flow in rural areas. Therefore, this paper introduces the e-commerce index in each region and uses the formula of Equation 1 to create a new indicator of rural information inequality.

Core explanatory variable: factor market distortion. Combined with previous studies, there are two types of measures on factor market distortion measures: one is the production function method and the other is the marketization index method (Wang, Sji, 2015). Comparatively, the marketization index method is able to demonstrate both the relative differences in the degree of factor market distortions across regions and also the changes of regional factor markets themselves over time (Wu, Tan, Wang, 2020). Therefore, in this paper, referring to the practice of previous scholars (Lin, Du, 2013), the degree of factor market development (overall factor market), the marketization index of technological achievements (technology factor market), the degree of marketization of the financial sector (capital factor market), and the index of human resources supply conditions (labor factor market) in each province and city in 2016 are matched with the CFPS database using the relative difference between the corresponding factor market index and the maximum value of the factor market index in the sample to present the degree of distortion of the corresponding factor market, on the basis of which

$$fac_{it} = (\max factor_{it} - factor_{it}) / \max factor \tag{2}$$

The formula $factor_{it}$ is the corresponding factor market index in each province, which $\max factor_{it}$ is the maximum value of the corresponding factor market index in each region.

Control variables: this paper follows the traditional literature and controls for age, age squared, gender, social trust and other relevant variables by combining individual characteristics, family characteristics, and social characteristics (Yu & Wu 2020). Table I provides a statistical description of the main variables.

Table 1: Descriptive statistics.

Variables	Observed value	Mean Value	Standard deviation	Minimum value	Maximum value
Outcome variable					
Information inequality (breadth)	2508	-5.05e-08	1.830	-3.347	1.000
Information inequality (intensity)	2508	-2.09e-07	3.148	-43.40	1.004
Information inequality (depth)	2508	1.82e-07	0.542	-1.389	0.532
Core variables					
Factor market distortion	2508	0.304	0.174	-2.68e-08	0.898
Technology market distortions	2508	16.57	3.368	6.10e-07	19.890
Capital market distortions	2508	3.508	1.644	3.81e-07	9.380
Labor market distortions	2508	13.13	2.933	-4.58e-07	20.470
Control variables					
Age	2508	38.82	11.13	18	60
Age squared	2508	1631	878.8	324	3600
Gender (male=1)	2508	0.626	0.484	0	1
Years of education	2508	7.579	4.743	0	19
Political capital (party member = 1)	2508	0.067	0.249	0	1
Health status (very healthy=5)	2508	3.253	1.136	1	5
Marital status (married=1)	2508	0.829	0.377	0	1
Social trust (yes=1)	2508	0.533	0.499	0	1
Social network (logarithmic)	2508	7.445	2.247	0	11.290
Farming (yes=1)	2508	0.629	0.483	0	1
Personal income (logarithmic)	2508	10.100	0.946	0	13.420
Outworking (yes=1)	2508	0.701	0.458	0	1
Household size	2508	4.467	2.101	1	15
Household savings (log)	2508	6.967	4.599	0	14.510
Government rating (very good=5)	2508	2.578	1.064	0	5
Eastern region (yes=1)	2508	0.327	0.469	0	1

3.3 Descriptive Analysis

According to Table II, it can be found that, relying on the 2018 e-commerce development index, the five provinces of Guangdong, Zhejiang, Beijing, Shanghai, and Jiangsu seize the leading position and are regarded as the first echelon of China's e-commerce development. Shandong, Fujian, Sichuan, and Anhui provinces gradually highlight the advantages of e-commerce and are regarded as the second echelon of e-commerce development in China. The four provinces of Heilongjiang, Guangxi, Xinjiang and Gansu have more room for e-commerce development and can be regarded as the fourth echelon of China's e-commerce development. The remaining provinces belong to the middle force of China's e-commerce development and are regarded as the third echelon of China's e-commerce development. The division of the four gradients also indicates that the scale of e-commerce development is not consistent across Chinese provinces and cities, indicating that there are certain gaps in the development of e-commerce in each province.

Subdividing each province's e-commerce index into scale, growth, penetration and support indices, it can be found that the leading five provinces are above the national average except for the growth index. Similar to the pioneer provinces, the growth index of the dominant provinces is also slightly lower than the national average. The indices of the middle provinces show the opposite trend with the pioneer provinces and dominant provinces - the scale index, penetration index and support index are lower than the national average, but the growth index is significantly higher than the national average, indicating that although the middle provinces do not yet have obvious scale advantages and superior support environment, they have all made efforts in e-commerce economy. The growth index of potential provinces is slightly equal to the national average, but the rest of the index is significantly lower than the national average. It indicates that the e-commerce development environment of potential provinces still needs further optimization, including access to corresponding support in logistics and capital.

Table 2: Results of e-commerce development index measurement by provincial administrative regions in 2018.

Rank	Province	E-commerce development index in 2018	Scale index	Growth Index	Penetration Index	Support Index
1	Guangdong	65.60	100	24.65	52.17	68.99
2	Zhejiang	52.62	61.62	11.94	87.29	53.04
3	Beijing	45.84	58.22	21.56	38.54	61.82
4	Shanghai	38.87	50.28	20.22	36.70	44.39
5	Jiangsu	33.05	48.36	14.71	34.35	27.86
6	Shandong	32.58	46.28	35.58	19.01	18.41
7	Fujian	31.44	24.29	33.48	42.82	30.01
8	Sichuan	29.86	24.40	63.30	11.56	15.91
9	Anhui	27.83	21.91	59.21	15.80	11.02
10	Shaanxi	25.73	11.25	68.38	10.02	13.46
11	Hunan	25.66	15.90	63.97	12.17	8.34
12	Henan	25.22	19.95	52.83	10.82	14.34
13	Chongqing	24.67	14.38	64.18	9.68	8.31
14	Hubei	24.64	20.25	46.76	13.08	16.21
15	Jiangxi	23.62	11.28	61.54	13.28	8.15
16	Hebei	22.24	14.61	44.43	15.35	14.75
17	Tianjin	20.26	9.76	44.45	10.78	71.90
18	Tibet	19.81	0	66.01	12.79	3.74
19	Ningxia	19.47	1.05	68.29	5.19	4.99
20	Jilin	19.33	3.40	62.15	2.20	10.82
21	Hainan	18.59	2.37	51.26	16.39	8.35
22	Shanxi	18.48	4.66	57.67	3.03	9.13
23	Guizhou	18.46	7.25	51.29	10.65	4.85
24	Yunnan	18.31	7.38	54.70	7.73	2.52
25	Qinghai	18.08	0.42	60.66	6.91	6.92
26	Liaoning	17.22	8.64	40.51	1.80	18.54
27	Inner Mongolia	17.02	4.80	49.95	6.02	8.23
28	Heilongjiang	16.72	3.05	53.40	1.68	9.83
29	Guangxi	16.26	6.67	46.06	6.66	5.38

Rank	Province	E-commerce development index in 2018	Scale index	Growth Index	Penetration Index	Support Index
30	Xinjiang	15.17	2.54	52.21	0.85	5.29
31	Gansu	12.85	3.02	39.92	6.53	2.53
32	Average	25.66	19.61	47.91	16.83	18.97

Table 3: Baseline regressions of elemental market distortions on rural information inequality.

	(1) Information inequality (breadth)	(2) Information inequality (breadth)	(3) Information inequality (intensity)	(4) Information inequality (intensity)
Factor market distortion	0.751*** (3.58)	0.615** (2.30)	1.544*** (4.37)	0.867** (1.98)
Age		0.133*** (5.17)		0.231*** (5.48)
Age squared		-0.001*** (-3.06)		-0.001*** (-2.80)
Gender		-0.100 (-1.39)		0.298** (2.57)
Education level		-0.075*** (-10.38)		-0.072*** (-6.09)
Political Capital		-0.471*** (-3.58)		-0.781*** (-3.62)
Health level		0.003 (0.09)		0.038 (0.80)
Marital status		0.122 (1.19)		0.092 (0.55)
Social trust		0.027 (0.20)		0.399* (1.80)
Social network		-0.041*** (-2.81)		-0.029 (-1.21)
Plantation industry		0.081 (1.14)		0.438*** (3.76)
Personal income (logarithmic)		-0.183*** (-5.01)		-0.432*** (-7.20)
Outworking		0.170** (2.37)		0.066 (0.56)
Household size		0.043** (2.57)		0.014 (0.49)
Household savings		-0.022*** (-3.17)		-0.031*** (-2.67)
Government evaluation		-0.010 (-0.30)		0.024 (0.44)
Eastern Region		0.041 (0.42)		-0.119 (-0.75)
Observed value	2508	2508	2508	2508

Note: The t-statistic is the data in parentheses; differences in confidence level significance are indicated by ***, **, and * among the 1%, 5%, and 10% levels, respectively. Same as below.

3.4 Empirical Model Design

The benchmark regression model set in this paper is as follows.

$$Ine_{\mathrm{i}} = \alpha + \beta Dist_{\mathrm{i}} + \lambda X_{\mathrm{c}} + \varepsilon_{\mathrm{c}} \qquad (3)$$

where i represents individuals, Ine represents rural information inequality, X_c represents a set of variables that affect rural information inequality, and ε_c is a random disturbance term. β represents the effect of factor market distortion on rural information inequality, as the coefficient of focus in this paper. β Being positive, represents that factor market distortion can significantly rural expanding information inequality; β being negative, represents that factor market distortion can significantly reduce rural information inequality; β being insignificant, represents that factor market distortion has no significant effect on rural information inequality.

4 EMPIRICAL ANALYSIS

4.1 Impact of Overall Factor Market Distortion on Rural Information Inequality

Table III shows the results of the benchmark regression of factor market distortions on information inequality. The results of model 1 indicate that the coefficient of factor market distortion is 0.751, which is significant at 1%, indicating that the likelihood of factor market distortion leading to increased information inequality in rural areas is as high as 75.1% when other variables are not controlled. The results of Model 2 indicate that factor market distortions still have a significant positive effect on information inequality when other control variables are controlled for, and are significant at the 5% statistical level. This suggests that factor market distortions have a significant effect on information inequality in rural areas. The results of model 3 show that factor market distortion has a significant positive effect on information inequality (intensity) and is significant at the 1% statistical level, indicating that factor market distortion has a significant inhibitory effect on the development of online shopping platforms and the increase of farmers' willingness to shop online in rural areas. The results of model 4 show that factor market distortion still has a significant positive effect on information inequality (intensity) after controlling for other variables, and the likelihood that factor market distortion will lead to an increase in the gap between farmers' willingness to shop online in each province reaches 86.7%.

In addition to the significant effect of factor market distortion on information inequality, some of its remaining characteristic variables also have a significant effect on information inequality. The positive coefficient of age and the negative coefficient of age squared indicate that the effect of age on information inequality has an inverted U-shape, i.e., as age increases, information inequality in rural areas increases and then decreases. It is easy to understand that the higher the level of education, the wider the range of exposure to people and the higher the probability of acquiring frontier information, thus, the more obvious the effect of mitigating information inequality. In addition, political capital, social network, personal income (logarithm), and household savings also play a role in mitigating information inequality to some extent. In contrast, farmers with out-of-home work experience and larger household size significantly raise information inequality. Possible explanations for this are that farmers with out-of-home work experience are more likely to use the internet for continuous access to information sources. Farmers with larger household size have higher household economic pressure, lower average education level (Li, Yang, 2014), and less probability of using the Internet to access information.

Based on the above regression results, it can be found that there is a significant positive effect of factor market distortions on rural information inequality, both from the information breadth perspective and by relying on the information intensity perspective test, i.e., factor market market distortions significantly widen information inequality in rural areas. Factor market distortion, as a special product of China's market-oriented reform, makes factors of production such as capital and labor deviate from their real prices, causing inefficient use of resources, industrial structure consolidation and other corresponding problems, which eventually affects the utility of Internet use by farmers in each region through resource mismatch and talent mismatch, and thus exacerbates information inequality in rural areas.

4.2 Impact of Factor Market Distortions in Technology, Capital, and Labor on Rural Information Inequality

The impact of overall factor market distortions on rural information inequality was analyzed above. To further investigate the impact of different factor market distortions on information inequality, this paper subdivides the factor markets. Based on the Cobb Douglas production function, this paper introduces three factors, namely, technology, capital, and labor, and further explores the impact of these three types of factor distortions on rural information inequality.

According to the regression results of Model 1 and Model 2 in Table IV, we are able to find that technology market distortions significantly widen information inequality, indicating that technology market distortions are not conducive to alleviating information inequality. The regression results of Model 3 and Model 4 show that capital market distortions increase information inequality. When there are distortions in the capital factor market, enterprises will consider the "opportunity cost" and prefer to inject capital into economically developed areas, thus reducing the frequency of Internet replacement and usage in remote rural areas. The results of Model 5 and Model 6 suggest that labor market distortions have a significant contribution to rural information inequality. The possible explanation is that with the accelerated urbanization process, the labor market segmentation problem has not been properly solved, and the opportunities and ways of free flow of labor factors are narrowly restricted, which leads to the lower willingness of rural residents with higher education and more knowledge to return to their hometowns for work, and the resulting "motivation effect" increases rural information inequality. The resulting "motivation effect" increases rural information inequality. According to the regression results of models 1 to 6, it can be found that the positive effect of labor market distortion on rural information inequality is the most significant and far exceeds the regression coefficient of technology market distortion.

Models 7 and 8 are the results of the full sample analysis with the inclusion of technology market distortions, capital market distortions, and labor market distortions, while other variables are controlled. According to the regression results of Model 7 and Model 8, it can be found that the positive effects of technology market distortion, capital market distortion, and labor market distortion on rural information inequality remain significant. This indicates that among all factor inputs, the continued attention of policy makers to the changes in labor market distortions will be more effective in alleviating rural information inequality. Information technology capability, which is the ability to use information resources, is in this paper being contrasted with the Internet use variable, where the breadth and intensity of Internet use is objectively constrained by an individual's knowledge base, mindset, and learning effects. Individuals who are socially advantaged can make deeper use of information technology by possessing leading digital resources and technological devices, which will further extend their own advantage, and this labor distortion will lead to inequality being continuously reproduced in the digital space (Shi 2014).

4.3 Treatment of Endogeneity

The above empirical analysis of factor market distortions does not consider endogeneity problems due to omitted variables and measurement errors, such as the quality of regional institutions and relational culture, which both affect rural information inequality. To mitigate the endogeneity problem caused by missing variables, this paper draws on previous scholars to construct as instrumental variables for the corresponding market distortions, where denotes the mean value of the corresponding market distortion. The advantage of this approach is that the data itself is used to construct the appropriate instrumental variables (Lewbel 1997).

Table 4: Impact of technology, capital, and labor market distortions on rural information inequality.

	(1) Information inequality (breadth)	(2) Information inequality (intensity)	(3) Information inequality (breadth)	(4) Information inequality (intensity)	(5) Information inequality (breadth)	(6) Information inequality (intensity)	(7) Information inequality (breadth)	(8) Information inequality (intensity)
Technology market distortions	0.437** (2.02)	0.834** (2.25)					0.125** (2.34)	0.170** (2.47)
Capital market distortions			0.545** (2.36)	1.752*** (4.42)			0.053** (2.16)	0.597*** (2.62)
Labor market distortions					0.984*** (4.01)	1.856*** (4.40)	0.759*** (3.02)	1.036** (2.24)
Control variables	No	No	No	No	No	No	Yes	Yes
Observed value	2508	2508	2508	2508	2508	2508	2508	2508

Table V summarizes the regression results for the second stage of the full-sample instrumental variables model. In the first stage, the regression coefficients of the instrumental variables are all significant at 1%, indicating that the selected variables have a strong correlation. The Wald test of the joint significance test passes the 1% significance test in Models 1 - 4, indicating that the test rejects the exogenous hypothesis that the corresponding market is distorted, thus supporting the appropriateness of using instrumental variables to run the regressions. The results of the second-stage regression in the table show that factor market distortions and labor market distortions still have significant effects on rural information inequality after the endogeneity issue is taken care of, thus validating the robustness of the baseline regression analysis of factor market distortions on rural information inequality.

4.4 Further Discussion

Following the previous formula for measuring information inequality, this paper again re-measures the rural information inequality indicators using the Chinese e-commerce development index. Among them, Model 1 is to test the overall regression results of factor market distortion on information inequality, and Models 2-Model 5 are to categorize 31 provinces into pioneer, dominant, middle and potential provinces according to the ranking differences of e-commerce development index and following the regional structure. Model 6 is to further consider the heterogeneity of factor markets and further test the degree of influence of different types of factor market distortions on information inequality of e-commerce in China. The regression results of Model 1 show that the coefficient of factor market distortion is 2.358, which is significant at 1%, indicating that there is a significant positive effect of factor market distortion on information inequality (e-commerce), i.e., factor market distortion exacerbates information inequality, corroborating the baseline regression results of this paper. The regression results of Model 2 to Model 4 show that the order of the effect of factor market distortion on information inequality is pioneer province → middle province → potential province → dominant province. The reason is that the application of big data, cloud computing and other transaction scenarios are more common and frequent in the pioneer provinces, and the factor market distortion will lead to inconsistent resource allocation within the provinces, which in turn will aggravate the e-commerce development gap among regions, thus leading to stronger information inequality. According to the China E-commerce Development Index Report (2018), the growth index of dominant provinces is lower than the national average, indicating that their growth rate is relatively slow, and thus the impact of factor market distortions on them is relatively weak. The regression results of model 6 show that for the information inequality caused by e-commerce development, we should pay more attention to the capital market distortion and technology market distortion, which means that in the future e-commerce development process, governments at all levels need to prevent the " credit constraint effect " and unproductive rent-seeking behaviors, emphasizing the combination of business ecology and government governance. This means that in the future development of e-commerce, governments at all levels need to prevent the "credit constraint effect" and non-productive rent-seeking behavior, emphasize the organic combination of business ecology and government governance, grasp the development direction of e-commerce from the industrial perspective, and realize the docking of e-commerce and digital economy, so as to provide important impetus for the development of digital countryside.

Table 5: Endogeneity tests of overall factor market distortions on rural information inequality.

	(1) Information inequality (breadth)	(2) Information inequality (intensity)	(3) Information inequality (breadth)	(4) Information inequality (intensity)
Factor market distortion	0.709** (2.43)	1.635*** (2.91)		
Technology market distortions			0.516* (1.79)	0.685* (1.97)
Capital market distortions			0.532** (2.03)	0.725** (2.16)
Labor market distortions			0.739** (1.98)	1.06** (2.13)
Control variables	Yes	Yes	Yes	Yes
Observed value	2508	2508	2508	2508

Table 6: Extended analysis of information inequality in rural areas due to distortion of elemental markets.

	(1) Information inequality (depth)	(2) Information inequality (depth)	(3) Information inequality (depth)	(4) Information inequality (depth)	(5) Information inequality (depth)	(6) Information inequality (depth)
Factor market distortion	2.358*** (54.11)	9.273*** (14.25)	0.583*** (15.74)	0.726*** (25.53)	0.671*** (77.71)	
Technology market distortions						0.515*** (13.30)
Capital market distortions						1.924*** (30.00)
Labor market distortions						-0.027 (-0.53)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Observed value	2508	443	362	1282	440	2508

5 CONCLUDING REMARKS AND RECOMMENDATIONS

In this paper, a new panel data based on CFPS (2018) micro data of farm households combined with macro data of China Sub-Provincial Market Report Index (2018) and China E-Commerce Development Index Report (2018) is composed to empirically analyze the relationship between factor market distortions and rural information inequality. It is found that: 1) rural information inequality indicators established using the breadth and intensity of Internet use have a significant positive effect of factor market distortion, i.e., overall factor market distortion significantly enhances rural information inequality. Subdividing into factor market types, labor market distortions have a more significant effect on rural information inequality. After testing with various regression analysis methods including instrumental variables, it is found that the above findings still hold. 2) Combined with the frontier technology environment, the positive effect of factor market distortion on rural information inequality remains significant using the rural information inequality index established in depth by the China E-commerce Development Index, and this positive effect is more pronounced for the pioneer provinces. Subdividing into factor market types, the positive influence of capital market distortion and technology market distortion on rural information inequality is more significant.

Combining the above findings, this paper draws the following policy implications: First, the government needs to accelerate factor market reform comprehensively, reduce excessive government intervention in factor markets, and strive to build the market as the center of resource allocation. Second, the government needs to implement the reform measures of "Increasing internet speeds and reducing costs", and in the process of increasing the rural network penetration rate, it can also consider using the Internet channel to break the separation and segmentation of the labor market, increase the probability of free flow of labor factors market, and then use the advantages of technical talents themselves to alleviate the rural information inequality. Thirdly, due to the late start of e-commerce projects, the development of e-commerce is not consistent in each province. Therefore, policy makers need to pay attention to the flow of factor inputs in pioneering regions and promote the degree of matching between e-commerce and traditional industries in advantageous regions, in addition, each province needs to combine its own characteristics and focus on the negative impact of different types of factor market distortions to ultimately guarantee the overall healthy development of e-commerce in China.

The shortcomings of this study are: first, due to the limitation of survey data availability, the study does not include macro data such as regional economic development level, thus not fully reflecting all the influencing factors limiting information inequality in rural areas of China. Secondly, this paper only considers the impact of technology, technology and information inequality in rural areas. Second, this paper only considers the degree of influence of factor market distortions of technology, labor, and capital on rural information inequality, and future research will focus on examining the influence of other factor market distortions, such as land, on rural information construction, in order to more comprehensively reflect the association between factor market distortions and rural information inequality.

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