Can Artificial Intelligence Reduce Regional Inequality? Evidence from China

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October 2021

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CRediT authorship contribution state:

Miao Hao: Conceptualization, Methodology, Writing, Review & Editing.
Shiyuan Li: Software, Formal analysis, Data Curation, Visualization.

Conflict of Interest statement

None

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Abstract: Based on the analysis of provincial-level data from 2001 to 2015, we find that regional inequality in China is not optimistic. Whether artificial intelligence, as a major technological change, will improve or worsen regional inequality is worthy of researching. We divide regional inequality into two dimensions: production and consumption, a total of three indicators. The empirical research is carried out to the eastern, central and western regions respectively. It is found that industrial intelligence improves the inequality of residents' consumer welfare among regions, while at the same time there is the possibility of worsening regional inequality of innovation. We also clarify the heterogeneity of the mechanisms that artificial intelligence promotes innovation in different regions.

Keywords: Artificial Intelligence; Regional Inequality; Innovation; Purchasing Power

1. Introduction

The widespread application of artificial intelligence is a major technological revolution, similar to many technological upgrades throughout history, it has greatly changed efficiency and productivity, and also has a mixed effect on workforce in the short term. Many studies have proved that artificial intelligence has not only improved the efficiency of industrial production but also brought about the decline of the labor market (Furman and Seamans, 2019), considering the differences in economic bases and factor endowments between different regions, regional inequality is bound to change to some extent. As one of the countries with vast territory and rich population, China's regional economic development has been unbalanced. According to the *China Statistical Yearbook*, as shown in Figure 1 and Figure 2, the gap between the eastern, central and western regions of China is widening, and the gap between the rich and the poor needs to be resolved. From Figure 3 and Figure 4 we can see that non-agricultural labor productivity also varies widely between regions.

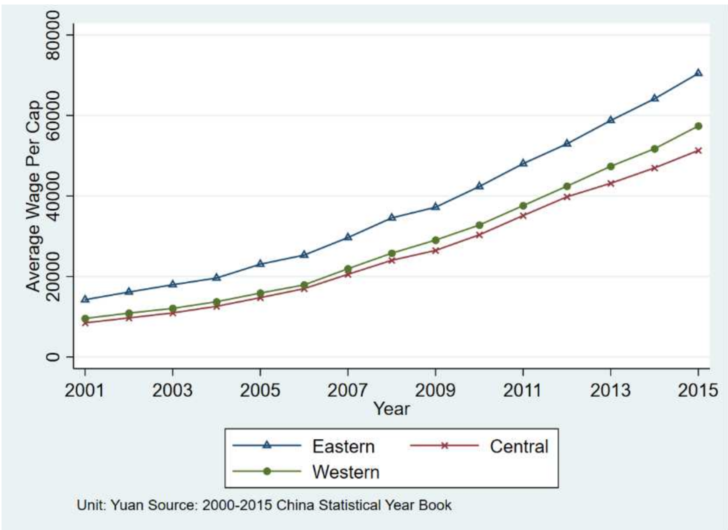

Figure 1. Evolution of cross-region dispersions of wage

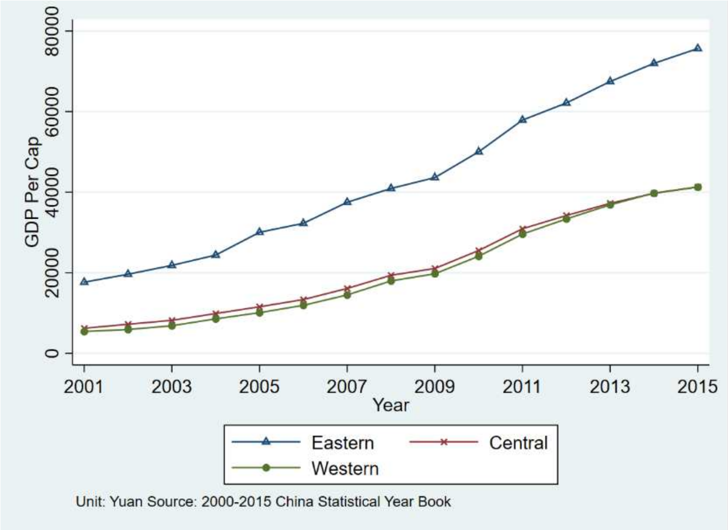

Figure 2. Evolution of cross-region dispersions of GDP per capital

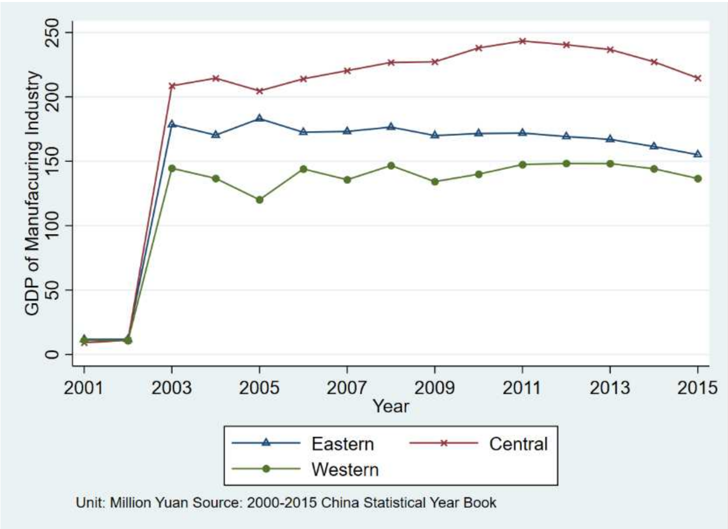

Figure 3. Evolution of cross-region dispersions of GDP of manufacturing industry

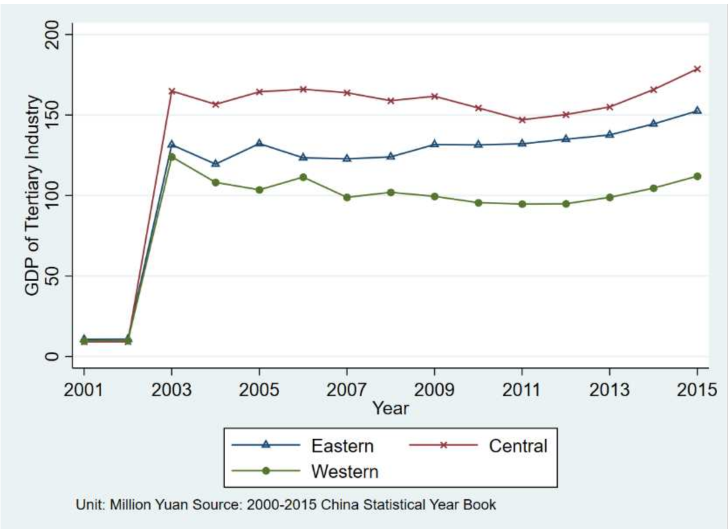

Figure 4. Evolution of cross-region dispersions of GDP of tertiary industry

In addition to the basic economic indicators, the China Academy of Information and

Communications Technology (CAICT) compiled the Digital Economy Competitive Index (DECI) and ranked various provinces in China. The results are shown in Table 1. It can be seen that there is notable regional inequality in China's digital economy, and the digital economy competitiveness of coastal provinces is significantly stronger than that of inland regions.

Table 1. Regional DECI Ranking of China in 2019 (Top 15)

Rank	Province	DECI
1	Guangdong	85.56
2	Beijing	84.19
3	Shanghai	82.17
4	Jiangsu	81.83
5	Zhejiang	78.40
6	Shandong	76.46
7	Tianjin	74.93
8	Fujian	74.55
9	Sichuan	73.62
10	Chongqing	73.57
11	Hubei	73.47
12	Anhui	72.14
13	He' nan	70.78
14	Shanxi	70.57
15	Hu' nan	69.59

With the rapid development of information and communication technology (ICT) and the popularization of the Internet, we have gradually entered the digital economy era. Due to the application of a large number of disruptive digital technologies such as mobile Internet, big data, cloud computing and artificial intelligence, the connotation of the digital economy has been expanding. As the main driving force of the current digital economy, artificial intelligence will bring new vitality to the development of all walks of life and become the core engine to promote global economic growth again. Similar to the previous technological revolution, artificial intelligence, as a means of transformation and upgrading, will inevitably have a huge impact on the production and consumption market. From the production side, industrial intelligence has a promoting effect on productivity and innovation, the job substitution effect and creation effect also have a direct impact on the labor market; From the perspective of consumption, consumer welfare will also be improved in regions with a higher level of intelligence. Since the development of artificial intelligence in different regions is not consistent, different regions have different endowments of R&D human resources (as shown in Figure 5) as well as innovation performance (as shown in Figure 6), and the extent to which artificial intelligence is used in different industries also varies (Guo, 2019), Intelligentization will have a non-negligible impact on the inequality between regions through the two dimensions of production and consumption.

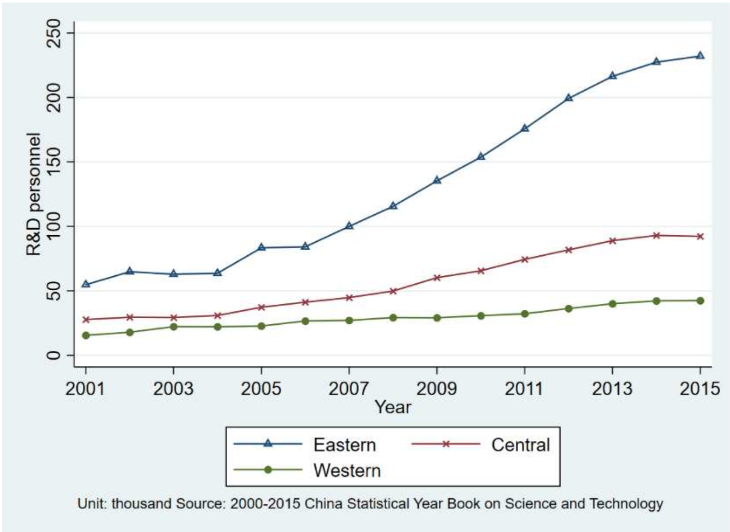

Figure 5. Evolution of cross-region dispersions of R&D full time personnel equivalence

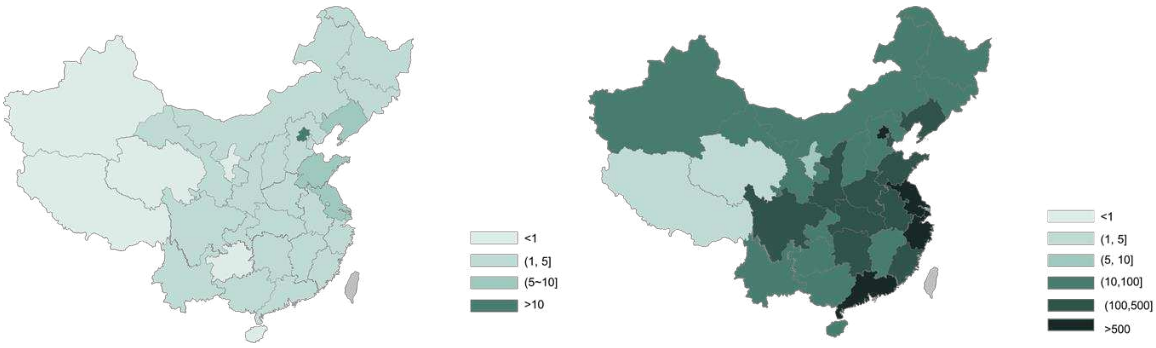

Figure 6. Provincial Innovation Index of 2001 and 2015

This paper presents an empirical study on how artificial intelligence has affected regional inequality in China. The inequality is divided into two dimensions: the production side and the consumption side. The influence mechanism of independent variables on regional indicators will also be analyzed. Based on the previous single index of regional inequality, we have added a multi-angle measurement, and broaden the comprehensiveness of the inequality research.

The paper proceeds as follows. The next section summarizes and discusses the previous related research. In section 3, the empirical design is described and gives out basic results. Section 4 analyses the impact of artificial intelligence on the change of regional development gaps. Robustness tests are conducted in section 5, and the last section provides the concluding remarks and the future research direction.

2. Literature review

2.1 Economic effect of AI

Most of the research on the economic effects of artificial intelligence is based on the impact of automation on the labor force. Artificial intelligence is bound to have a direct negative impact on the labor market. For one thing, skill-biased technological change will lead to the shift in employment towards more-educated workers (Autor and Katz, 1999), for another, changes in the content of work due to technological progress especially the rapid improvement of skills in a detailed industry will increase the demand for educated labor (Autor et al., 1998; Autor et al., 2003). These have led to a growing gap in the competitiveness of high-skilled and low-skilled labor in the market. Industrial intelligence will replace the labor with a low level of education and promote the demand for the labor with a high level of education, making the employment structure polarized. Due to the talent screening mechanism in economically developed areas, its employment structure is unipolar (Sun and Hou, 2019). In this way, skilled labor is replenished and unskilled labor is squeezed out. Automation also increased the skill premium, which widens the wage gap between high- and low-skilled workers. Moreover, the advancement of intelligence will not only widen the wage gap between jobs with different skills but also create intergenerational gaps, that is, the wage gap between older workers and younger workers (Sachs and Kotlikoff, 2012). Although labor will be replaced by automation in the long run, this replacement will only occur when the price of the machine is lower than the wage (Hemous and Olsen, 2018). There are also some researchers argue that under this premise. When the price of machines drops, middle-skilled labor is most easily replaced (Feng and Graetz, 2016). There have also been empirical studies in the UK and the US that have shown that, under the background of industrial intelligence, the jobs and wages of high-skilled and low-skilled workers gradually increased, while those of middle-skilled workers gradually decreased (Autor et al., 2006; Goos and Manning, 2007; Goos et al., 2009).

Although artificial intelligence has a replacement effect on the traditional labor force, the increased demand for products due to automation will create new jobs and new tasks (Alexopoulos and Cohen, 2016). The labor income reduction and job replacement brought about by automation will be offset to some extent by the reduction in production costs and the increase in demand for non-automated jobs (Acemoglu and Restrepo, 2018a). But the offsets are not exactly equal, if we decompose changes in the production task content into displacement effects caused by automation and reinstatement effects driven by new tasks, it is found that automation is developing rapidly but productivity creation is still slow (Acemoglu and Restrepo, 2019). Especially as intelligence becomes more sophisticated, compared with the replacement of physical power by automation, the replacement of brain power by computerization will cause a wider shock on the workplace. From this point of view, the creation effect promotes the formation of polarization, which stems from consumers' preference for diverse specializations, the reduction of automation costs and the work codification (Autor and Dorn, 2013).

To sum up, the impact of artificial intelligence on the labor market has not been agreed upon, Technological optimism pays too much attention to long-term results, overestimating the spread of new technologies, underestimating the infrastructure requirements for the widespread deployment of new technologies, and ignoring the potential threats to stable employment. Economic pessimism overestimates the speed and depth of the deployment of new technologies and ignores the employment creation role of new technologies (Long et al., 2020).

In general, the role of artificial intelligence in economic development cannot be underestimated. From the perspective of improving welfare, artificial intelligence can free people from routine tasks and let them pursue their interests (Makridakis, 2017), and it offsets the inhibitory effect of aging on the economy by improving the rate of return on capital, total factor productivity and alleviating the shortage of labor supply (Chen et al., 2019). But from the perspective of pursuing equality, although it will not reduce the total employment, it will change the employment structure (Dauthy et al., 2018; Autor and Salomons, 2018). The substitution effect is aimed at low-skilled jobs, and the creation effect is aimed at high-skilled jobs, which will increase income inequality (Acemoglu and Restrepo, 2018b), and there are study shows that automation at different skill levels can even have the opposite effect on inequality (Acemoglu and Restrepo, 2018c). How will artificial intelligence affect the economy is still a topic worth discussing

2.2 why regional inequality

High-quality regional development should be balanced. Different regions have different factor endowments, development histories and policy tendencies, resulting in unbalanced regional development trends. Admittedly, the appropriate regional inequality is conducive to the division of labor and cooperation, but for the overall economy, especially the economies in backward regions, long-term serious inequality will lead to the decline of the overall social welfare, which is harmful to the effective allocation of resources, thus impeding the rapid economic development. Regional inequality was first thought to be caused by geographical factors, as research continues, the role of such natural factors has gradually weakened, while other human factors have gradually become prominent. The regional gap is fundamentally the gap of total factor productivity (Hall and Jons, 1999). From the perspective of international environment, economic globalization and free trade are important reasons for regional inequality in China (Fujita and Hu, 2001), and the uneven distribution of foreign investment among regions will also aggravate regional inequality (Shen and Geng, 2001). From the perspective of domestic industries, the adjustment of industrial structure will have an impact on regional inequality in the short run, while in the long run, the change of regional economic disparity is mainly due to the difference of industrial growth (Gan and Zheng, 2010). From the policy point of view, the urbanization and marketization process led by the reform and opening up policy accelerated the regional unequal development (He and Liang, 2004). Besides, when the overall development strategy is not consistent with the regional endowment, resources have to be inclined to non-dominant industries in order to achieve the goal, thus affecting the speed of capital accumulation, and backward areas are more difficult to get rid of the influence of strategic "sequelae" (Lin and Liu, 2003).

The choice of regional inequality index is always a worthwhile problem. Income inequality is the direct cause of inequality in macroeconomic development, cities affected by job substitution are not consistent with cities whose production efficiency has been improved, thus widening regional inequality (Zeira, 1998; Berger and Frey, 2016). Wan (2008) proposed that giving the particularity of national conditions, research on inequality in China needs to pay attention to the selection of indicators. Income inequality can neither fully reflect the inequality in welfare or utility, nor can it fully reflect economic inequality. We know from a lot of previous studies that the application of new technological achievements such as robots has lowered employment wages, making labor's share of national income declining (DeCanio, 2016; Autor and Salomons, 2018; Acemoglu and Restrepo, 2020). Considering that high income is often accompanied by a high cost of living, purchasing power can better measure the welfare of residents (Choi et al., 2020). In addition, The innovation output measured by the number of invention patents is agglomerating in space, the cause of regional innovation ability difference mainly lies in the innovation efficiency difference between different areas, and it is influenced by the innovation environment, including the innovation entities, government support and industrial structure, with the application and development of artificial intelligence, innovation environment is changing so that the inequality of regional innovation is increasing (Li, 2007). Wang et al. (2010) made the first empirical analysis of regional innovation inequality in China, and the results show that the inequality of innovation capabilities in China's eastern, central, and western regions has worsened over time, which has severely affected the development of the overall economy.

Based on the above research, we will verify the impact of the development of artificial intelligence on social well-being from the perspective of inequality at the macro-regional level. Specifically, the inequality between regions is comprehensively analyzed from the two dimensions, the production side, that is, innovation inequality, and the consumption side, that is, purchasing power inequality. This paper not only expands the empirical research on the economic utility of artificial intelligence but also attempts to improve the regional inequality measurement index. This work complements the research on artificial intelligence in the field of social economics and will also be helpful to future research on social and economic welfare.

3. Empirical analysis

We choose the Chinese provincial panel data and enterprise patent data from 2001 to 2015 for empirical analysis. Due to the severe missing data of the Tibet Autonomous Region, we excluded the data of that province. The data for this study were obtained from *China Statistical Yearbook, China Statistical Yearbook on Science and Technology, China Labor Statistical Yearbook* and China National Bureau of Statistics official website.

Our analysis so far suggests that industrial intelligence is widely distributed across Chinese provinces and geographic dispersion has been on the rise. In this section, we carry out a time series analysis to test the possible influence of industrial intelligence on innovation and purchasing power. To be specific, we investigate whether and how the application of artificial intelligence affects the behavior of regional inequality.

As for the variables, $Innovation_{it}$, we use two indicators to reflect innovation. First, the number of invention patents granted is widely used by previous studies. Patents are strongly linked to enterprise R&D due to their commercial value, which makes it a reasonable indicator to measure innovation (Hagedoorn and Cloodt, 2003). Secondly, the urban innovation index from *China's Urban and Industrial Innovation Report* is used to express regional innovation, which is more macro and comprehensive than the index of patent quantity. It not only focuses on the number of patents, but also takes into account the average value of such patents. In addition, it also measures entrepreneurship as a type of innovation. Following Choi (2020), $PurchasingPower_{it}$ computed as the average nominal wage divided by the price index of province i in year t. Int_{it} reflects the degree of industrial intelligence of province i in year t (Sun and Hou, 2019). X_{it} is a set of control variables. ε_{it} is the error term.

We select the following control variables. Living Cost (*LC*) is measured by the proportion of per capita consumption expenditure (including housing expenditure) in the disposable income of urban households in each province. Industrial Structure Reforming (*SR*) is measure by the proportion of the added value of the tertiary industry in GDP of each province. Trade Openness (*TRA*) is the proportion of total export-import volume in GDP of each province. Urbanization (*UR*) is the proportion of urban population in the total population of each province. Human Resource Investment (*HI*) is the proportion of education funding fiscal expenditures of the state in the general budget expenditures of local governments in each province. Development of finance (*DF*) is ratio of deposits balance to loans balance at year-end to GDP in each province. R&D personnel full-time equivalent (*RD*) shows the human capital investment of R&D activities. *ManftGDP* is the percentage of the gross domestic product of the secondary industry of the total GDP, reflecting the industrialization of the region. The basic summary statistics are shown in Table 2.

Table 2: Summary statistics

Variables	Observations	Mean	Standard deviation	Minimum	Maximum
Patent (hundred)	405	8.49	23.51	0.01	155.65
Innovation Index	450	47.85	107.9	0.23	896.52
Purchasing Power	450	309.95	184.16	79.32	1120.51
INT	450	12.48	8.38	1.24	57.74
LC	450	72.7	6.03	55.82	89.62
SR	450	41.46	7.98	28.3	79.65
HI	450	18.87	2.72	11.96	27.45
TRA	450	32.32	39.84	3.57	172.15
UR	450	49.16	14.99	23.96	89.61
DF	450	258.46	91.72	127.93	757.46
RD	450	7.71	6.45	0.76	36.1
ManftGDP	424	0.47	0.08	0.17	0.67

Our main estimating equations are as follows:

$$Innovation_{it} = \alpha_0 + \alpha_1 Int_{it} + \gamma X_{it} + \varepsilon_{it}$$

$$PurchasingPower_{it} = \beta_0 + \beta_1 Int_{it} + \gamma X_{it} + \varepsilon_{it}$$

Interpreting α_1 and β_1 as the causal impact of industrial intelligence on the side of production and consumption. The province and time factors were controlled for all the models, and the selection of fixed effect and random effect model was determined by the results of Hausman test. Baseline empirical results are shown in Table 3.

Table 3: The impact of industrial intelligence on innovation and purchasing power

	(1)	(2)	(3)
	Invention patent	Innovation Index	Purchasing power
INT	3.0398***	25.1004***	11.3312***
	(0.3277)	(1.4855)	(0.8661)
LC	0.9134***	0.3745	-0.2037
	(0.2649)	(1.2543)	(0.7313)
SR	0.2004	3.2585**	-1.3328
	(0.3289)	(1.5215)	(0.8870)
HI	1.8126***	2.9318	3.2593**
	(0.4878)	(2.3003)	(1.3411)
TRA	-0.1560***	-2.4119***	-0.5372***
	(0.0572)	(0.2747)	(0.1601)
UR	-0.1334	-0.9640	-0.3211
	(0.1672)	(0.6633)	(0.3867)
DF	-0.0057	-0.0066	0.4199***
	(0.0298)	(0.1394)	(0.0813)

RD	1.5651***	5.6089***	-2.3842**
	(0.3650)	(1.7392)	(1.0139)
ManftGDP	-30.5803	31.7297	-279.8791***
	(21.5574)	(99.0763)	(57.7609)
Year FE	Yes	Yes	Yes
_cons	-129.7454	-363.6366	92.1609
	(35.7749)	(164.7247)	(96.0336)
N	405	424	424
R-squared	0.844	0.830	0.979

Note: standard errors are in parentheses; *p<0.1, **p<0.05, ***p<0.01.

Nationwide, the basic result indicate that the level of industrial intelligence has a significant promoting effect on the total number of invention patents, urban innovation index and purchasing power, that is, the application of artificial intelligence not only promote the enterprise innovation output but also boosted the corporate entrepreneurship, moreover, it has a significant promoting effect on the improvement of residents' welfare. Due to differences in index connotation, the promoting effects of industrial intelligence on the innovation index and the number of invention patents are different, the enhancement of innovation index is far greater than that of the invention patents number, it means that the improvement of innovation by artificial intelligence is reflected not only in the innovation output of enterprises, but also in the driving force for the vigorous development of entrepreneurial enterprises and the effect of increasing patent value. Among the control variables, the cost of living has a significant positive impact on the number of invention patents granted, the upgrading of the industrial structure significantly improves the urban innovation index, and the level of financial development has a positive effect on the improvement of residents' purchasing power. Human capital investment has a significant positive effect on both the number of invention patents and purchasing power promotion. Trade openness and R&D personnel full-time equivalent have significant effects on the three dependent variables. Trade openness significantly inhibits the growth of the three dependent variables, while R&D personnel full-time equivalent promotes the two innovation indicators but harms purchasing power. The degree of industrialization has a significant negative effect on purchasing power improvement.

4. Heterogeneous analysis

To test the impact of artificial intelligence on regional inequality, we divided the samples into three sub-samples--the eastern, central and western regions--for regression, to investigate the differences in the impact of artificial intelligence on the three dependent variables between regions. The division of the eastern, central and western regions is based on economic development and related policies, combined with its geographical location factors. With a long history of development, superior geographical location, a highly qualified labor force and solid infrastructure, the eastern region has played a leading role in economic development. The central region is rich in energy and mineral resources and has a good foundation for heavy industry, connecting the east and linking the west. The western region is deep inland, with a vast territory and complex terrain. Although the economic development gap between the western region and the central and eastern regions is relatively large because of its late development, its development potential is also considerable due to its resource endowment and national policy tendency. The empirical results are shown below.

Table 4: The regional heterogeneous impact of industrial intelligence on invention patent

	(1) Eastern	(2) Central	(3) Western
INT	2.2851***	1.0202**	-0.0801
	(0.7499)	(0.4294)	(0.1080)
Control variables	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
_cons	-201.7517	-45.4082	-14.1593
	(131.3839)	(19.5164)	(5.4358)
N	151	116	138
R-squared	0.873	0.744	0.822

Note: standard errors are in parentheses; *p<0.1, **p<0.05, ***p<0.01.

Table 5: The regional heterogeneous impact of industrial intelligence on innovation index

	(1) Eastern	(2) Central	(3) Western
INT	24.6144***	5.2728***	7.3227***
	(3.0669)	(1.4277)	(1.4631)
Control variables	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
_cons	-1340.7156	-31.1764	-158.0145
	(585.9474)	(63.7596)	(73.3703)
N	159	118	147
R-squared	0.855	0.926	0.859

Note: standard errors are in parentheses; *p<0.1, **p<0.05, ***p<0.01.

Table 6: The regional heterogeneous impact of industrial intelligence on purchasing power

	(1) Eastern	(2) Central	(3) Western
INT	6.9182***	3.1686**	10.8053***
	(1.5118)	(1.4238)	(1.9447)
Control variables	Yes	Yes	Yes
_cons	49.0215	221.0116	45.2505
	(288.8418)	(63.5856)	(97.5267)
N	159	118	147
R-squared	0.980	0.997	0.993

Note: standard errors are in parentheses; *p<0.1, **p<0.05, ***p<0.01.

From the point of the invention patent granted number, the improvement of industrial intelligence has the most significant effect on the patent output in the eastern region, followed by the central region, while the western region is not significantly affected. For the coefficient of them, the promotion effect in the eastern region is stronger than that in the central region, which is because enterprises in the eastern region have a good foundation for innovation and strong advantages in R&D human resources endowment. Therefore, it can be concluded that the application of artificial intelligence in the three regions is also different, combined with the innovation efficiency gap, it will lead to the further aggravation of innovation inequality from this perspective.

From the perspective of the urban innovation index, industrial intelligence significantly promotes the growth of the innovation index in the three regions. Although in terms of promoting efforts, the eastern region is still leading, the central and western regions also get a strong boost. The difference between the results of this index and the invention patent index comes from the different connotation of them. The construction of the urban innovation index also includes the total registered capital of newly established enterprises in each city to measure the innovation in forms other than patents. In this way, compared with the empirical results of the former dependent variable, we can draw a conclusion that, for the western region, industrial intelligence promotes its innovation mainly by promoting entrepreneurship, which is closely related to the policy orientation and huge development potential of the western cities.

From the point of the index of residents' purchasing power, Industrial intelligence has significantly promoted the improvement of the living welfare of the residents in the eastern, central and western regions. It is worth noting that the results are somewhat different from those of the previous two indicators, that is, industrial intelligence has the strongest effect on improving the purchasing power of residents in western China, which means the application of artificial intelligence can significantly increase the utility of western consumers and improve their livelihoods. What’s more, the application of artificial intelligence has narrowed the inequality of the living quality between regions, truly practicing the slogan of "artificial intelligence makes life better".

To sum up, on the production side, the widespread application of artificial intelligence may exacerbate the innovation inequality in the three regions. However, from the point of consumption, Industrial intelligence will not only comprehensively optimize people's living utility, but also improve the purchasing power of residents in the western region, which will correspondently reduce the inequality of residents' living welfare between regions to a certain extent.

5. Endogeneity Check

Considering the endogenous bias caused by reverse causality, we examine whether explained variables and control variables have a significant impact on industrial intelligence. Referring to the method from Petia Topalova (2011), industrial intelligence was taken as the dependent variable to make a regression of the economic development index, the number of invention patents granted, the urban innovation index and the purchasing power of each province. The results show that industrial intelligence is almost uncorrelated with the economic development index, which indicates that industrial intelligence is not a complete endogenous variable. Among the three previous explained variables, residents' purchasing power does not have a significant reversed effect on industrial intelligence, but some of the results of the invention patent and urban innovation index show significant relation, our analysis of this result is as follows:

1) The industrial structure of the western region is relatively unitary, and innovation is mainly concentrated in the industrial sector. Therefore, the output of its invention patents will make a

particularly significant contribution to its development of industrial intelligence.

2) The urban innovation index is a comprehensive indicator. Firstly, it takes into account the average commercial value of patents. Because the application range of artificial intelligence in the eastern region is wide and deep, the innovation output will have a higher price elasticity of supply. The higher the patent price is, the more enterprises are inclined to carry out intelligent upgrading, and the higher the industrial intelligence degree is. Secondly, it includes the total registered capital of the newly established enterprises. According to the *China Enterprise Development Data Annual Report*, the vast majority of newly established enterprises are located in the eastern region, and their business types are mainly in emerging industries, therefore, the arrival of new enterprises in the eastern region will give a strong push to its level of industrial intelligence.

Table 7: Robustness regression results

	(1)
	INT
LC	-0.2056**
	(0.0993)
SR	0.0562
	(0.0775)
HI	-0.0139
	(0.1598)
TRA	-0.0302
	(0.0253)
UR	0.0052
	(0.0313)
DF	0.0166
	(0.0141)
RD	-0.1514
	(0.3027)
ManftGDP	-4.5499
	(6.2988)
Year FE	Yes
_cons	21.3835
	(10.4471)
N	424
R-squared	0.964

Note: standard errors are in parentheses; *p<0.1, **p<0.05, ***p<0.01.

Table 8: Robustness regression results

	(1)	(2)	(3)
	INT	INT	INT
Eastern invention patent	0.0110		
	(0.0067)		
Central invention patent	-0.1116		

	(0.0744)		
Western invention patent	0.4594***		
	(0.1752)		
Eastern innovation index		0.0220**	
		(0.0096)	
Central innovation index		-0.0528	
		(0.1541)	
Western innovation index		-0.0671	
		(0.1657)	
Eastern Purchase Power			0.0007
			(0.0040)
Central Purchase Power			0.0001
			(0.0076)
Western Purchase Power			0.0013
			(0.0033)
_cons	7.5940	9.8961	5.6114
	(0.7840)	(0.9110)	(2.0259)
N	450	450	450
R-squared	0.216	0.211	0.221

Note: standard errors are in parentheses; *p<0.1， **p<0.05， ***p<0.01.

To enhance the robustness, and reduces endogenous bias caused by reverse causation. Considering the later industrial intelligence will not affect the current level of innovation and purchasing power. this variable lagged one and two phases respectively and the results are still robust.

Table 9: Robustness regression results

	(1) Invention patent	(2) Invention patent	(3) Innovation Index	(4) Innovation Index	(3) Purchasing power	(4) Purchasing power
L.INT	3.3340***		27.4207***		11.7218***	
	(0.3546)		(1.7478)		(0.9876)	
L2.INT		3.0449***		27.0987***		9.7812***
		(0.3636)		(1.9955)		(1.0601)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
_cons	-121.5227	-130.0137	-358.9473	-332.7119	151.4563	290.0905
	(34.9155)	(34.5694)	(174.9454)	(191.4679)	(98.8486)	(101.7160)
N	388	365	402	378	402	378
R-squared	0.873	0.899	0.837	0.845	0.980	0.982

Note: standard errors are in parentheses; *p<0.1， **p<0.05， ***p<0.01.

6. Discussion and conclusion

With the rapid advancement of artificial intelligence, the topic of how intelligence affects people's work and life has become increasingly intensified. Inequality is a major problem that must be solved in the progress of economic development. Previous studies have reached basic conclusions about the impact of artificial intelligence on labor market inequality. This paper expands the scope of the concept of inequality, measures regional inequality from two dimensions of production side and consumption side, and conducts empirical research on the impact of artificial intelligence on it. This research not only investigates the effect of artificial intelligence on inequality from the comprehensive perspectives but also divides the indicator of innovation into two indexes and analyzes the different mechanisms of artificial intelligence's promoting effect on innovation in different regions.

We conclude that the effect of artificial intelligence development is heterogeneous among regions, which is closely related to the resource endowment and policy tendency of the region. The deterioration of regional inequality caused by artificial intelligence is mainly reflected in innovation. When the innovation is measured by the output of invention patents, the central and eastern regions will benefit the most, while the western regions will not benefit significantly. When it is measured by the urban innovation index, all three regions benefited significantly. This shows that the influence of artificial intelligence on innovation is not only through the explicit way of patent output, but also through the incentive to entrepreneurship and innovation to promote regional innovation implicitly. The improvement of regional inequality caused by artificial intelligence is reflected in the increase of residents' purchasing power, in other words, the improvement of living welfare of all residents, especially those in backward areas, is largely benefited from the application of artificial intelligence.

This paper broadens the horizon for the research on the economic effect of artificial intelligence, lays a foundation for the future in-depth study of artificial intelligence, and also provides a reference for designating differentiated innovation, entrepreneurship and income distribution policies. On the basis of this paper, further research can be carried out as follows: As a general technology, artificial intelligence has the characteristics of spillover, that is, it will have ripple effects on related industries. Therefore, inter-industry interaction can be further introduced to classify and compare the impact of artificial intelligence technology on regional inequality within and between industries, so as to improve the differentiated formulation of industrial policies.

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