AI's Effects on Economic Growth in Aging Society: Induced Innovation and Labor Supplemental Substitution*

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Abstract: *This paper employs industrial robot installations that represent the level of smart manufacturing as the proxy variable of artificial intelligence (AI). Based on cross-country panel data and China's provincial panel data, we create a two-stage least square (2SLS) regression model to examine the effect of an aging population on AI applications and AI's effect on economic growth. In this manner, we aim to test whether AI has a substitutive effect on labor against the backdrop of an aging society and the kind of such a substitutive effect. Our findings suggest that the labor shortage arising from an aging society will prompt an economy to adopt smart manufacturing more broadly, i.e. an aging society is a driver of AI development. Smart manufacturing has a positive effect on local GDP and helps shore up the slowing economy resulting from an aging society. AI is an important tool for coping with the challenges of an aging society. Current AI development is an "induced innovation," and its substitutive relationship with labor is a "supplemental substitution" rather than "crowding-out substitution." If these characteristics are properly maintained, AI will contribute more to China's economy against the backdrop of an aging society.*

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1. Introduction and Literature Review

An aging population and artificial intelligence (AI) are among critical drivers of China's economic transformations. The rising cost of labor as a result of diminishing demographic dividend poses a constraint to China's economic development. For instance, Li *et al*. (2012) point to China's diminishing labor cost advantage. Based on changes in China's demographic structure, Lu and Cai (2014) expect China's potential growth rate to plummet. As the core driver of a new round of technology and industrial revolution, AI is reshaping all aspects of economic activity, including manufacturing, distribution, exchange, and consumption. With its great potentials, AI is widely expected to become a new driver of China's economic growth.

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Smart manufacturing[1] is the primary AI application in economic activity. By substituting a part of traditional jobs, smart manufacturing reduces the aggregate labor demand of an economy, thus offsetting the negative impact of aging population on economic growth - a phenomenon we refer to in this paper as “supplemental substitution.” However, smart manufacturing also has unwanted consequences such as the replacement of traditional jobs, unemployment, and widening income gaps. Such consequences make some people worse off in an aging society - a phenomenon we refer to in this paper as “crowding-out substitution.”

Is “supplemental substitution” or “crowding-out substitution” the dominant effect of AI? To be more specific, will AI mitigate or offset the negative economic growth impact of an aging population by compensating for a shrinking workforce? Should the government adopt policies to support AI-related industries? These questions have aroused extensive attention and heated debates among scholars, the public, and policy-makers (Schwab, 2017). Unraveling the interactions between AI and economic development in an aging society will contribute to academic research and offer a policy-making reference.

The interplay between AI and the labor market has become an increasingly popular topic of research over recent years. Existing empirical studies on this topic have generally employed the following two analytical methodologies:

In the first methodology, experts are invited to score the characteristics and substitutability of various jobs in a country, and then evaluate the possibility for each occupation to be replaced by machine learning AI applications. Following this approach, Frey & Osborne (2017) reckon that 47% of over 700 occupations in the United States can be replaced in a short time. Subsequent studies have forecasted the AI’s labor substitutability in other countries (Pajarinen & Rouvinen, 2014; Brzeski & Burk, 2015). Based on this approach, Chen (2018) finds that 76.8% of China’s current working population are likely to be impacted by AI technologies.

The drawback of this forward-looking approach is twofold. First, the result of the estimation is not robust enough. Referencing Frey & Osborne’s methodology, Arntz *et al*. (2016) re-estimate that only 9% of occupations in the U.S. can be replaced by automation. Furthermore, this framework overlooks the labor market response to change in technology that will result in a new equilibrium. The crowding-out effect of AI on labor may thus be overestimated.

The second methodology employs robot density as a proxy variable of AI to investigate the effects of a technology shock under a general equilibrium framework. Based on this method, Acemoglu & Restrepo (2018a) point to the complex employment effects of smart manufacturing. Such effects are subject to capital interest rate and the relative level of labor price, while labor price, in turn, is influenced by the level of AI applications. Based on the data of 17 countries from 1993 to 2007, Graetz & Michaels (2015) find that with rising wages and total factor productivity (TFP), robotic technology led to an increase in the annual GDP growth rates of these countries by 0.37 percentage points. Another research based on German data did not find any evidence that AI will cause unemployment (Dauth *et al*., 2017).

The second methodology offers a comprehensive analysis of AI’s effects on such dimensions as productivity, employment rate, average wage, and work intensity. Studies based on this methodology mainly adopt an instrumental variable (IV) method for regression analysis, which only leads to the result of the local average treatment effect. The conclusion holds only under specific conditions. More importantly, IV approach often removes the interactions between AI and the labor market as an endogenous noise, and therefore cannot discuss the overall general equilibrium result.

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[1] In their discussions on Germany's Industry 4.0, Uhlmann et al. (2017) define smart manufacturing as a manufacturing system based on the cognitive ability (“or smartness”) of machines as the basis of effective interactions. Smart manufacturing refers to cooperation of more complex and digital forms between man and machines in a distributed industrial production environment. Unlike traditional industrial manufacturing model, man-machine cooperation in smart manufacturing adopts a data-driven model based on an information and physical system and the internet.

Both methodologies contain an exogenous assumption, i.e. AI's development and application are entirely determined by exogenous technology progress. Such an assumption overlooks one important fact: The application and innovation of smart manufacturing are an endogenous choice of manufacturers to maximize profitability under current factor price and available technologies. When labor cost rises with an aging population, smart manufacturing will generate a higher economic return, and manufacturers will have a stronger motive to adopt AI technology. In other words, the relationship between AI and economic development is subject to age structure. Correlation suggested by data cannot be construed as a causal relationship. Instead, it should be interpreted as a result of general market equilibrium (Abeliansky & Prettner, 2017; Acemoglu & Pascual, 2018).

Internationally, there has been a growing interest in how the labor market affects AI's development. Based on the theoretical assumption that AI devices perfectly substitute labor, Abeliansky & Prettner (2017) predict that countries with a low population growth rate adopt smart technologies earlier than others. Reduction of population growth rate by 1% corresponds to an increase in robot density by close to 2%. According to their empirical study on 722 commuting zones in the U.S., regions with a higher degree of aging population correspond to a greater number of robot integrated firms. This positive correlation is particularly striking for sectors more dependent on medium-aged labor (24-55 years old).

Nevertheless, these studies fail to fully control for the variable of labor quality in their empirical analysis. Both the levels of education and health should be controlled at the same time. An aging population has dual effects on the labor market, including a direct effect on the size of the workforce and an indirect effect on labor quality. Whether indirect effect increases or reduces human capital remains controversial academically (Gradstein & Kaganovich, 2004). If labor quality - education and health - is not controlled for in the regression equation of AI on an aging population, the regression result simultaneously contains direct and indirect effects, whose implications cannot be interpreted with clarity.

As such, the existing body of literature lacks a systematic review and empirical research of AI's development and economic effects in an aging society. From the dimensions of population aging as a motive for AI development and AI as an instrument in coping with an aging population, this paper attempts to carry out an empirical study based on cross-national panel data and China's provincial panel data to test whether AI has any substitutive effect on labor and what kind of substitutive effect there exists.

2. Empirical Hypotheses

According to Trajtenberg (2018), AI-based technology innovation can be "human enhancing innovation" or "human replacing innovation." These types of innovation exert different effects on the labor market: The human enhancing AI has a complementary relationship with labor, i.e. as the population ages and labor becomes scarce, AI's driving force to economic growth is diminishing; the human replacing AI, however, has a substitutive relationship with labor, which implies that with scarcer labor and higher wage cost, AI will boast a relatively higher economic value and play a bigger role in promoting the economy in an aging society. As in the words of Hicks (1963), "the relative price change of production factors itself offers an incentive to specific types of innovations and inventions to conserve the use of factors that become pricier." Wage hikes make it lucrative to develop and deploy AI technologies to replace labor. This effect is referred to as "induced innovation."

Induced innovation offers the following policy implications: First, it indicates that manufacturers will respond to a shifting labor market through technology selection and innovation. In addition to offering tax incentives and R&D subsidies, the government should also improve the factor market to promote AI industries, so that the role of price signal in optimizing resource allocation comes into full play. Another implication is that AI is unlikely to cause mass unemployment since AI deployment is, to some extent, a spontaneous adjustment of manufacturers to a labor shortage. That is to say, the labor substitution effect of AI is a supplemental rather than a crowding-out effect.

Referencing Abeliansky & Prettner's (2017) theoretical approach, this paper specifies its empirical hypotheses, and tries to understand AI's interactions with the labor market from a general equilibrium perspective. In an aging society, slowing labor growth has led to an increasingly striking labor shortage and rising equilibrium wage in the short run. As firms find it harder and costlier to hire workers, they will be forced to reduce their optimal workforce and output, as manifested in slowing economic growth. From a longer perspective, however, the rising cost of labor will bring AI's cost-effectiveness increasingly into play. AI technologies that used to be an economically impractical start to be deployed on a broader scale. Firms employ smart equipment to make up for the labor shortfall and boost their output, as manifested in the extensive use of AI equipment and rapid economic growth despite an aging population.

AI and automation technology are more extensively deployed in the manufacturing industry, where young workers concentrate (Yang, *et al*., 2018). Therefore, this paper focuses on industrial manufacturing and uses industrial robot installation that depicts the level of smart manufacturing as the proxy variable of AI. Based on the above discussion, this paper puts forward the following empirical hypotheses: First, an aging population will promote industrial robot installation; second, as the demographic structure becomes dominated by the elderly, the marginal positive effects of industrial robots on economic growth will increase.

3. Aging Population Propels Smart Manufacturing

3.1 Data Source and Variable Specification

In this section, we use the data set of the International Federation of Robotics (IFR) and the country data from the World Bank database to estimate the effects of an aging population and industrial robot installation and deployment in various countries to test our first empirical hypothesis. This part of work references the research design of Abeliansky & Prettner (2017) and Acemoglu & Restrepo (2018). Due to the different focus of research, we have controlled for relevant variables (education and health) of labor quality and whether the effects of AI vary across countries with different manufacturing shares or economic development levels. The two studies mentioned earlier, especially Acemoglu & Restrepo (2018), did not adequately address developing countries. This paper carries out an analysis to fill the gap of discussion to developing countries, which is of great importance.

IFR data include the installation and stock of industrial robots[2] in various sectors of 50 countries from 1993 to 2016, covering 90% of the installation information of the global industrial robot market. To match data from different databases, this paper employs the data of 14 countries with industrial robot installations from 2007 to 2016.[3] We also extract the following country-level variables of corresponding years from the World Bank database: the number of population aged between 15 and 65 years, population aged above 65 years, the size of workforce, employment rate, per capita GDP, gross secondary school enrolment, life expectancy at birth, crude birth rate (CBR), as well as value-added from manufacturing industry as a share of GDP.

The dependent variable that we are concerned with is robot density, which is defined by the number

[2] By IFR's definition, industrial robots are "automatically controlled, reprogrammable, multipurpose manipulator, programmable in three or more axes, which can be either fixed in place or mobile for use in industrial automation applications."

[3] These 14 countries are: Brazil, Germany, France, S. Korea, Canada, the U.S., Mexico, Japan, Thailand, Spain, Italy, India, the UK, and China. These countries have a significant amount of industrial robot installations, accounting for 84.8% of total industrial robot installations in all IFR member countries in 2016.

Table 1: Statistical Description of Cross-Country Data

Variable	Mean	Standard deviation	Min.	Max.
Robot density	0.907	1.355	0.002	8.340
Potential support rate	6.070	3.070	2.277	12.81
Six-phase-lag gross secondary school enrolment rate (%)	93.02	16.39	45.36	124.1[4]
Life expectancy at birth (years)	78.45	4.387	65.38	83.98
Share of manufacturing in GDP (%)	18.40	6.920	9.583	32.37

of cumulatively installed industrial robots in a country divided by the total employment of the same year. The higher this indicator, the higher the level of smart manufacturing in this country. The critical independent variable is potential support rate (PSR), which is defined by the population aged between 15 and 64 years divided by the population aged above 65 years. The lower this indicator, the higher the degree of an aging population for a country. Compared with the support rate, the PSR offers the advantage of differentiating the burdens that elderly persons and juveniles incur to the working-age population.

As mentioned earlier, an aging population will not only change the size of the workforce, but is correlated with labor quality in complex ways as well. This paper will focus on how the shrinking workforce resulting from an aging population influences AI's development. Therefore, we need to **control for relevant labor quality variables.** For this reason, we include gross secondary school enrolment with a six-phase lag and life expectancy at birth in the regression. Table 1 offers a statistical description of key variables.

3.2 Regression Model

As Figure 2 shows, a country's level of the aging population is significantly positively correlated with robot density. Given that such positive correlation may be caused by other interferences, this paper not only includes relevant control variables, but employs the ordinary least square (OLS) model, fixed-effect model, and instrumental variable (IV) model regression to test the effect of an aging population on AI development. The baseline regression model is as follows:

$$\lg(R_{it}) = \beta_0 + \beta_1 \cdot PSR_{it} + \gamma X_{it} + \delta_i + \lambda_t + \epsilon_{it}$$

Where, R_{it} is robot density of country i in year t per 1,000 employed population; PSR_{it} is country i's potential support rate in year t; X_{it} is a string of control variables, including per capita GDP, life expectancy, and six-phase-lag gross secondary school enrolment rate; δ_i is the country fixed effect; λ_t is the year fixed effect.

[4] By the World Bank's definition, gross secondary school enrolment rate refers to the total number of secondary school students divided by the number of school-age population. Since the total number of secondary school students may include students not in the expected age bracket, gross secondary school enrolment rate may exceed 100% under certain conditions.

Direct regression of potential support rate on robot density may lead to deviations in the estimation coefficient due to the endogeneity problem. For instance, unobservable variables may exist and simultaneously affect a country's potential support rate and level of smart manufacturing. This paper employs the instrumental variable (IV) method to deal with the possible endogeneity problem. A good IV must meet two conditions: First, it should have a strong correlation with the key independent variable; second, it meets the exclusivity requirement, i.e. it influences dependent variables only through the key independent variable.

This paper selects the crude birth rate (CBR) with a lag of 20-45 years as an instrumental variable (IV). The lower limit is set to be 20 years due to missing crude birth rate data of some countries, which prevents us from forming balanced panel data. The upper limit is set to be 45 years since the World Bank's data can be traced to 1960 at the earliest, while this paper employs IFR robot installation data as of 2007. Since aging population in the current phase is largely determined by historical fertility rate (Lee & Zhou, 2017), the gross fertility with a lag of 20-45 years is highly correlated with the demographic structure in the current phase. Meanwhile, the fertility rate with a lag of 20-45 years is weakly correlated with non-demographic variables that determine technology selection in the current phase. Overall, this is an acceptable IV. This paper employs a two-stage least square (2SLS) model to estimate the coefficient of the key independent variable.

3.3 Regression Results

Panel A in Table 2 shows the OLS and IV estimation results of robot density with respect to potential support rate. Column (1) is the regression result of robot density with respect to potential support rate after controlling for country and year fixed effects, which shows that the correlation between demographic structure and robot density is statistically significant. Column (2) further controls for such covariates as the natural logarithm of per capita GDP, six-phase-lag gross secondary school enrolment rate, from which we may find that the regression coefficients are at the same quantitative level and remain significant. This finding suggests that after taking labor quality into account, our conclusion remains robust.

Columns (3) to (4) are the 2SLS estimation results of IV method. By comparing the regression coefficients of latter and first rows of regression coefficients, we may discover that the coefficient estimated with IV appears to be somewhat higher: Take Column (4) for instance, an increase of potential support rate by one percentage point corresponds to a decline in robot density by 0.49%. This implies that the endogeneity deviation in the OLS regression result is not serious, and such deviation tends to cause an underestimation rather than overestimation. In a word, both OLS estimation and IV estimation suggest that the potential support rate has a significantly negative effect on robot density: Countries with a higher percentage of working-age population relative to aging population tend to install fewer industrial robots, and vice versa.

While an aging population has a noticeable effect that drives AI applications in various countries, the driving forces and economic effects of AI applications may vary across industries. For instance, an empirical study on AI's application and the number of nurses at elderly care institutions in the U.S. reached a very different conclusion with another study based on data from the manufacturing industry (Lu *et al*., 2018). In discussing the effect of demographic structure on smart manufacturing, therefore, we should also take industry difference into account. Results of Panel B in Table 2 show that first, countries with a higher manufacturing share tend to install more industrial robots. On average, an increase in the manufacturing industry share of GDP by each percentage point corresponds to an increase in robot density from 6% to 7%.

Second, the symbol of the interaction term is significantly negative, which verifies our guessing: An aging population has a more significant effect on AI in countries with a higher manufacturing share. Lastly, after controlling for the variables of manufacturing share and interaction term, the coefficient

Table 2: Effects of Demographic Structure on AI Application

	(1)	(2)	(3)	(4)
Panel A				
VARIABLES		lgR		
lgPSR	-0.4728***	-0.3431***	-0.5575***	-0.4929***
	(0.0739)	(0.0820)	(0.0764)	(0.1031)
Covariates	NO	YES	NO	YES
Model	OLS	OLS	2SLS	2SLS
Country FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Observations	140	140	140	140
R^2	0.993	0.995	0.993	0.994
Panel B: Manufacturing share/ developing country				
VARIABLES		lgR		
PSR ×Manufacturing share	-0.0122**	-0.0113**		
	(0.0051)	(0.0049)		–
PSR ×Dummy			0.2345**	0.1679*
(Developed country=1)			(0.0903)	(0.0927)
PSR	-0.0432	-0.1388	-0.4576***	-0.3457***
	(0.1776)	(0.1734)	(0.0786)	(0.0922)
Manufacturing share	0.0671**	0.0640**		
	(0.0318)	(0.0308)		
Dummy			1.1193*	1.3345**
(Developed country=1)			(0.6252)	(0.6035)
Covariates[5]	NO	YES	NO	YES
Model	OLS	OLS	OLS	OLS
Country fixed effects	YES	YES	YES	YES
Year fixed effects	YES	YES	YES	YES
Observations	140	140	140	140
R^2	0.994	0.994	0.994	0.995

Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

[5] Since the share of the manufacturing industry and developed/developing country classification are highly correlated with per capita GDP, we did not include the logarithm of per capita GDP in the analysis of Panel B.

of the potential support rate becomes no longer significant. The implication is that demand for AI technologies mainly derives from a labor shortage that comes with an aging population. Overall, this finding is consistent with the "induced innovation" theory: When labor price hikes relative to other factors, labor-saving new technologies are more likely to be developed and deployed.

The last two columns of Panel B are a comparative analysis of developing and developed countries. The result shows that on average, robot density is 1.1-1.3 times higher in developed countries than in developing countries. Nevertheless, an aging society has a more significant impact on the robot density in developing countries than in developed countries. As a developing country, China should pay more attention to whether industrial robots can be used to compensate for the labor shortage that comes with an aging population.

4. Smart Manufacturing Promotes Economic Growth

4.1 Data Source and Variable Specification

This paper employs the International Federation of Robotics (IFR) dataset and China's provincial panel data (excluding Hong Kong, Macao and Taiwan) to investigate the effect of AI applications on China's economic growth in an aging society and test the second empirical hypothesis. Here, the dependent variable that this paper is concerned with is the GDP aggregate of various provincial-level regions, hereafter as province, and data are directly obtained from the National Bureau of Statistics (NBS) national database.

The key independent variable in this section is robot density. Similar to the treatment of a cross-country analysis, robot density is obtained by dividing the cumulative quantity of industrial robots in each province by the total employed population of the province. Due to data availability constraint, we cannot directly obtain the number of robot installations in each province for each year. Besides, relatively complete industry-specific robot installation data are available only in the IFR China dataset after 2010.[6] Meanwhile, the industry-specific number of robot installations in 2015 and thereafter is absent from the dataset that we have obtained. Given the data quality and availability, data employed in this paper are from 2010 to 2014. For robots whose purpose of use is not declared, we assign unclassified robots to each sector following the interpolation and proportional assignment method referencing Acemoglu & Restrepo (2017).

Inspired by Acemoglu& Restrepo (2017), this paper employs Bartik instrumental variable (IV) method to calculate the robot technology shock intensity at the provincial level as the substitution variable for the level of smart manufacturing. We first calculate the robot density in each industry and each year based on the national industry-specific robot installation data and annual employment data of various industries from 2010 to 2014. Then, we calculate the technology shock intensity for the year based on the industrial structure of each province. Bartik IV equation is as follows:

$$B_{it} = \sum_{j} R_{jt} \cdot l_{ijt} \tag{1}$$

Where B_{it} is the robot density of province i in year t estimated based on the technology shock intensity. R_{jt} is robot intensity of sector j in year t, and l_{ijt} is the number of people employed in industry

[6] Major two-digit industries in this database include: agriculture, forestry, livestock and fishery; mineral extraction; food, beverage, and tobacco; clothing and leather products; timber products (including furniture); paper product publishing and printing; plastics and chemical products, metals, electronic and electric products; automobiles; other transportation equipment; all other manufacturing sectors; water, electric power, and gas supply; construction; education, R&D, and other non-manufacturing.

Table 3: Statistical Description of China's Provincial Panel Data

Variable	Mean	Standard Deviation	Min.	Max.
Robot density estimated based on technology shock intensity	0.014	0.010	0.001	0.049
Logarithm of GDP	7.076	1.006	3.787	8.822
Manufacturing as a share of GDP	0.398	0.0970	0.0720	0.530
Logarithm of GDP from primary industry	4.618	1.119	1.854	6.173
Logarithm of GDP from secondary industry	6.315	1.086	2.615	8.053
Logarithm of GDP from tertiary industry	6.181	1.008	3.182	8.108
Support rate	3.012	0.640	1.944	5.189

in province i in year t as a share of total employment in the year. Industry-specific robot density is calculated as follows: First, the national industry-specific (two-digit industries) employment numbers are obtained by consolidating the sector-specific (three-digit sectors) employment data from *China Labor Statistics Yearbook* from 2010 to 2014 referencing IFR's industry classification (two-digit industries). Then, IFR's national industry-specific (two-digit industries) cumulative robot installations are divided by employed population to obtain an industry's robot density.

An important control variable in this section is the support rate. Different from previous cross-country analysis, this paper employs support rate rather than potential support rate to measure the demographic structure. The support rate is defined as the percentage of the population aged between 15 and 64 divided by population aged below 15 and at or above 65 years, which is equivalent to the reciprocal of dependency ratio. In most cases, the two variables of support rate and potential support rate are highly correlated. Therefore, we believe that whether support rate or potential support rate is controlled for will not have any significant impact on the result.

When testing the first empirical hypothesis, we find that regions with a higher manufacturing share also have a higher robot density. In testing the second hypothesis, therefore, we also use manufacturing share as a control variable. Manufacturing as a share of GDP is obtained by dividing the manufacturing value-added in various provinces by local GDP, and the mean value is 39.8%, or double the mean value of the corresponding variable in cross-country analysis. The implication is that conclusions from previous studies on OECD countries may not apply to China (Acemoglu & Restrepo, 2018). It is thus necessary to carry out a study with China's provincial-level data. Table 3 offers a statistical description of the variables employed.

4.2 Regression Model

This paper is interested in whether AI applications will increase economic output in an aging society and mitigate the negative shock of a falling workforce. We specify the regression equation as follows:

$$\lg(Y_{it}) = \beta_0 + \beta_1 \cdot B_{it} + \beta_2 \cdot SR_{it} + \beta_3 \cdot B_{it} \cdot SR_{it} + \gamma X_{it} + \delta_i + \lambda_t + \epsilon_{it} \qquad (2)$$

Where Y_{it} is the natural logarithm of GDP aggregate of province i for year t or the output value of a certain industry in province i in year t. B_{it} is the robot density of each province created with Bartik IV method. SR_{it} is support rate of i in year t. X_{it} is the share of manufacturing in GDP of the province. δ_i is the province fixed effect. λ_t is the year fixed effect. Considering the complex interactions between smart manufacturing and an aging population, we include support rate and the interaction term between technology shock intensity and support rate into the regression equation.

Compared with the variable of actual robot density, the variable of robot density estimated with technology shock intensity offers one advantage: It is exogenous compared with many unobservable variables at the provincial level. This will reduce the interference of endogeneity bias to the estimated regression coefficient.

4.3 Regression Result

Table 4 reports the regression result of GDP aggregate of each province against local robot density. Column (1) is the regression result after the inclusion of the key independent variable and demographic structure. Columns (2) and (3) are results after the step-by-step inclusion of the interaction term and manufacturing share, and Column (4) additionally controls for the fixed effects of province and year. In comparison with the estimation coefficients of robot density estimated based on technology shock intensity, it can be found that robot intensity has a significantly positive effect on regional economic development. Take the regression result controlling for the fixed effects for instance, for each percentage point of an increase in robot density, local GDP aggregate will rise by about 0.17%. There will be a difference in the size of estimation coefficients under different regression model specifications, but the direction of the symbol is the same and remains statistically significant, i.e. the result has the same robustness.

As can be seen from the coefficients of the support rate variable in Row 2, provinces with a younger population have a higher regional gross output value. This conclusion is consistent with relevant previous studies (Tian *et al*., 2013). The third row is the coefficient of the interaction term between robot density and support rate. The negative coefficient of interaction term explains that AI plays a stronger role in promoting economic development in provinces with older populations. To some extent, this result implies that AI helps mitigate the labor shortage arising from an aging society. As can be seen from the coefficients of Row 4, AI has a more significant positive effect on the economy in provinces with higher manufacturing shares. This result is consistent with our previous discussions and findings. On the whole, these results suggest that despite slowing economic growth as a result of an aging population, the development of smart manufacturing may partially compensate for a labor shortage in an aging society. Hence, developing AI may offer a countermeasure in shoring up a slowing economy in an aging society.

This paper further investigates AI's positive effects on the value-added of different industries, as shown in Table 5. Columns (1), (3) and (5) respectively employ the natural logarithm of the value-added of primary, secondary, and tertiary industries in each province as a dependent variable, and robot density and support rate as independent variables. The result suggests that robot applications have significantly increased the value-added of various industries. Columns (2), (4) and (6) additionally introduce the interaction term between robot density and support rate, and control for the fixed effects of province and year. It can be found that after controlling for the fixed effect, AI has an insignificantly positive effect on the value-added of the primary industry, which is probably due to the limited use of robots in the primary industry.

AI has the most significant positive effect on the value-added of the secondary industry, which verifies the assessment of relevant studies (Yang, *et al*., 2018). Take the regression result of Column 4

Table 4: Regression Analysis of China's Provincial-Level Data

	(1)	(2)	(3)	(4)
	Explained variable: natural logarithm of GDP aggregate			
Robot density estimated based on technology shock intensity	48.44^{***}	191.5^{***}	144.3^{***}	12.30^{***}
	(7.940)	(48.33)	(37.61)	(3.616)
Support rate	0.194^{***}	0.946^{***}	0.807^{***}	0.0768^{***}
	(0.0739)	(0.212)	(0.176)	(0.0283)
Interaction term between the first two variables		-46.53^{***}	-35.16^{***}	-4.301^{***}
		(13.74)	(11.08)	(1.050)
Share of manufacturing industry			4.230^{***}	0.921^{***}
			(0.630)	(0.257)
Constant term	5.819^{***}	3.582^{***}	2.499^{***}	6.754^{***}
	(0.294)	(0.731)	(0.509)	(0.132)
Fixed effect of province	No	No	No	Yes
Fixed effect of year	No	No	No	Yes
Sample size	155	155	155	155
Coefficient of determination R^2	0.297	0.368	0.523	0.999

Notes: Numbers in parentheses are robust standard errors; *** p<0.01, ** p<0.05, * p<0.1.

that controls for the fixed effects of province and year, for instance, each percentage of increase in robot density will cause the value-added of local secondary industry to rise by 0.27%. AI's positive effect on the value-added of the tertiary industry is statistically significant, but is somewhat smaller compared with the effect on the secondary industry. Similar to the conclusions of Table 4, the coefficient of the interaction term suggests that the younger the demographic structure of a province, the smaller positive effect of AI on its economic growth.

5. Concluding Remarks and Discussions

This paper investigates the effect of an aging population on AI's development and the effect of AI applications on the local economy. First, results based on cross-country panel data suggest that the older a country's population is, the faster its robot density growth will grow. This implies that the labor shortage in an aging society will prompt manufacturers to deploy smart manufacturing more broadly. This effect is particularly striking for countries with higher manufacturing shares in GDP.

Second, results from China's provincial-level panel data suggest that even after controlling for the degree of an aging population, smart manufacturing still has a significantly positive effect on local GDP. This effect is particularly significant for the value-added of the secondary industry. These empirical results support the research hypotheses of this paper: On the one hand, an aging population will prompt manufacturers to adopt AI technology more broadly, and promote AI development. On the other hand,

Table 5: Industry-Specific Regression Analysis

	(1)	(2)	(3)	(4)	(5)	(6)
	lg(GDP of primary industry)		lg(GDP of secondary industry)		lg(GDP of tertiary industry)	
Robot density	28.10***	5.963	52.90***	19.51***	49.36***	15.83***
	(10.41)	(5.946)	(8.764)	(7.339)	(7.521)	(4.444)
Support rate	-0.648***	0.101**	0.104	0.115**	0.333***	0.090***
	(0.131)	(0.0422)	(0.0838)	(0.0554)	(0.0772)	(0.0308)
Interaction term between the first two variables		-2.820		-6.956***		-5.393***
		(1.911)		(1.964)		(1.178)
Constant term	6.198***	2.057***	5.264***	5.343***	4.493***	6.597***
	(0.433)	(0.179)	(0.328)	(0.248)	(0.280)	(0.135)
Fixed effect	No	Yes	No	Yes	No	Yes
Sample size	155	155	155	155	155	155
R^2	0.159	0.998	0.278	0.998	0.356	0.999

Notes: Numbers in parentheses are robust standard errors; *** p<0.01, ** p<0.05, * p<0.1.

smart manufacturing helps cushion the impact of an aging population on the economy. AI is an important tool for coping with the challenges of an aging society.

These results suggest that AI development is an "induced innovation" - a natural market response to the labor shortage. Deployment of AI technology is an inherent result of a change in factor price rather than an exogenous impact of a "creative destruction" style. AI's effect on the labor market, therefore, is "supplemental substitution" rather than "crowding-out substitution." Assuming that these attributes remain constant, we expect that AI will contribute more to China's economy in the context of an aging society. Our empirical findings not only contribute to improving the theoretical framework of previous researchers, but provide a reference for national policy-making as well.

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