

DOES ROBOT ADOPTION EXACERBATE THE FERTILITY SLUMP IN CHINA? EVIDENCE FROM SURVEY DATA

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Abstract. As an integral part of automation technology, robots have significantly transformed the labour market structure and wage distribution, which further may also influence family reproductive behaviour. As a country with a huge population, China is experiencing a severe low fertility trap. It is crucial to determine whether the widespread use of robots exacerbates this fertility decline. To investigate the effects of robots on household fertility decisions, we utilize data primarily from the China Labor-force Dynamics Survey (CLDS) and the International Federation of Robotics (IFR). Our empirical analysis shows that increased exposure to robots significantly decreases the likelihood of childbearing in Chinese households. This result still holds across various robustness tests. Specifically, it is found that robot adoption reduces fertility through three key channels: investment in human capital, employment instability, and income inequality. These findings offer insights into the micro-level mechanisms that link robot adoption with fertility decisions. The conclusions provide ideas on how to ensure appropriate fertility levels in the age of artificial intelligence.

Keywords: robot adoption, fertility choice, employment instability, human capital investment, income inequality, micro-level mechanisms.

JEL Classification: J13, O33.

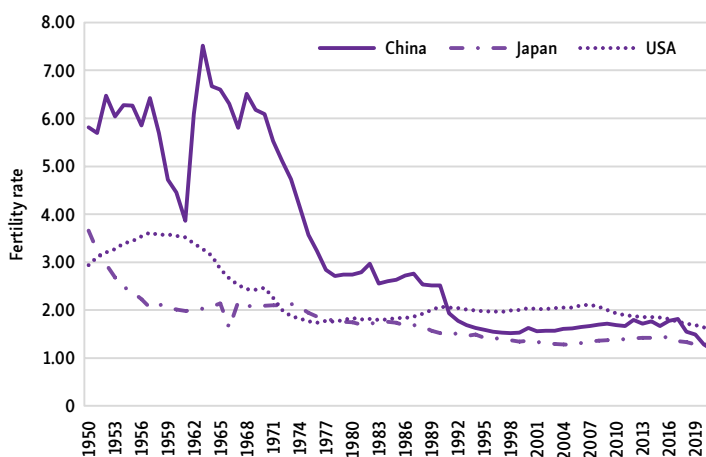
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1. Introduction

The phenomenon of declining fertility rates has become a significant demographic concern worldwide. By 2024, more than half of the countries and regions globally have experienced a Total Fertility Rate (TFR) below the replacement level of 2.1 children per woman, which is essential for maintaining population stability. Notably, approximately 20% of these countries are experiencing “ultra-low” fertility, characterized by an average of fewer than 1.4 live births per woman (United Nations, 2024). This decline in fertility has profound implications for population aging, with recent research indicating that the impact of reduced fertility on aging populations now exceeds that of increased longevity (Prettner & Bloom, 2020; Abeliasky & Prettner, 2023). The demographic shift resulting from these trends poses challenges to sustainable economic development and social stability. As such, identifying the underlying causes of low fertility has become a key focus for scholars in the fields of economics, demography, and sociology.

While industrialized countries experienced declining fertility and entered a low-fertility state earlier than China, the rapid pace of China's fertility decline has led it to fall below that of industrialized countries such as the United States and Japan (Figure 1). By 2021, the fertility rate becomes only 1.16. This rapid fertility decline accelerates the aging of population structure in China, while the GDP per capita has not yet to reach the levels of developed countries. In 2021, the government relaxed its family planning policies by allowing families to have three children, along with additional incentives. However, the impact of these policies on unlocking fertility potential has been relatively limited. China's Bureau of Statistics reports that 1.06 million fewer births occurred in 2022 than in 2021. China may face a more severe low fertility problem than developed countries.

The economic history of humanity demonstrates that technological advancements have profoundly influenced demographic changes. The theory of Galor (2005) posits that technological progress, particularly after the Industrial Revolution, accelerated the demographic transition by increasing the demand for human capital and encouraging investment in education. Since completion of the Second Industrial Revolution in developed countries in the mid-20th century, fertility rates have rapidly declined, as observed in the United States (Figure 1). This empirical trend partly supports the hypothesis that technological progress contributes to fertility decline. In the current period, robot automation represents a new wave of technological advancement. The latest data from the International Federation of Robot shows that global industrial robot installations rose from 159,000 in 2012 to 553,000 in 2022. A growing number of Chinese firms are adopting industrial robots to replace human labor in production processes (Mai et al., 2025). This change has exerted a profound impact on China's economy (Li & Zhou, 2024). In 2012, installations numbered only 23,000, but by 2022, they had reached 290,000, accounting for 52% of global installations. China differs from other countries in terms of labor market structure, employment protection, and income distribution policies, which can mediate the influences of robots on fertility trends. Therefore,



Notes: Data from the World Bank (n.d.)

Figure 1. The fertility rate of China, Japan, USA

it is necessary to use empirical data to investigate whether and how the increasing robots influence the fertility behavior of households in China.

In the context of China, we examine the impact of robots on household fertility choices and the ways through which this effect occurs, using data from the CLDS and IFR. Following Acemoglu and Restrepo (2020), an index of robot exposure at the city level is constructed by combining industry-level robot penetration with baseline employment shares. This index reflects the extent of robot adoption in a given city, which is then matched to household survey data based on the city of residence. A low fertility rate can accelerate population aging, further increasing the demand for robots due to rising labor costs (Acemoglu & Restrepo, 2022a). This suggests the possibility of reverse causality in our baseline regression. Thus, we employ the instrumental variable method by constructed using robot installation density in the United States, which captures exogenous technological advancements in robot (Anelli et al., 2021).

Our empirical analysis shows that robot adoption reduces the probability of childbearing in Chinese households. To test its robustness, we employ various methods, including substituting alternative measures of key independent variables, changing the dependent variable indicator, controlling for other potential influences, expanding the age range of the sample, enlarging the sample size, and Excluding influences of universal two-child policy. An additional focus of this study is to examine the mechanisms through which robot exposure influences fertility choices. These mechanisms include promoting private investment in education, increasing employment instability, and exacerbating income inequality. Moreover, we investigate the moderating effects of labor skills, work institutions, age, ancestral halls culture, and regional economic conditions on the relationship between robot exposure and fertility behavior.

Our work makes four significant contributions to the existing literature. First, it has found new micro-level evidence on the influence of robot adoption on household fertility decisions. While only a limited number of studies have explored the link between robot adoption and fertility, notable exceptions include Anelli et al. (2021), who find no statistically significant effect for the full sample in the U.S. commuting zones. Using NUTS-2 regional data at the macro level, Matysiak et al. (2022) examine the effects of robots on total fertility rates across six European countries. Differing from them, our study demonstrates that robot adoption has a significantly detrimental impact on household reproductive behavior at the micro level.

Second, this study examines the causes of the declining fertility rate in China from the viewpoint of technological progress. As the country with the second largest population and economy, China's demographic and economic changes have garnered significant scholarly attention. Recent studies have highlighted various factors contributing to the rapid fertility decline, including increased female employment (Fang et al., 2013), urbanization (Guo et al., 2012), and rising female education levels (Zhang & Zhao, 2023). However, no study has yet investigated the influences of technological advances on fertility decline in China. Our work seeks to determine whether the adoption of robot, as a driver of technological progress, is a key factor in China's fertility decline.

More importantly, this study uncovers the "black box" of how robot adoption influences household fertility choices. The mechanisms through which robot adoption affects fertility

behavior have not been thoroughly explored, and the question of how robot adoption impacts fertility remains unclear. This research identifies three key channels: encouraging private investment in education, increasing employment instability, and exacerbating income inequality. By examining these pathways, this study establishes a connection between robot adoption and individual fertility decisions. Additionally, it extends the discussion by examining the differing effects of robot adoption on fertility, considering various characteristics of laborers.

This study is organized as follows: The literature review and the hypotheses are presented in Section 2. Section 3 describes the data, empirical strategy, and variables. Section 4 exhibits the empirical results, including baseline regression, endogeneity analysis, and robustness checks. Section 5 examines the mechanism of robot adoption influencing fertility. Furthermore, the extensive analysis is provided in Section 6. Finally, Section 7 concludes the study.

2. Literature review and hypothesis

2.1. Literature review

The literature related to our study can be broadly categorized into two key strands: the relationship between technological progress and fertility, the relationship between robot and labor market.

2.1.1. *The relationship between technological progress and fertility*

The theory proposed by Galor (2005) suggests that technological progress diminishes fertility choices within the modern growth regime. The introduction of steam engines in industrial production represents a significant technological advancement during the Industrial Revolution. Franck and Galor (2015) examine the influence of industrial technology on the decline of fertility in France during the 19th century. Human capital formation is identified as a crucial mediating variable in this process. This assertion is further supported by microdata from Brazil (Rosen & Simmons, 1971), South Carolina (Wanamaker, 2012), and data from 21 OECD countries (Madsen & Strulik, 2023). Since the 1990s, the rapid advancement of Internet technology has transformed individuals' work and lifestyles. Increased broadband access reduces birth rates by enhancing participation in social networking environments and increasing consumption of information and media (Nie et al., 2023). However, Billari et al. (2019) present evidence from German data indicating that broadband internet positively impacts the fertility of highly educated women by alleviating the challenges of balancing work and family. Different types of technological progress may influence fertility behavior through various pathways.

As a kind of biased technological change in recent years, the impact of robots on fertility has also begun to attract attention. However, only a limited number of studies have explored this topic, primarily concentrating on the effects of robots on fertility within the United States (Anelli et al., 2021) and various European regions (Matysiak et al., 2022). These studies neglect to examine the underlying mechanisms by which robotic adoption impacts fertility rates. Utilizing European panel data, Costanzo (2025) posits that exposure to robots delays the age at which women in medium-educated cohorts have their first child, while also indicating a positive correlation for other educational cohorts. This suggests a heterogeneous impact of

robotics on reproductive behaviors across different educational levels. Furthermore, Almeida and Sequeira (2023) present a theoretical model aimed at elucidating the relationship between robot and fertility rate. Unfortunately, within this theoretical framework, the effects of robots on fertility remain ambiguous and are contingent upon the costs associated with raising children.

2.1.2. The relationship between industrial robot and labor market

The impacts of robot adoption on labor markets primarily focus on employment and wage skill premiums, with the effects on employment receiving greater attention from scholars (Acemoglu & Restrepo, 2018). However, empirical findings about influence of robot applications on employment have not yielded a unified perspective. From a macro-level analysis, Graetz and Michaels (2018) suggest that robot adoption does not significantly reduce the total employment rate based on panel data from 17 countries. In the context of U.S. labor markets, Acemoglu and Restrepo (2020) find that robot adoption lowers the employment rate. Conversely, using a similar empirical strategy, Dauth et al. (2021) find that robot installation does not decrease the aggregate level of employment in Germany but instead alters the job distribution across industries. Based on a panel of OECD countries, Bordot (2022) reports that a 10% increase in industrial robot stock results in a 0.42% increase in the unemployment rate. The inconsistency in these findings implies that the net effect of robots on overall employment varies by region. This situation arises because robot adoption has displacement effect, the productivity effect, and the composition effect on labor demand, with the net impact determined by the relative strength of these effects (Acemoglu & Restrepo, 2020). Jung and Lim (2020) suggest that the displacement effect reduces the demand for low-skill labor within manufacturing. It leads to a decrease in routine occupation employment (Autor et al., 2015). Conversely, the robots increase non-routine jobs and generate more jobs in the service sector (Acemoglu & Autor, 2011; Kariel, 2021; Dauth et al., 2021). Moreover, robots significantly impact the labor market by altering wages (Giuntella et al., 2025). As a routine-biased technological change, the adoption of robots exacerbates the wage disparity between non-routine tasks that face a low risk of automation and routine tasks that are highly susceptible to automation (Autor & Dorn, 2013; Lankisch et al., 2019; Brall & Schmid, 2023).

Few studies have investigated the connection between robot adoption and childbearing using data from developed countries. However, there is currently a lack of literature examining the impact of robot applications in developing countries on reproductive behavior. More importantly, the mechanisms through which the application of robots affects fertility choice have yet to be elucidated. Therefore, our study, which investigates the relationship between these two factors and explores the channels of influence using survey data from Chinese households, is both valuable and constructive.

2.2. Hypothesis

Existing studies have highlighted the various socio-economic implications of robot adoption, which may subsequently influence the economic behavior of individuals. The prevalent utilization of robots is likely to affect fertility decisions. However, the channels through which robots impact families' reproductive choices have not been thoroughly explored. This section

discusses the potential pathways through which robots may influence family fertility.

The first pathway through which robots influence fertility is through investment in human capital. According to theory of the skill-biased technological change, robot adoption leads to a rise in the skill premium in the labor market (Lankisch et al., 2019). The technological change elevates the demand for high-quality human capital, resulting in increased returns (Galor & Tsiddon, 1997). These heightened returns to human capital will impact families' educational decisions in two primary ways. On the one hand, higher returns of human capital lead families to prioritize the quality of their children, encouraging greater investment in their education. According to Becker's quantity-quality theory of children, parental investment in quality reduces the number of children chosen when constrained by limited family income (Becker & Lewis, 1973). On the other hand, increased returns to human capital also prompt adult workers to invest more time and resources in their own education (e.g., pursuing higher education and vocational training), which delays the time of first birth and reduces the child-bearing (Monstad et al., 2008; Brand & Davis, 2011). In conclusion, the widespread use of robots, a significant manifestation of technological progress in the modern era, diminishes reproductive choices through increased household investment in human capital. We refer to this influence as the "human capital effect".

The second pathway through which robots affect fertility is through unstable employment. The task-biased technological change theory argues that automated technological progress leads to labor market polarization (Autor & Dorn, 2013). The automation technologies, represented by increased robotic applications, exert a substitution effect on medium-skilled workers performing routine tasks while simultaneously boosting the employment opportunities of low-skilled workers in the service sector and high-skilled workers engaged in abstract tasks. Although automation technologies can increase employment in the service sector, these jobs typically lack social security and are characterized by low wages and instability (Autor et al., 2019). The impact of robots with lower intelligence on workers engaged in abstract tasks may initially be positive. However, the negative repercussions will likely become more pronounced as artificial intelligence algorithms advance. Existing research indicates that as robots proliferate across industries, job rotation increases, leading to heightened employment instability (Brougham & Haar, 2018). Most households primarily derive their income from wages, and job instability increases income uncertainty (Giuntella et al., 2025). Given that instability in future income may render childcare and education costs unaffordable, families are inclined to decrease the likelihood of childbearing (Sommer, 2016). In summary, the application of robot may diminish families' reproductive choices by increasing employment instability. We refer to this influence as the "employment effect" in this study.

Income inequality represents the third channel through which robotic adoption affects fertility. From the perspective of skill bias, the implementation of robot lowers the wages of low-skilled workers due to heightened substitution effects while simultaneously increasing the wages of high-skilled workers (Card & DiNardo, 2002; Sato et al., 2008). This widening wage gap contributes to an increase in income inequality (Brezis & Rubin, 2024). In terms of task bias, robots raise wages for workers engaged in abstract tasks and lower wages for those involved in routine tasks, further widening the wage disparity between these two groups (Autor & Dorn, 2013; Acemoglu & Restrepo, 2022b). Many scholars concur that the

large-scale application of robots will exacerbate income inequality (Berg et al., 2016). From the lens of cost constraints, high-income groups tend to opt for a smaller number of children due to the high opportunity costs associated with childbearing (Sato et al., 2008). Meanwhile, low-income groups are forced to reduce their fertility number, constrained by the direct cost pressures arising from financial hardship. Thus, the exacerbation of income inequality exerts a negative impact on fertility behavior. From the perspective of relative deprivation, widening income inequality erodes low-income groups' perception of social equity and heightens their anxiety about their children's future development prospects, thereby curbing the fertility behavior of low- and middle-income households. In light of the reference point effect in consumer behavior, the consumption patterns of high-income groups serve as a benchmark for low-income households. To match the consumption standards of affluent groups, these households are inclined to lower their fertility number (Japaridze, 2019; Wu & Zhao, 2024). In summary, the application of robot may decrease household fertility rates by increasing income inequality. We refer to this influence as the "inequality effect" in our study.

Based on the preceding discussion, we hypothesize that increased robots decrease child-bearing behavior within households. Three pathways contribute to this effect: incentives to invest in human capital, increasing employment instability, and widening income inequality. Accordingly, we propose the following hypotheses:

H1: *Increased robot adoption discourages families from choosing to have children.*

H2a: *Increased robot adoption lowers the probability of having a child through heightened investment in human capital.*

H2b: *Increased robot adoption reduces fertility behavior by increasing employment instability of laborers.*

H2c: *Increased robot adoption decreases the probability of having a child by exacerbating income inequality in the communities where the workforce is located.*

3. Data and methods

3.1. Data

To investigate how robot adoption affects fertility choice, we merge data from the CLDS (Na, 2022), International Federation of Robotics [IFR] (2025), China Industrial Statistics Yearbook (National Bureau of Statistics of China, 2022a), and China Urban Statistics Yearbook (National Bureau of Statistics of China, 2022b).

The CLDS is conducted by the Centre for Social Science Surveys at Sun Yat-sen University. It provides data on the labor force aged 15–64 at individual, household, and community levels for the years 2011, 2012, 2014, 2016, and 2018. However, the survey conducted in 2011 was limited to a single province. Beginning in 2012, the sample expanded to cover 29 provinces across China, excluding Hong Kong, Macau, Taiwan, Tibet, comprising 401 villages, 14,214 households, and 23,594 individuals, making it nationally representative.

Additionally, data regarding the robots is collected from the IFR (2025). This dataset has been utilized by numerous scholars, such as Anelli et al. (2021) for Europe, and Zhou et al. (2024) for China. While some limitations in the IFR data have been noted (Anelli et al., 2021),

it remains the best available resource for examining the effects of robots in China. The stock of robots by industry is employed to construct an index that measures the level of robot adoption in each city in China.

Furthermore, employment data by industry and relevant city-level statistics are collected from the China Industrial Statistics Yearbook and China Urban Statistics Yearbook, respectively. These data sources will be used to calculate robot exposure by year and city. We aggregate the CLDS data at individual, household, and community levels for the years 2012, 2014, 2016, and 2018, and subsequently match it with robot exposure data by city and year. Ultimately, this process yields a panel dataset. Following the methodology of van Wijk and Billari (2024), we select all female respondents aged 18 to 45 who are of childbearing age.

3.2. Variables

Dependent variable. The dependent variable is the fertility behavior of individuals. Existing literature, such as that by Zhang and Zhao (2023), typically identifies the completed fertility rate and the age at first birth as key variables that represent an individual's reproductive behavior throughout their life course. However, these two variables do not effectively capture the temporal changes in reproductive behavior. They are primarily suited for measuring fertility behavior in cross-sectional data rather than in panel data. To examine the impact of robot adoption on temporal changes in individuals' reproductive behavior, we have chosen to use a dummy variable indicating the presence or absence of newborn children to measure fertility behavior during each period, in line with the methodologies employed by Castro (2018) and Anelli et al. (2021). The presence of newborns is determined by whether the birth date of the child reported in the questionnaire falls within the year of the survey.

Independent variable. The key independent variable is robot adoption. To measure this, we construct a metric for robot penetration in the Chinese labor market at the city level, following the methodology of Acemoglu and Restrepo (2020). Compared to developed countries, China has been slow to adopt industrial robots on a large scale, resulting in a lack of comprehensive data on industrial robots across various sectors, particularly from earlier periods. Consequently, we selected 2005 as the baseline year for assessing exposure to robots, and calculate the metric as following:

$$\text{Exposure to Robots}_{j,t-1}^{\text{China}} = \sum_{k \in K} l_{j,k}^{2005} \left(\frac{R_{k,t-1}^{\text{China}}}{l_{k,2005}^{\text{China}}} \right), \quad (1)$$

where, $l_{j,k}^{2005}$ is the distribution of employ across industries k and cities j in 2005; $l_{k,2005}^{\text{China}}$ is the total number of workers employed in industries k in 2005; $R_{k,t-1}^{\text{China}}$ denotes the number of robots installed in the industries of China in $t - 1$.

Control variables. At the individual level, we account for factors such as marital status (mar), education level (edu), hukou type (atype), self-reported health status (health), maternity insurance coverage (insur), and individual wage income. At the household level, we include variables such as the type of house ownership (house) and household debt (debt). At the community level, we consider the logarithm of the labor force size (pop) and the logarithm of the number of new births in the past year (baby). Detailed definitions and descriptive statistics of these variables can be found in Tables 1–2, respectively.

Table 1. Definition of variables

Type	Variable Name	Description
Independent variable	Industrial robot (robot)	The exposure to robot is calculated by (1)
Dependent variable	Fertility behavior (new)	1 if the respondent had a new family member born in the survey year, otherwise 0
Control variables	Education level (edu)	1 = No education, 2 = Primary school, 3 = Junior high school, 4 = General high school, 5 = Vocational high school, 6 = Technical school, 7 = Secondary specialized school, 8 = Junior college, 9 = Bachelor, 10 = Master, 11 = PhD
	Marital status (mar)	1 if the respondent is married, otherwise 0
	Hukou type (atype)	1 if the respondent has a non-agricultural Hukou (residence permit), otherwise 0
	Health level (health)	Lower values indicate lower self-perceived health level
	Maternity insurance (insur)	1 if the respondent has maternity insurance, otherwise 0
	Personal income (income)	Logarithm of the respondent's wage income
	House ownership (house)	1 if the respondent owns a house, otherwise 0
	Family debt (debt)	1 if the respondent has borrowed debt, otherwise 0
	Population size (pop)	Logarithm of the community's population
	Newborn babies last Year (baby)	Logarithm of the number of newborns in the community last year

Table 2. Descriptive statistics of main variables

Variable	N	Mean	SD	Min	Max
new	5.712	0.076	0.266	0	1
robot	5.712	0.183	0.271	0.005	2.200
edu	5.712	3.622	2.326	1	11
mar	5.712	0.914	0.280	0	1
health	5.712	2.286	0.959	1	5
insur	5.712	0.108	0.310	0	1
atype	5.712	0.251	0.434	0	1
income	5.712	9.740	1.211	2.485	15.60

3.3. Empirical strategy

To examine the influence of robot adoption on the childbearing behavior of household, we estimate the following regression model with fixed effects of region and year.

$$new_{ijt} = \alpha_0 + \alpha_1 robot_{j,t-1} + \beta X_{ijt} + \gamma_t + \delta_j + \varepsilon_{ijt}, \quad (2)$$

where, new_{ijt} is equal to 1 if individual i has a new child in city j at period t , and zero otherwise. $robot_{j,t-1}$ is robot exposure in city j at period t . The lag of one period for robot variable

allows us to account for which household may need to adjust their life course decision in response to robot exposure. X_{ijt} denotes the control variables at the individual, household, and community levels. γ_t denotes time fixed effects to account for possible trends in variables, δ_j denotes region fixed effects, and ε_{ijt} is a random error.

4. Empirical results

4.1. Baseline regression

This part first examines whether adoption of robots influences the fertility behavior of individuals by estimating Eq. (2). Since the dependent variables are binary choice variables, the probit model with two fixed effects is estimated, and results are presented in Table 3. We control for year and region fixed effects in the regression models. In Column (1), the coefficient of robot is significantly -0.083 without any additional control variables. Furthermore, when additional control variables are included in the Column (2), the result confirms the negative impact of robot on fertility behavior, with an estimated coefficient of -0.074 . This implies that the probability of childbearing declines by 7.4%. Notably, the baseline regression results support Hypothesis 1 (H1).

This finding is in contrast to the results reported by Anelli et al. (2021), who, using data from the United States, found no significant effect of robot exposure on the fertility behavior. They reported positive and negative roles on unmarried and married births, respectively. In China, the proportion of non-marital births is notably low, primarily due to traditional Chinese family values that regard marriage as a prerequisite for childbearing, which exposes children born out of wedlock to social stigma. Furthermore, China's household registration system links children's household registration to their parents' marital status, further curbing non-marital births. As a result, the fertility behavior of Chinese families differs to some extent from that of families in other countries.

Table 3. Baseline regression

Variables	(1)	(2)
	new	new
robot	-0.083^{***} (0.023)	-0.074^{***} (0.021)
Control variable	No	Yes
Year fixed effect	Yes	Yes
Region fixed effect	Yes	Yes
Observations	5.712	5.712
Pseudo R2	0.132	0.150

Note: The reported coefficients are mean marginal effects. Robust standard errors are reported in parentheses. *, **, *** indicate significant at the 10%, 5% and 1% levels, respectively.

4.2. Endogeneity problem

The calculation of exposure to robots indicates that its variation depends on employment shares prior to the onset of robotization (Matysiak et al., 2022). This raises concerns about the endogeneity of robot exposure. To address this problem, we use the instrumental variable approach to estimate the linkage between robot adoption and fertility. The instrumental variable is constructed using the industry-specific stock of robots in the US, which serves as a proxy for advancements in robotization in developed economies. The Bartik instrumental variable for robot adoption is calculated as follows:

$$\text{Exposure to Robots}_{j,t-1}^{IV} = \sum_{k \in K} l_{j,k}^{1990} \left(\frac{R_{k,t-1}^{US}}{L_{k,1990}^{US}} \right), \quad (3)$$

where, $l_{j,k}^{1990}$ is the distribution of employ across industries and cities; $L_{k,1990}^{US}$ is the total number of individuals employed in industries k in 1990; $R_{k,t-1}^{US}$ denotes the stock of robots in the US across industries in year $t - 1$. According to Wooldridge (2010), there are three reasons to consider this instrument as reasonable. First, it satisfies the correlation requirement for instrumental variables with endogenous variables. As a proxy for advancements in robotization, the adoption of robots in the US fosters the adoption of robots in the industries of China through foreign trade. Second, the instrument is exogenous, as the robots in the US are not affected by the fertility behavior of households in China. Third, the robots in the US are not associated with other explanatory variables in the model. It is unreasonable to anticipate that robots in the US affect fertility behavior directly in China through other explanatory variables. Therefore, the proposed instrument is theoretically valid and helps alleviate our endogeneity issues.

Using the instrumental variable approach, we estimate model (1). In Column (1) of Table 4, the correlation between the instrumental variable and robot exposure in China is significantly positive. The Cragg-Donald Wald F statistic and the Kleibergen-Paap rk LM statistic confirm the validity of the instrumental variable. Column (2) indicates that the estimated coefficient for robot exposure is significantly -0.432 . These findings from the instrumental variable estimator further support Hypothesis 1 (H1).

Table 4. Result for instrument variable method

Variables	(1)	(2)
	robot	new
robot		-0.512^{***} (0.190)
Exposure to Robots $_{j,t-1}^{IV}$	0.630^{***} (0.002)	
Control variable	Yes	Yes
Year fixed effect	Yes	Yes
Region fixed effect	Yes	Yes
Cragg-Donald Wald F statistic	123.78^{***}	
Kleibergen-Paap rk LM statistic	3280.09	
Observations	5.712	5.712

Note: The reported coefficients are mean marginal effects. Robust standard errors are reported in parentheses. *, **, *** indicate significant at the 10%, 5% and 1% levels, respectively.

4.3. Robustness checks

To further bolster the robustness of our findings, we have implemented the following methodologies:

- (1) Replacing measures of core independent variables. First, we replace the industrial robot exposure calculated in the previous section with the employment share of each industry based on data from 2006. Since the development of the industrial robot industry in China began after 2006, we use 2006 as the base period for constructing robot exposure in our robustness testing. In Column (1) of Table 5, the results indicate that robot exposure, with 2006 as the base period, has a significantly negative coefficient, demonstrating that robot adoption adversely affects the reproductive behavior of female laborers.
- (2) Replacing dependent variable indicator. The number of children born is chosen to replace the indicator of whether new children have been born. Poisson model with robust standard errors is more suitable to examine the effect of robot application on the number of children than using a linear model. In Column (2) of Table 5, the results show that robot adoption has a negative effect on the fertility behavior after the dependent variable replacement, and the findings remain robust.
- (3) Excluding influences of other technology. Internet technology facilitates the dissemination and expansion of information regarding fertility, which is changing women's perceptions about fertility behavior. To accurately identify the effect of robot adoption on fertility behavior, an internet penetration variable is included to further control for the effects of Internet development on fertility behavior. This variable is measured by number of Internet users divided by resident population at the city level. Column (3) of Table 5 indicates that robot adoption affects negatively fertility behavior.
- (4) Increasing the age range of the sample. While females aged 18 to 45 years are typically considered to be within the optimal age range for childbearing, women from other age groups also give birth. Therefore, a sample of women aged 15 to 50 years is selected for robustness testing. The results reported in Column (4) of Table 5 indicate that the relationship between robot adoption and fertility behavior remains robust.
- (5) Further increase in sample. The baseline regression sample, which includes only women of childbearing age, overlooks households where the respondents are men with women of childbearing age as spouses. Therefore, this section expands the sample to include these households. The results in Column (5) of Table 5 demonstrate that the conclusions drawn from the baseline regression remain robust.
- (6) Excluding influences of universal two-child policy. China began to implement the universal two-child policy in 2016. To eliminate the confounding impact of China's universal two-child policy on the research conclusions, we added the interaction term between the two-child policy dummy variable and robot exposure as a control variable. The results are reported in Column (6) of Table 5. It indicates that robot adoption still exerts a significantly negative impact on fertility behavior.

Table 5. Robustness tests

Variables	(1)	(2)	(3)	(4)	(5)	(6)
robot	−0.067** (0.023)	−0.278*** (0.027)	−0.069*** (0.025)	−0.074*** (0.020)	−0.061*** (0.023)	−0.045*** (0.017)
Control variable	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Region fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5,712	2,965	5,452	7,051	8,616	5,712

Note: The reported coefficients are mean marginal effects. Robust standard errors are reported in parentheses. *, **, *** indicate significant at the 10%, 5% and 1% levels, respectively.

5. Mechanism tests

According to the theoretical analysis, robot adoption affects household fertility behavior through three main channels: human capital investment (the human capital effect), employment instability (the employment effect), and income inequality (the inequality effect). The next step is to empirically test these channels through which robot adoption influences fertility behavior. Following the methodology of Hayes (2022) and Zhou et al. (2024), we estimate regression model (4) to examine the mechanisms driving this relationship.

$$M_{ijt} = \alpha_0 + \alpha_1 robot_{j,t-1} + \beta X_{ijt} + \gamma_t + \delta_j + \varepsilon_{ijt}, \quad (4)$$

where, M_{ijt} denotes mediating variables, including the human capital investment, employment instability and income inequality.

To test the human capital effect, we measure household human capital investment by examining the total education expenditure on both adults and children. Household human capital investment consists of two components. The first involves adults investing in their own human capital by allocating more funds toward training and acquiring higher qualifications. The second involves adults investing household resources in the education of children, placing a higher emphasis on their quality. The household questionnaire section of the CLDS provides data on both types of expenditure.

Column (1) of Table 6 reports the results about the estimated regression (4), where human capital investment is used as the mediating variable. We can find that robot adoption affects positively the human capital investment. It implies that increased robot adoption leads households to allocate more resources to education and training for both adults and children. Thus, by driving increased human capital investment, robot adoption decreases the likelihood of childbearing. These empirical results support our hypothesis (H2a) and confirm the human capital effect.

To test the employment effect, we measure employment instability by examining whether an individual experiences job loss. The CLDS data includes information on changes in work status. If a worker undergoes loses their job, the employment instability variable is set to 1; if not, it is set to 0. The employment instability variable is thus binary. A probit model is employed to investigate the role of robot adoption on the employment instability of the labor force.

In Table 6, Column (2) presents the estimated model (4) with employment instability as the mediating variable. It indicates that robot adoption has a significantly positive effect on job instability. This instability arises from increased job competition and technological unemployment due to robot adoption (Autor et al., 2019). Employment instability creates uncertainty about future earnings (Alderotti et al., 2021). As a result, employment instability can discourage individuals from having children (Billari, 2005). Therefore, robot adoption decreases the likelihood of childbearing by increasing job instability. This empirical result supports our hypothesis (H2b) and confirms the employment effect.

To measure income inequality, Kakwani index is used to depict the relative level of income deprivation among individuals in each community. The Kakwani index emphasizes the relative sense of deprivation between individuals and their reference group mean (Kakwani, 1980). This method provides a more accurate reflection of income inequality as perceived by individuals, focusing on their sense of relative deprivation. Compared to the Gini coefficient, the Kakwani index places greater emphasis on revealing disparities between individuals or groups (Chakravarty, 1988; Idrees & Ahmad, 2017). Following methodology of Kakwani (1980), we calculate the Kakwani index using household income data.

When income inequality is used as the mediating variable, the estimated regression model (4) is presented in Column (3) of Table 6. It shows that robot adoption has a positive effect on income inequality. This discovery aligns with the existing literature, which suggests that robot adoption exacerbates wage disparities through mechanisms like the skill premium (Lankisch et al., 2019) or wage polarization (Autor & Dorn, 2013). Our empirical results support these perspectives. As income inequality increases due to greater robot adoption, households may opt to have fewer children, reducing the probability of childbearing, as they seek higher consumption patterns similar to those of higher-income groups (Japaridze, 2019). Additionally, income inequality has been shown to lower a region's total fertility rate (Sato et al., 2008; Macan & Deluna, 2013). Low-fertility environments can influence individual fertility decisions by altering societal attitudes toward childbearing, similar to the peer effect discussed by Ciliberto et al. (2016). Thus, robot adoption reduces the probability of childbearing by increasing income inequality, consistent with our hypothesis (H2c). This evidence further supports the inequality effect previously outlined.

Table 6. Mechanism tests

Variables	(1)	(2)	(3)
	Human capital investment	Employment instability	Income inequality
robot	1.216*** (0.340)	0.490*** (0.079)	0.009** (0.004)
Control variable	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes
Region fixed effect	Yes	Yes	Yes
Observations	5.712	5.712	5.712

Note: The reported coefficients are mean marginal effects. Robust standard errors are reported in parentheses. *, **, *** indicate significant at the 10%, 5% and 1% levels, respectively.

Among the three effects discussed, the human capital effect is the most pronounced, followed by the employment effect, while the income inequality effect is the least significant. This indicates that the primary mechanism through which robot adoption influences family fertility behavior is by incentivizing investment in human capital and increasing employment instability.

6. Extended analysis

We further explore the heterogeneity in the linkage between robot adoption and fertility behavior, considering the potential influence of additional factors. This extended analysis examines whether the role of robot adoption on fertility choice varies by labor skill levels, institutional work attributes, ancestral halls culture, age, and regional economic conditions.

6.1. Labour skills

We first categorize the labor force's skills into two groups according to generic skills. Educational attainment serves as a direct measure of the level of generic skills, with individuals possessing post-secondary education classified as high-skilled labor and those without classified as low-skilled labor (Lordan & Neumark, 2018). Additionally, we divide the labor force's skills into two groups based on specialized skills. The presence of certificates and participation in job training programs reflect the level of specialized skills. Workers who lack certification and have not received training are deemed to have a limited level of specialized skills.

Columns (1) and (2) of Table 7 report the results about impact of robot adoption on fertility among workers with high and low generic skills, respectively. The results indicate that the coefficient associated with robot exposure are not statistically significant for workers with high generic skills. In contrast, for workers with low generic skills, the coefficient of robot is significant. This suggests a disparity in the role of robot adoption on the fertility choice based on their skill levels; specifically, robot adoption decreases the likelihood of childbearing

Table 7. The regression results, by labor force skill group

Variables	(1)	(2)	(3)	(4)
	High generic skills	Low generic skills	High specialized skills	Low specialized skills
robot	-0.054 (0.035)	-0.092*** (0.034)	-0.120 (0.104)	-0.068*** (0.025)
Control variable	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes
Region fixed effect	Yes	Yes	Yes	Yes
Observations	1.105	4.370	345	5.236

Note: The reported coefficients are mean marginal effects. Robust standard errors are reported in parentheses. *, **, *** indicate significant at the 10%, 5% and 1% levels, respectively.

for female workers with low generic skills but does not significantly impact those with high generic skills. The differential effects of robots on high- and low-skilled workers contribute to this variation. According to Lankisch et al. (2019), robot adoption exerts a substitute effect on low-skilled workers, while its role on high-skilled workers remains ambiguous. The substitute effect of robots on low-skilled labor may reduce the probability of childbearing through its influence on employment status and income.

Columns (3) and (4) of Table 7 present the estimated results regarding the impact of robot exposure on the fertility behavior of high- and low-specialization skilled labor groups, respectively. For workers with high specialized skills, the estimated coefficient for robot exposure does not reach statistical significance. In contrast, for workers with low specialized skills, the coefficient is significant. This indicates a disparity in the role of robot adoption on the fertility behavior of workers with high versus low specialized skills; specifically, robot adoption reduces the likelihood of childbearing for workers with low specialized skills without significantly affecting those with high specialized skills. This phenomenon can be attributed to the surge in robot adoption, which necessitates a shift and reconfiguration of job skills. Industrial robots are increasingly replacing workers who lack sufficient specialized skills, leading to instability in employment and income that compels female workers to limit their reproductive choices.

6.2. Attributes of work institutions

For political reasons related to maintaining social stability, state-owned enterprises and institutions are typically restricted from laying off workers and often provide more stable employment opportunities in China (Guo et al., 2021). Based on the characteristics of the employing enterprises and institutions, we divided the sample into two sub-samples: workers in state-owned enterprises or institutions and those in non-state-owned enterprises or institutions. We then estimate the relationships between robot adoption and workers' reproductive behavior separately for these two sub-samples.

Table 8 displays the estimated results regarding the influences of robot adoption on the fertility behavior of workers in non-state-owned and state-owned enterprises or institutions, respectively. The findings indicate that robot exposure significantly reduces the probability of fertility for laborers in non-state-owned enterprises or institutions, while no significant effect is observed for workers in state-owned enterprises or institutions. This discrepancy can be attributed to the fact that female employees in non-state-owned enterprises or institutions typically experience more flexible employment arrangements, which often translate into less income stability and irregular working hours, along with potentially lower levels of social security. Consequently, the adoption of robot exacerbates their vulnerability to the "penalty effect" associated with maternity, increasing the likelihood of hindered wage growth and career advancement in such non-state-owned environments. As a result, the detrimental impact of robot on reproductive choices is significantly more pronounced for those employed in non-state-owned enterprises or institutions compared to their counterparts in state-owned settings.

Table 8. The regression results with different attributes of work institutions

Variables	(1)	(2)
	Non-state-owned	State-owned
robot	−0.090*** (0.029)	−0.044 (0.036)
Control variable	Yes	Yes
Year fixed effect	Yes	Yes
Region fixed effect	Yes	Yes
Observations	4.560	824

Note: The reported coefficients are mean marginal effects. Robust standard errors are reported in parentheses. *, **, *** indicate significant at the 10%, 5% and 1% levels, respectively.

6.3. Ancestral halls culture

The role of culture is pivotal in elucidating the phenomenon of fertility transition (Baudin, 2010; Beach & Hanlon, 2023). In China, the cultural significance of ancestral temples profoundly influences reproductive choices. Communities that maintain ancestral temple organizations tend to prioritize lineage continuation, leading to a greater propensity for childbearing compared to those lacking such organizations. The CLDS provides data about indicator of whether an ancestral hall exists in the households' community. We classified the sample into two groups based on the presence of an ancestral temple organization within the households' community. Our analysis estimates the impact of ancestral temple culture on the linkage between robotics and reproductive behavior. The findings are detailed in Table 9. It was observed that the adoption of robots significantly diminishes the likelihood of fertility in households from communities without ancestral temple organizations, whereas no significant effect is noted for households in communities with such organizations. This outcome can be attributed to the fact that the presence of ancestral temple culture mitigates the adverse effects of robotic applications on fertility behavior.

Table 9. The regression results with different ancestral temples culture

Variables	(1)	(2)
	Ancestral temple	Non ancestral temple
robot	−0.020 (0.013)	−0.068** (0.053)
Control variable	Yes	Yes
Year fixed effect	Yes	Yes
Region fixed effect	Yes	Yes
Observations	336	4.713

Note: The reported coefficients are mean marginal effects. Robust standard errors are reported in parentheses. *, **, *** indicate significant at the 10%, 5% and 1% levels, respectively.

6.4. Age of labours

Women of varying ages exhibit differences in fecundity, job stability, and family structure, which may influence the relationship between robot adoption and reproductive behavior. Following the classifications established by Anelli et al. (2021), we categorize the female labor force into three age groups for heterogeneity tests. Columns (1) to (3) in Table 10 present the estimated results regarding the impact of industrial robot adoption on the fertility behavior of female laborers aged 18–25, 26–35, and 36–45, respectively.

The results indicate that robot has a significant negative effect on the likelihood of fertility for the 18–25 and 26–35 age groups, whereas no significant effect is observed for female workers in the 36–45 age group. Moreover, this negative effect is more pronounced in the 18–25 age group compared to the 26–35 age group. This discrepancy may be attributed to younger female workers being more vulnerable to job insecurity and having a greater incentive to invest in human capital. In contrast, older women tend to have more stable family relationships and work status, leading to a decline in fertility intentions. Therefore, the potential economic effects of robot applications are less likely to impact their reproductive behavior.

Table 10. The regression results, by age group

Variables	(1)	(2)	(3)
	18–25	26–35	36–45
robot	–0.119** (0.055)	–0.053* (0.028)	–0.052 (0.052)
Control variable	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes
Region fixed effect	Yes	Yes	Yes
Observations	1.179	1.721	2.033

Note: The reported coefficients are mean marginal effects. *, **, *** indicate significant at the 10%, 5% and 1% levels, respectively. Standard errors are reported in parentheses.

6.5. Regional economic level

China exhibits notable disparities in the geographical distribution of economic development, with developed eastern regions contrasted against relatively underdeveloped central and western regions (Yang et al., 2022). Statistical analysis indicates that robot application is predominantly focused in the eastern region (Zhou et al., 2024). In order to explore regional variations in the linkage between robot adoption and fertility choices, we categorize the sample into three subsets: workers residing in the eastern, central, and western regions. We then estimate the effect of robot adoption on workers' fertility behavior separately. Table 11 present the estimated results about the influences of robot on the fertility behavior of laborers in the three regions. Only households with workers in the eastern region exhibit a significantly negative role of robot on the probability of fertility, while the effect is insignificant in the central and western regions. This phenomenon can be attributed to the fact that more increased robot exposure intensifies labor market competition in the eastern region, thereby diminishing families' desire to have children.

Table 11. The regression results with different regional economic level

Variables	(1)	(2)	(3)
	Eastern	Central	West
robot	−0.083*** (0.025)	−0.043 (0.070)	−0.012 (0.094)
Control variable	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes
Region fixed effect	Yes	Yes	Yes
Observations	2.680	1.430	1.602

Note: The reported coefficients are mean marginal effects. Robust standard errors are reported in parentheses. *, **, *** indicate significant at the 10%, 5% and 1% levels, respectively.

7. Conclusions and discussion

This study employs China Labor Dynamics Survey (CLDS) data to investigate the influence of robot adoption on individuals' fertility behavior. It not only assesses the direct impact of robots on the fertility behavior of households but also explores the mechanisms through which robots influence fertility choice. We conduct detailed endogeneity and robustness analyses to account for potential confounding factors. Finally, we investigate the heterogeneity of the relationship between robot and fertility behavior.

Our analysis reveals that the adoption of robot significantly reduces the likelihood of fertility among Chinese households. However, our conclusions are different from those of Matysiak et al. (2022), who examined the macro-level impact of robots on total fertility rates across various countries. Our study focuses on the micro-level linkage between robot adoption and fertility behavior, providing empirical evidence to support the negative influence of robot adoption on total fertility.

The most significant finding of our study is that robot use decreases the likelihood of fertility through three pathways: "human capital effect," "employment effect," and "inequality effect." The "human capital effect" suggests that robot adoption encourages families to invest more in education, thereby reducing fertility behavior. The "employment effect" indicates that robots lower the probability of fertility by increasing employment instability. Lastly, the "inequality effect" reveals that robot adoption diminishes fertility behavior among reproductive-age workers by exacerbating income inequality. The findings from the mechanism tests fill a void in the studies regarding the pathways through which robot adoption influences fertility behavior. This research offers insights into the actual micro-founded mechanisms that explain the relationships between robot adoption and fertility.

Our findings from mechanism analysis have several practical implications for alleviating the negative effects of robot application on fertility behavior. Firstly, the government should enhance public investment in education to counteract the adverse effects of robot adoption on fertility rates. Secondly, the government should strengthen the employment protection system to prevent discrimination against women of childbearing age or pregnant women in the labor market. Enhancing women's employment protection will significantly mitigate the negative impact of robots on childbearing. Thirdly, the government should implement

improved income redistribution policies to incentivize families to have children by reducing income inequality, such as a robot tax. Finally, to mitigate the fertility impact of adoption, effective policies must account for demographic and regional differences. Analytical findings on group heterogeneity show that low-skilled workers, younger individuals, and non-state employees are more vulnerable to robot's negative effects. Policies should focus on job security for these groups and provide inclusive childcare to support work-family balance. Moreover, regions that lack ancestral hall culture or have developed economies show fertility choice are more susceptible to the pressure of robot competition. To address this, governments should implement targeted measures, such as employment protection and subsidies for education and childcare.

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Author contributions

Lei He conceived the study, and were responsible for the design and development of the data analysis, and wrote the first draft of the article. Qin Wang were responsible for data collection and analysis.

Disclosure statement

The authors declare that they have no conflict of interest.

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