Robot and Well-being: Average Gains, Divergent Lives [*†]

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Abstract

Does automation enhance or erode subjective well-being (SWB)? Using a large-scale longitudinal survey of Chinese residents, we find that greater robot exposure significantly increases self-reported SWB: a one-unit rise in robot exposure predicts a 0.285-point gain on a 5-point scale. These average gains mask sharp distributional differences. Positive effects are concentrated among high-skill workers and individuals with higher socioeconomic status, while the unemployed and lower-status groups experience losses in well-being, leading to a widening dispersion of SWB. Evidence on mechanisms suggests that automation increases income, reduces working hours, improves health, and strengthens self-confidence for those who remain employed, whereas displaced workers experience the opposite changes. We also document suggestive shifts from collectivist to more individualistic sources of well-being. Overall, automation brings "average gains" for the masses while leading to "divergent lives" across groups.

Keywords: Automation; Well-being; Technological advancement; Inequality.

JEL Codes: I31, O30, J20, I10, H75

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1 Introduction

Understanding the determinants of subjective well-being (SWB) has long been central to economics, from classical welfare theory to contemporary studies using subjective measures of life satisfaction and happiness (Walras, 1874; Arrow, 1950; Easterlin, 1974). While early research emphasized income and employment in raising SWB (Akerlof and Yellen, 1990; Clark and Oswald, 1996; Stevenson and Wolfers, 2013), subsequent work in sociology and psychology highlighted the roles of family relations, cultural norms, and psychological states (Cohen and Wills, 1985; Inglehart and Baker, 2000; Ryan and Deci, 2001). Amid rapid technological change in the twenty-first century (Turkle, 2011; Sunstein, 2018), there is a growing need to understand how automation affects SWB, which is both central to economic theory and effective policy making.

Since 2000, automation has transformed economic activities worldwide. Prior research documents substantial substitution effects, with robots replacing human labor and giving rise to job displacement (Frey and Osborne, 2017; Acemoglu and Restrepo, 2019). Meanwhile, automation can generate new tasks, reduce routine burdens, and raise productivity, thereby reshaping long-run growth dynamics (Autor, 2015; Jones and Liu, 2024). To clarify these divergent welfare implications, we examine how automation affects SWB in China, a global leader in industrial robot adoption. Since 2010, China has experienced rapid growth in robotics, becoming the world's largest installer of robots by 2013 and holder of the largest robot stock by 2016 (Figure 1). These developments, combined with substantial regional variation in robot penetration, provide a valuable setting to assess its welfare consequences.

The key issue revolves around whether automation enhances well-being through productivity gains or reduces it by raising unemployment. We begin by estimating the average treatment effect (ATE) of robot exposure on SWB. We then study heterogeneity by work status and socioeconomic status (SES) to uncover distributional patterns. Finally, we draw on multiple data sources, including large-scale individual/household-level surveys and county-level statistical yearbooks, to explore mechanisms through which automation may raise SWB. These analyses also shed light on a broader shift from collectivist to more individualistic sources of well-being. We elaborate these findings below.

We construct a panel dataset linking SWB from the China Family Panel Studies (CFPS) with prefecture-level robot exposure derived from the International Federation of Robotics (IFR).[1] Robot exposure is constructed using a shiftshare design that combines (i) pre-treatment

1. Chinese administrative regions include four levels: provinces, prefectures, counties, and towns. The "prefecture-level" here is identical to the "city-level" used in other studies (Giuntella et al., 2024). Our data is based on the number of industrial robots, and we use "robot" throughout the paper for simplicity.

variation in prefectures' industrial composition with (ii) sector-level robot adoption over time. To alleviate endogeneity concerns arising from unobserved individual characteristics or local economic trends, we estimate models with individual fixed effects and province-year fixed effects. In addition, we use a standard Bartik instrument that replaces China's sectoral robot adoption with those observed in the United States and other advanced economies, thereby isolating plausibly exogenous variation in robot penetration across Chinese prefectures.

Our findings indicate that an additional robot per thousand workers increases reported SWB by 0.285 points on a five-point scale, equivalent to 7.8% of the sample mean. These *average gains* are not evenly distributed. Using ordered response models, we find that positive effects are concentrated among individuals who were ex-ante better-off, highlighting the *divergent lives* of different groups. The 2SLS estimation using Bartik instruments yields similar findings. We further assess the identifying assumptions of the Bartik design following Goldsmith-Pinkham, Sorkin, and Swift (2020); Borusyak, Hull, and Jaravel (2022), and find support for both the "quasi-random shift" and "exogenous share" conditions. Furthermore, we conduct a battery of robustness tests, including a long-differenced model to deal with transitory shocks, measurement error, or serial correlation, a dynamic analysis to consider possible time lags, and additional models to alleviate concerns of migration, attrition, and other confounding factors.

We then explore the distributional effects of automation across different SES groups. The positive effects of robot exposure are much stronger for individuals who are better educated, live in urban areas, have higher social status, or work in occupations with lower substitutability. This indicates that individuals with higher SES capture a disproportionate share of the welfare gains. In addition, we conduct heterogeneity analyses by occupation and work status. The positive effects are concentrated in higher-skill occupations, whereas adverse impacts are more pronounced among lower-skill workers. Similarly, robot exposure raises SWB among employed workers (both job finders and employed stayers) while reducing SWB among the unemployed (both job losers and unemployed stayers). Overall, the aggregate gains are driven primarily by improvements among the employed (better-off), implying that rising average happiness in China is accompanied by widening inequality.

We then investigate the channels through which automation influences SWB. First, we document an *income effect*: automation raises individual income and increases regional productivity.[2] Second, automation reduces working hours, increases leisure time, raises job satisfaction, and improves health, which we refer to as the *leisure and health effect*. Third,

2. While income may not necessarily boost subjective well-being, rising income at least raises the probability of reaching the SWB turning point (Stevenson and Wolfers, 2013), especially in China.

it strengthens individual self-confidence, known as the *self-identification effect*. These channels jointly contribute to the *average gains* from automation, yet they differ sharply across groups: employed workers benefit through higher income, improved health conditions, and enhanced self-identification, whereas unemployed individuals experience declines along the same dimensions, reinforcing the *divergent lives* documented above.

Beyond these average and distributional effects, we provide suggestive evidence that automation reshapes the underlying sources of well-being. In particular, individuals appear to shift from collectivist to more individualistic pursuits: they are more likely to live alone and engage in self-care, spend more time on self-fulfilling activities, and display rising political apathy. These patterns suggest that rising SWB is increasingly tied to individualistic rather than familial or collectivist recognition, consistent with classic studies linking modernization to reductions in social capital (Coleman, 1988; Putnam, 2000).

Literature. We contribute to the literature on the economic impact of automation in three ways. First, while existing research has primarily examined its impact on employment (Frey and Osborne, 2017; Acemoglu and Restrepo, 2018, 2020), occupations (Autor, Chin, Salomons, and Seegmiller, 2024), and income disparities (Autor and Dorn, 2013; Goos, Manning, and Salomons, 2014; Moll, Rachel, and Restrepo, 2022), much less is known about its effect on subjective well-being. Our study comprehensively analyzes how automation affects individuals' SWB.[3] Second, this study helps reconcile the ongoing debate on whether robots substitute existing jobs (Acemoglu and Restrepo, 2019; Giuntella, Lu, and Wang, 2024), create more new jobs (Autor, 2015; Graetz and Michaels, 2018; Mann and Püttmann, 2023; Autor et al., 2024), or both (Autor and Thompson, 2025). We help clarify the issue by analyzing its heterogeneous effects on individuals with different SES or work status, highlighting its distributional outcomes.[4] Third, we provide novel evidence for how automation exacerbates inequality. Existing studies have shown that robot exposure mainly hurts low-skilled workers and intensifies wage inequality (Moll et al., 2022; Hémous and Olsen, 2022; Acemoglu and Loebbing, 2022; Edin et al., 2023), and we extend their findings to "SWB inequality," showing how it benefits the better-off at the cost of the worse-off.[5]

3. A few relevant works focus on job satisfaction (Deming, 2017; Liu, 2023), emotions (Petriglieri, Ashford, and Wrzesniewski, 2019; Nazareno and Schiff, 2021), and health (Gunadi and Ryu, 2021; Gihleb, Giuntella, Stella, and Wang, 2022; Lu and Fan, 2024; Liu, Luo, and Seamans, 2024; Wang, Zhang, and Liu, 2024; Luo, Tang, Yang, and Zou, 2025; Giuntella, Konig, and Stella, 2025), yet our discussion on well-being can summarize all above factors' effects.

4. Our overall effect sheds light on the change in SWB of the Chinese population as we employ a representative household survey. Other studies restrict to certain samples for different research purposes, like Dauth et al. (2021) (private workers), Bessen et al. (2023) (workers), and Giuntella et al. (2024) (urban dwellers).

5. The findings contrast with generative AI that benefits low-skilled workers more (Babina et al., 2024; Brynjolfsson et al., 2025), but aligns with technological change and domestic outsourcing (Bergeaud et al., 2025).

We also speak to the literature on determinants of SWB. While prior studies primarily emphasize cultural and psychological factors,[6] we examine the role of technological advancement, analyzing how automation has both increased and polarized SWB in China. Our study links closely with Easterlin's earlier works (Easterlin et al., 2012, 2021) that pose two stylized facts on happiness in China (1990-2010): (i.) the Chinese did not experience a remarkable increase in SWB as they did in GDP per capita; (ii.) modernization has decreased SWB for persons in the bottom third of the income distribution and increased SWB for the top third. On the one hand, our analysis highlights automation's crucial role in increasing SWB in China, which partly explains the increase in SWB since 2010. On the other hand, our findings confirm Easterlin's arguments by showing widening SWB inequalities in China even after 2010.

Moreover, our study relates to the research on decaying social capital and rising individualism driven by technological advancement. Modernization and technological progress are hypothesized to shift SWB orientations from collectivism to individualism (Coleman, 1988; Putnam, 2000), but existing research lacks causal inference and clear mechanisms.[7] Our study provides some of the first causal evidence on how automation transforms the sources of SWB in China, illustrating the channels through which robot penetration fosters individualistic SWB.

The remainder of this paper is organized as follows: Section 2 presents background information. Section 3 introduces the data and empirical strategies. In Section 4, we estimate the effects of automation on SWB, identify the causal effect, and conduct robustness checks. In Section 5, we examine the heterogeneous effects and reconcile our findings with existing research. Section 6 provides potential channels whereby automation fosters SWB, and shows how it boosts individualism. Section 7 summarizes the research findings. An illustrative model is provided in Appendix E to further elucidate our findings.

6. Classic works have examined the relationship between SWB and psychological traits (Lazarus and Folkman, 1984), social capital (Coleman, 1988), cultural beliefs (Inglehart and Baker, 2000), institutional environments (Frey and Stutzer, 2000), and demographic characteristics (Blanchflower and Oswald, 2008). Recent studies also shed light on the influence of creative destruction (Aghion, Akcigit, Deaton, and Roulet, 2016).

7. Extant works have analyzed the role of social media (Putnam, 2000), globalization (Castells, 2000), artificial intelligence (Brynjolfsson and McAfee, 2014), and digital technology (Sunstein, 2018) in eroding traditional collectivist norms and boosting individualism.

2 Background

2.1 Automation in China

Since the reform and opening-up in 1978, China has achieved remarkable economic breakthroughs. As the core driving force of its economic rise, China's manufacturing sector surpassed that of Germany, Japan, and the United States in 2006, 2008, and 2010 (in terms of value added), respectively, establishing itself as the world's leading manufacturing powerhouse. However, the reliance on low-end, export-oriented manufacturing has limited China's long-term economic growth potential. Amid fading demographic dividends and intensified geopolitical competition, China has reoriented its industrial development focus towards adopting advanced technologies.

To this end, the Chinese government has promoted industrial transformation by prioritizing automation. A battery of policies has been implemented to promote automation, with conspicuous achievements.[8] According to IFR's World Robotics Technology Report, the installation of industrial robots in China has surged from 56,078 in 2010 to 268,195 in 2021. Meanwhile, China surpassed Japan and the U.S. to lead in both industrial robot installations and stocks worldwide in 2013 and 2016, making it the world's largest market for industrial robots, as shown in Figure 1.

During our sample period, automation has advanced significantly across different regions of China. Figure A3 illustrates the temporal evolution of robot penetration, showing a substantial increase from 2006 to 2018. Meanwhile, the figures highlight substantial regional heterogeneity in robot penetration across China. For instance, coastal prefectures and inland developed prefectures exhibit higher levels of robot exposure.

The rapid process of automation has reshaped China's economy, enhancing productivity, increasing efficiency, and improving social welfare. However, the process is associated with rising unemployment (Giuntella et al., 2024) and increasing psychological stress (Lu and Fan, 2024), which may adversely impact SWB. Previous research has primarily focused on its direct effects on the unemployed, overlooking the potential benefits for employed workers. For example, increased productivity may lead to higher incomes, time savings from robots can reduce work pressure, and social comparison may boost employed workers' self-confidence. This suggests a scenario that *automation harms the well-being of a small*

8. In 2014, Chinese President Xi Jinping advocated for accelerated automation to boost China's global manufacturing competitiveness. During the period from 2016 to 2020, the government provided substantial fiscal support for manufacturers to adopt robots and other high-end technologies. In 2017, robotics technology was formally incorporated into the government's work report. By 2021, China's fourteenth "Five-Year Plan" aimed to further integrate robot technology into various sectors of the Chinese economy.

subset of people (the unemployed) but enhances SWB for a larger group (the incumbents). There is abundant anecdotal evidence supporting this view,[9] and this study empirically tests the hypotheses above.

2.2 Subjective Well-being of the Chinese

China has experienced remarkable economic growth and extensive social transformation, which significantly enhanced the well-being of Chinese residents due to increased income, improved living standards, and better public services. According to the World Values Survey, the proportion of Chinese respondents considering themselves "very happy" rose from 8.5% in 1990 to 28.5% in 2012. More recently, the poverty alleviation campaign advanced the nation toward its stated goal of building a "moderately prosperous society", paying more attention to boosting citizens' well-being. The 2022 UN World Happiness Report ranks China 72nd out of 156 countries, with its happiness index rising to 5.383 from 4.89 in 2012. Domestic surveys, like CFPS, also reflect this trend, with average life satisfaction scores rising from 3.48 in 2010 to 4.02 in 2020 (on a 5-point scale).

Confucianism emphasizes filial piety and kinship relations, while socialist ideology promotes service to society (Chen, Ma, and Sinclair, 2022). Historically shaped by these values, Chinese society has prioritized family involvement, kindred support, and broader social contribution-hallmarks of collectivist norms. However, these traditional ideals have come under strain amid rising income inequality, intensifying work pressure, and a weakening social safety net. Recently, cultural trends such as "lying flat" (tang ping) and "Buddha-like" (fo xi) attitudes-resembling the NEET phenomenon in the UK-have become prevalent. These movements advocate abandoning conventional success metrics and emphasize personal well-being, reflecting a broader shift toward individualistic values. In light of these changes, it is essential to reassess the sources of SWB and examine how automation may be contributing to this value reorientation. These trends have implications not only for individual well-being but also for statesociety relations in China and other developing countries.

9. According to a McKinsey report, high-skilled workers and business leaders generally have a more optimistic view of automation. More information can be found at McKinsey: The Future of Work.

3 Research Design

3.1 Data

3.1.1 Robot Exposure Rate

We measure the automation process by constructing prefecture-level robot exposure rates from the International Federation of Robotics (IFR). The IFR provides the most comprehensive data on industrial robots, frequently used to examine the influence of automation (Graetz and Michaels, 2018; Acemoglu and Restrepo, 2020). We obtain data on industrial robots for major economies, including the United States, Japan, Germany, Sweden, South Korea, and China. The data include information on robot stocks and installations for 19 industries, 14 of which are within the manufacturing sector: paper and printing, textiles, wood and furniture, "other" vehicles, basic metals, non-metals, plastics and chemicals, food and beverages, "other" manufacturing industries, metal products, general machinery, rubber and plastics, electronics, and automotive (in increasing order of robot installations, as shown in Figure A1).

We measure China's prefecture-level employment shares across sectors and the overall employment in 2000 using public use microdata from China's 2000 Census.We choose $t_0 = 2000$ as the base year as large-scale robot adoption only began after 2000, particularly after 2010. As shown in Figure 1, robot installations and stocks in China experienced exponential growth only after 2010. Thus, we focus on robotics data after 2010.

We then combine the above data to construct a measure of robot exposure across China as follows:

$$Robot\ exposure_{p,t} = \sum_{r \in R} l_{r,p,t=t_0} \frac{Robot_{r,t}}{L_{r,t=t_0}}. \tag{1}$$

where $l_{r,p,t=t_0}$ is the share of prefecture p's employment in industry sector r in the base year $t_0 = 2000$. The numerator ($Robot_{r,t}$) measures the number of robots adopted in sector r and year t; and the denominator ($L_{r,t=t_0}$) measures the number of workers (in thousands) employed in sector r in 2000.[10] Thus, robot exposure rate $Robot\ exposure_{p,t}$ measures the number of robots adopted per 1,000 workers of prefecture p in year t. We conduct several identification checks in subsection 4.4 for the validity of this Bartik design.

By relying on predetermined industrial composition before the automation process, we avoid any mechanical correlation or mean reversion with changes in employment outcomes.

10. To address the discrepancy between sector classifications provided by the IFR and those used in China, we reclassify manufacturing industries into six major categories: manufacturing, education, construction, mining, gas, and agriculture, elucidated in subsection A.1.

However, the penetration of robotics may still be endogenous to sector-specific trends in China and/or differential trends across prefectures that have varying robot exposure rates. If these trends are also correlated with employment, working hours, mental health, self-identification, or general SWB, our estimates may be biased. To mitigate this concern, we follow the identification strategy developed by Acemoglu and Restrepo (2020) and utilize exogenous robot exposure based on the penetration of robotics across industries in other major economies. Specifically, we construct a Bartik instrument that proxies sector exposure to robotics in China using the penetration of robotics in the same industries in the U.S.:

$$Robot\ exposure_US_{p,t} = \sum_{r \in R} l_{r,p,t=t_0} (\frac{Robot_{r,t}}{L_{r,t=t_0}})_{US}. \tag{2}$$

As before, $l_{r,p,t=t_0}$ is the share of employment for prefecture p and sector r in China in 2000, but $(\frac{Robot_{r,t}}{L_{r,t=t_0}})_{US}$ represents robot penetration (robots per thousand workers) in U.S. sector r in year t. We also construct similar instruments using robot adoption in Japan, Germany, Sweden, South Korea for robustness checks.

This Bartik-style "shift-share" instrument interacts local sector shares with broader sector-specific shifts (i.e., shift in the penetration of robotics) (Goldsmith-Pinkham et al., 2020). By leveraging the penetration of robots across industries over time in other developed countries, this measure plausibly isolates exogenous variation in China's robot exposure that is driven primarily by advances in the robotics technology frontier, which is arguably orthogonal to China-specific sector shocks or labor-market trends.[11] Further, the share parameter, $l_{r,p,t=t_0}$, capitalizes on variation across prefectures with respect to sector specialization. Thus, prefectures with a higher concentration of employment in industries that were more prone to automation, are more intensely treated relative to prefectures that specialized in industries with little to no exposure to robotics.

3.1.2 Individual SWB

Our study utilizes SWB and related information from the China Family Panel Studies (CFPS). Conducted by the Institute of Social Science Survey at Peking University, CFPS is a nationally representative social survey covering 162 counties/districts across 25 provinces in mainland China, ensuring broad representativeness. The survey captures various facets

11. Our measure (using robot installation data) is arguably less affected by trade-related confounders than a few studies using data on robot imports/exports (See e.g., Acemoglu and Restrepo (2022)), as the number of imported robots is more heavily influenced by both local socioeconomic conditions and the bilateral relationship in global trade network. Our measure has incorporated such trade shocks, and we further alleviate the concern by controlling for imports/exports in subsection 4.4.

of economic and social welfare among Chinese residents, including economic activities, educational attainment, family relations, and health status.

We use data from five survey waves between 2010 and 2018 to estimate the relationship between robot exposure and SWB.[12] In CFPS, respondents rate their current life satisfaction on a scale from 1 (very dissatisfied) to 5 (very satisfied), and we use this measure as our primary proxy for individual SWB.[13] Additionally, we control standard demographic factors considered in the happiness literature, including gender, age, age squared, ethnicity, household registration type, marital status, education level, party membership, and household size.

3.1.3 Other Data Sources

CGSS. The Chinese General Social Survey (CGSS), launched in 2003, is the first nationally representative, comprehensive social survey in China, documenting the social structure, economic conditions, and life quality in China. It includes questions on individual time allocation across different activities, as well as attitudes toward inter-generational support. Thus, we use it to track how robot exposure influences individuals' values and behaviors.

CSS. The China Social Survey (CSS) is a nationwide survey initiated by the Chinese Academy of Social Sciences in 2005. The survey incorporates a battery of questions on social issues. We use it to analyze the implications on social support and kinship relations.

ISCIU. The Ideology Survey of Chinese Internet Users (ISCIU), obtained from Ma and Wang (2015), is frequently used to study the political attitudes of the Chinese. We use it to measure individuals' political participation.

3.2 Descriptive Analysis

Table A1 and Table A2 present summary statistics for robot exposure and other variables used in our analysis. On average, respondents report a SWB score of 3.64 out of 5. Figure A2 illustrates both its cross-sectional distribution and temporal evolution, revealing a rising share of respondents expressing higher levels of satisfaction over time. Regarding robot exposure, the mean exposure rate is 0.20, increasing markedly from 0.048 in 2010 to

12. The 2020 and later waves are not used due to the COVID-19 pandemic.

13. CFPS also surveyed respondents about their happiness, yet the question was suspended during the second and third waves (2012, 2014) and suffered from substantial missing data. Hence, we use self-reported life satisfaction to measure SWB. Figure A2 shows that both life satisfaction and subjective happiness are left-skewed, with most responses falling between 3-5 and 8-10, respectively.

0.454 in 2018. Figure A3 displays the geographic spread of robot exposure across Chinese prefectures, which gradually expanded from major urban centers to less developed regions.

In Figure 3, we plot the raw data to visualize the relationship between robot penetration and SWB. The scatter plots depict a positive correlation (Panel A), and the result remains robust when using optimal bin choices (Panel B) following Cattaneo et al. (2024). In Panels C and D, we replace the number of robot installations with stocks and obtain consistent results. Overall, robot penetration positively predicts SWB, giving rise to *average gains*. Nonetheless, Figure 2 shows distinct patterns between the employed and unemployed: the positive effect applies only to the employed, while the effect turns negative for the unemployed. In section 5, we conduct further heterogeneity analyses to further investigate these divergent patterns.

3.3 Empirical Strategy

We employ panel data from 2010, 2012, 2014, 2016, and 2018 to construct the baseline regression in Equation 3, where SWB_{ipt} denotes individual i's level of SWB in prefecture p in year t, and $Robot\ exposure_{pt}$ represents robot exposure rate in prefecture p in year t. β_1 is the coefficient of interest. If it is significantly positive, then automation is generally beneficial to residents' subjective well-being. $Control_{ipt}$ represents individual-level controls, including gender, age, age squared, ethnicity, household registration type (*hukou*), marital status, education level, party membership, and household size. Given that the construction of robot exposure resembles a generalized difference-in-differences, we additionally control for the interaction terms of a series of predetermined (2009) variables at the prefecture level $P_{p,t=2009}$ (including the share of agricultural/industrial output, unemployment rate, total population (logged), GDP per capita (logged), and average wage (logged)) with the year dummies T_t to mitigate potential confounding effects from initial prefecture characteristics and its trends.

$$SWB_{ipt} = \beta_0 + \beta_1 Robot\ exposure_{pt} + \gamma Control_{ipt} + \eta P_{p,t=2009} \# T_t + \mu_i + \delta_{mt} + \epsilon_{ipt} \quad (3)$$

As for fixed effects, we adopt individual fixed effects (μ_i) to control for unobserved heterogeneity, including personality traits, family backgrounds, cultural norms, and other time-invariant factors. Thus, our estimation only leverages within-individual variation across time, which aligns with the Bartik identification strategy illustrated below. In addition, we control for province-year fixed effects (δ_{mt}, m stands for province) to control for time-varying regional characteristics that may shape both robot penetration and SWB (like industrial policies). As for standard errors, we adopt two-way clustering by prefecture and

by year or clustering at the prefecture level with bootstrap, and further use other clustered standard errors in robustness checks to allow for various forms of correlation.[14]

We then turn to the instrumental variables (IV) strategy. Following Acemoglu and Restrepo (2020), Gihleb et al. (2022), and Anelli et al. (2024), we instrument for China's robot exposure (defined in Equation 1) using U.S.'s robot exposure (defined in Equation 2). The first stage and second stage are as follows:

$$Robot\ exposure_{pt} = \alpha_0 + \alpha_1 IV_{pt} + \alpha_2 Control_{ipt} + \alpha_3 P_{p,t=2009} \# T_t + \mu_i + \delta_{mt} + \epsilon_{ipt} \quad (4)$$

$$SWB_{ipt} = \theta_0 + \theta_1 Robot\ \widetilde{exposure}_{pt} + \theta_2 Control_{ipt} + \theta_3 P_{p,t=2009} \# T_t + \mu_i + \delta_{mt} + \epsilon_{ipt} \quad (5)$$

Recent studies highlight the importance of testing the assumptions underpinning the Bartik instrument (Adao et al., 2019; Goldsmith-Pinkham et al., 2020; Borusyak et al., 2022). They argue that either quasi-random robot shifts or exogenous initial sector shares are crucial for generating consistent estimates. We conduct a series of identification checks in subsection 4.4. For the "quasi-random shift" approach, we re-estimate the effects of automation at the shock level (Goldsmith-Pinkham et al., 2020), and re-compute standard errors following Adao et al. (2019) and Conley (1999), with robust findings. For the "exogenous share" approach, it is considered as a difference-in-differences design (Borusyak et al., 2022). We analyze its pre-trends by using lagged robot exposure and get insignificant results. We also calculate the Rotemberg weights of different sectors and control for sectors' base shares or linear trends. This excludes the possibility that all of the identifying variation comes from a single sector and our estimates may be inconsistent if the sector experienced a unique trend. Taken together, these checks enhance the validity of our Bartik design.

4 Average Gains from Automation

4.1 Baseline Results

We present the baseline estimates from Equation 3 in Panel A of Table 1. In columns (1)-(6), we progressively control for the trend of pre-determined factors, province-level fixed effects (FE), province-year-level FE, prefecture-level FE, and individual-level FE. Overall, the effect of robot exposure on SWB is positive and statistically significant, for both two-way clustered standard errors by prefecture and by year and bootstrapped standard errors over prefectures. In our preferred specification shown in column (6), each additional robot

14. Throughout the paper, we stick to the specification with individual FE and province-year FE to ensure consistent interpretation. Alternative specifications are noted when conducting analysis at different levels.

per 1,000 workers raises SWB by 0.285 points, or 7.8% of the sample mean (3.64). For each standard deviation (s.d.) increase, SWB increases by 0.055 points (1.5% of the sample mean).

To benchmark the magnitude of our estimated effect, we compare it with findings from related studies on SWB in China. Li (2021) shows that a one s.d. (8.8 p.p.) increase in the sex ratio reduces parental SWB by approximately 0.09 s.d., while doubling of household income raises SWB by 0.11 s.d.. In comparison, our estimate suggests that a one s.d. increase in robot exposure raises SWB by 0.055 units, or approximately 0.052 s.d. (0.055 / 1.062). This effect is comparable to either a 5 p.p. reduction in the sex ratio or a 47% increase in household income, both sizable in magnitude. To put these magnitudes into context, average SWB in China rose by approximately 15.52% (0.54 units) between 2010 and 2018. A back-of-the-envelope calculation suggests that the growth in automation could account for at least one-fifth (up to one-half) of this improvement.[15] These are sizable magnitudes but are plausible since they include both the direct effects of automation and its other ramifications (the overall effect).

To address potential confounding from labor market entry and exit, we restrict the sample to individuals that always remain in the labor market, known as the "labor market pool." Panel B of Table A3 shows similar results with the full sample in Panel A. To further assess whether changes in work status drive our results, we restrict the sample to individuals who maintain the same work status throughout the period-referred to as the "stayer pool." Panel C confirms similar patterns. In column (6), the estimated effect is largest for stayers, suggesting that changes in work status (robot's displacement effect) may partially attenuate the main effect. We discuss this in detail in section 5.

Finally, we turn to other SWB measures that may reflect broader patterns. Following Benjamin et al. (2014), we consider three sets of measures: evaluative measures (self/family life satisfaction), emotional measures (feeling pleased, difficult, or distracted), and eudaimonic measures (connectedness, happiness, hopefulness, or worthwhileness). Figure A4 shows consistent results with our baseline. Panel A shows that robot exposure boosts self-based and family-based SWB. Panel B indicates improvements in emotional well-being. Panel C demonstrates that robot exposure enhances eudaimonic well-being by fostering social connectedness and reinforcing a sense of purpose, happiness, and hopefulness.

15. Robot exposure in China has increased by approximately 0.4 units during 2010-2018 (0.23 units during 2010-2016), accounting for $21\% \sim 48\%$ of the total SWB change ($\frac{0.285\times(0.445-0.048)}{4.02-3.48} = 20.95\%, \frac{0.285\times(0.282-0.048)}{3.62-3.48} = 47.64\%$) in China.

4.2 LPM and BUC Estimator

Using ordinal variables to measure SWB can be problematic, so we recode SWB as a binary variable using different thresholds and employ a linear probability model (LPM) in Table 1.[16] From Panels B to E, coefficients remain positive across model specifications and threshold definitions, yet the effects are most significant when using 3 or 4 as thresholds, both economically and statistically. Specifically, a one s.d. increase in robot exposure increases the probability of moving from "neutral and below (<=3)" to "satisfied and above (>=4)" by 3 p.p. and from "satisfied and below (<=4)" to "very satisfied (5)" by 2 p.p., while the effects on transitions from "dissatisfied and below (<=2)" to "neutral and above (>=3)" (0.4 p.p.) and from "very dissatisfied (1)" to "dissatisfied and above (>=2)" (0.1 p.p.) are much smaller. These results suggest that the positive effects of automation are primarily driven by the better-off group. Figure A5 visualizes this heterogeneity using subgroups, showing that automation primarily facilitates transitions from "neutral (3)" to "satisfied (4)," benefiting the already contented group.

We next quantify the magnitude of the estimated effect. Table A5 reports the distribution of life-satisfaction transitions between 2010 and 2018. The largest shifts are from 3 to 4 (11.1%), from 3 to 5 (10.6%), and from 4 to 5 (10.9%), indicating increasing polarization in which those initially better-off move further upward. Table A4 aggregates these transitions into a high (45) versus low (13) comparison, showing a net increase of 16.9 percentage points in the high group. Our estimates imply that one unit of robot exposure raises the probability of moving from the low to the high group by 15.5 p.p., which accounts for 38.7% of the observed increase in SWB ($\frac{0.155\times(0.445-0.048)}{0.289-0.13} = 38.70\%$).

Considering that traditional fixed effects estimator for the ordered Logit model might be inconsistent, we use the "blow-up and cluster" (BUC) estimator proposed by Baetschmann et al. (2015) for robustness. As shown in Table A6, robot exposure still positively predicts SWB, with larger economic significance. In our preferred specification (column (3)), one s.d. increase in robot exposure brings 14.46% increase in odds ratio (satisfied v.s. dissatisfied) across all cutoffs. Table A7 further illustrates the marginal effects of robot exposure for groups with different satisfaction values. The results highly accord with Table 1 and Figure A5, where robot exposure is associated with higher SWB among more satisfied individuals (scored 4 or 5) and lower SWB among less satisfied ones (scored 3 or below). We further explore the distributional implications of this heterogeneity in section 5.

16. Recent studies caution that the conclusions drawn from such models can be sensitive to distributional assumptions about the latent SWB variable (Bond and Lang, 2019; Liu and Netzer, 2023).

4.3 IV Estimation and Long Difference

To better identify causal effects, we employ a two-stage least squares (2SLS) strategy using the instrumental variables defined in Equation 2, with results reported in Table 2. Panel A presents estimates from the ordinal specification. Across all columns, the KleibergenPaap Wald F-statistics exceed 16.38, surpassing the 10% critical threshold proposed by Stock and Yogo (2002), thus alleviating weak instruments concerns. The first-stage regression results in column (1) also confirm the instrument's strong validity. Columns (2)-(7) show 2SLS estimates using robot data from the U.S., with varied fixed effects. In all cases, robot exposure positively predicts SWB. Our preferred specification in column (7) indicates that a one s.d. increase in robot exposure raises SWB by 0.061 points, equivalent to 1.67% of the sample mean. This effect is slightly larger than the OLS estimates (0.055), further reinforcing the instrument's validity. Similarly, Table A8 shows the 2SLS estimates using robot data from other major economies, with consistent results.

Panels B through E assess the robustness of our IV estimates using binary specifications. The effects are strongest and most significant when using 3 or 4 as the threshold, consistent with earlier findings in Figure A5 and Table 1. These results suggest that the observed SWB gains are primarily ascribed to individuals with relatively high levels of well-being.

To alleviate biases arising from transitory shocks, measurement error, or serial correlation over time (Griliches and Hausman, 1986), we employ a long-difference model in the spirit of Acemoglu and Restrepo (2020) and Dechezleprêtre et al. (2025). Column (1) of Table A9 shows that an additional s.d. more robot exposure leads to 0.055-point increase in SWB, roughly a 10% increase to the sample mean. Columns (2)-(3) show that this effect is robust to alternative weighting methods, while columns (4)-(6) confirm the results using data on robot stocks rather than flows. In addition, it is possible that automation takes time to affect individuals' well-being. Figure A6 plots the regression coefficients of leading (1-4 years) robot exposure on SWB. The effects remain robust across time, which help alleviate the concern about spurious correlation and support consistent effects.

4.4 Identification Checks

The validity of our shift-share instrument requires that, conditional on province-year and individual fixed effects, other unobserved factors in the error term are uncorrelated with (1) shifts in the penetration of robotics (i.e., *shocks*) and (2) initial prefecture-specific shares (i.e., *shares*). Below we conduct a series of checks to test these assumptions and verify that our estimates are free from pre-trend issues and pass other statistical tests recommended by the shift-share literature (Goldsmith-Pinkham et al., 2020; Borusyak et al., 2022). Regarding

the exogeneity of the sectoral *shocks*, we re-estimate the effects of automation on SWB at the shock level (sector-year) in Table A10. The effect remains positively significant across different specifications. To verify that sector-level automation shocks are effectively randomly assigned across prefectures, we regress the shocks on initial prefectural characteristics and year dummies using weighted least squares. Table A11 reports the coefficients and standard errors for each prefecture-level variable, as well as the joint χ^2 statistic. The coefficients are jointly insignificant, indicating that our shocks meet the requirement of treatment balance.

We further deal with the issue of clustering or spillover. To address the issue of clustered shock exposure as highlighted by Adao et al. (2019), we re-calculate standard errors using their adjustment in Table A12, with robust evidence. To account for the presence of spatial and temporal spillover, we report the heteroskedasticity-and-autocorrelation-consistent (HAC) standard errors with varying spatial cut-offs and time windows in Table A13. Although confidence intervals widen, the point estimates remain stable.

To assess the exogeneity of the exposure *shares*, we construct two sets of pseudo robot exposures. We first randomly assign base sector-level employment share and then randomly draw sector-level robot installations. These pseudo exposures preserve the shift-share structure but break the link to actual economic conditions. As shown in Figure A7, the distribution of pseudo effects is centered around zero and lies far from the distribution of our baseline estimates. This suggests that the main findings are unlikely to be driven by mechanical correlations or misspecification of the shift-share design.

We further test for pre-trends by examining whether future robot exposure predicts past SWB. For instance, we regress SWB in 2010-2012 (or other periods before 2016) on robot exposure in 2016-2018. As reported in Table A14, both OLS and 2SLS estimates are statistically insignificant in this falsification test. In addition, we use earlier, alternative datasets before the surge of robot adoption in China (2007). Table A15 reports insignificant results, supporting the parallel-trends assumption: in the absence of the automation shock, regions with higher subsequent robot exposure would have followed similar SWB trajectories as those with lower exposure.

Next, we check the sensitivity of baseline results to sectors with large Rotemberg weights. We first control for the base (2000) shares of six sectors at the prefecture level. As shown in Table A16, our results remain robust. To further address potential sector-specific trends, we follow Gihleb et al. (2022) and incorporate base-sector-share linear time trends. Table A17 shows similar results, indicating that our identifying variation is not driven by any single sector and is robust to sector-specific trends.

Lastly, we account for possible local confounders. We control for a range of predetermined (2000 proxy) demographic characteristics in Table A18, and the results remain un-

changed. Additionally, given that some robots are imported (Cheng et al., 2019), the automation process may be confounded by trade and offshoring. Also, our instrument may capture trade conditions that affect both robot penetration and higher SWB. We test its influence by controlling for trade and offshoring at the prefecture-year level in Table A19. The results continue to show large and significant effects, suggesting that trade and offshoring are unlikely to drive our estimated effects.

4.5 Other Robustness Checks

We also conduct a battery of checks to corroborate our findings, with detailed analysis shown in Appendix C. We first exclude the influence of digital technology that has advanced simultaneously with automation in Table A20 with a horse-race regression, obtaining robust results. We address the migration issue in Table A21 by selecting individuals whose *hukou* (household registration) remain unchanged during the sample period, and deal with sample attrition in Table A22 by keeping individuals participating in all five waves of the survey. The results indicate that migration and attrition problems pose minimal threat to our findings. We then adopt alternative clustering levels and conduct different sample screenings in Table A23, with robust findings.

5 Divergent Lives of Different Groups

Our analysis highlights pronounced heterogeneity in the well-being effects of automation, with the better-off group gaining much more from automation. This pattern helps reconcile our findings with the prevailing view that automation can displace workers and may threaten well-being. While acknowledging the displacement effect, we argue that it mainly affects workers in low-skilled occupations who are less able to benefit from the channels we identify. We examine heterogeneity by work status and find that the positive effects concentrate on the employed stayers. Although SWB itself might be nonlinear and non-additive across groups, the overall positive effect implies that the gains among beneficiaries quantitatively dominate the losses. Nonetheless, the results also reveal that robotics acts as a kind of "polarization technology," exacerbating existing inequalities in China.

We begin by estimating the heterogeneous effects of automation across different socioeconomic dimensions. Table 3 provides direct evidence that individuals with higher ex-ante socioeconomic status (more educated, urban, higher status, employed, lower substitutability) experience substantially larger gains in SWB from automation. The magnitude of these heterogeneous effects is also sizable: for example, the impact on the high-education group

is more than three times that for the low-education group. This pattern reflects that automation mainly replaces low-skilled workers (typically with lower education). In column (5), we calculate the probability of one's occupation being replaced by robots (AIOS) and find similar results: the less likely that one's job can be replaced, the more SWB rises with robot exposure. The 2SLS estimates in Panel B reinforce these patterns. Taken together, automation not only raises average well-being but also systematically shifts the distribution toward those with greater human capital or occupational resilience.

We further explore such a polarization effect by examining heterogeneity across occupational groups. Figure A8 illustrates that the positive effects concentrate in high-end roles, such as leadership and technical positions, whereas the negative impacts are more pronounced in low-end jobs, particularly in the agricultural and industrial sectors. The divergence reflects differences in substitutability to automation: robots can replace routine manual labor but are far less likely to displace high-skilled professionals such as doctors, lawyers, or executives. Consequently, automation is associated with higher well-being among high-skilled workers and lower well-being among more replaceable occupations. This is consistent with Autor and Thompson (2025) that automation can raise wages and decrease employment in occupations where it eliminated low-end tasks.[17] While low-skilled workers suffer from unemployment, others benefit from rising productivity (see section 6), which helps explain our overall positive average effect.

Why does automation enhance overall SWB even as it raises unemployment? Giuntella et al. (2024) document that a one s.d. increase in robot exposure is associated with roughly a 5% increase in reported unemployment and a 7.5% decrease in actual employment. Other studies also find negative effects on job satisfaction or mental well-being (Nazareno and Schiff, 2021; Lu and Fan, 2024). We emphasize the stark contrast in automation's impact across employment-status groups, where unemployed people would suffer more from robot penetration. Following Giuntella et al. (2024), we classify individuals into three work categories: employed, unemployed, and out of the labor market.[18] Results from both OLS and 2SLS estimation confirm this asymmetry. As shown in Figure 5 (Panels A and B), robot adoption significantly boosts SWB among the employed but has negative effects on the unemployed. This also aligns with the pattern observed in the raw data plotted in Figure 2. Overall, the gains among the majority employed population outweigh the losses, which

17. Large-language models (LLM) may also threaten these jobs, but we focus exclusively on robotics. Interested readers may refer to Brynjolfsson et al. (2025).

18. The employed include the workers and those who plan to work within the next six months. A person out of the labor market is one who does not want to work, has the financial means not to work, is unable to work, does not need to work, has not looked for a job in the last month, or has been unable to work within two weeks. The unemployed are the rest of people.

helps explain our main finding of a positive average impact.

To account for dynamic employment transitions, we refine our classification into four categories: job finders (from unemployed to employed), employed stayers, job losers (from employed to unemployed), and unemployed stayers. Figure 4 plots the raw data for these subgroups: the positive correlation exists only for job finders and employed stayers. The effect does not apply to unemployed stayers and even reverses for job losers. Panels C and D of Figure 5 confirm the above heterogeneity results using both OLS and 2SLS estimation, consistent with a causal interpretation of these patterns. Although we cannot attribute job loss to robot substitution, individuals who retain or gain employment are not displaced by automation. Hence, the net effect of automation is positive, which turns insignificant when adding the displacement effect. Overall, the gains among the majority employed population outweigh the losses, which helps explain our estimated positive average effect.

Finally, we briefly discuss the potential benefits of automation. A growing literature has proposed several mechanisms: the productivity effect, where automation increases output, spurs product innovation, and stimulates demand for goods and services (Autor, 2015; Autor et al., 2024); the reallocation effect, where it generates new tasks and employment opportunities, promoting labor mobility and sectoral shifts (Dauth et al., 2021; Koch et al., 2021), along with related channels like capital deepening and accumulation. These mechanisms are deeply intertwined, making it infeasible to isolate their individual contributions within a reduced-form framework. Nonetheless, we can examine how these aggregate effects manifest in SWB. In section 6, we find that increases in income, expanded leisure time, and enhanced self-identification are major channels through which automation raises SWB. In contrast, the unemployed experience deterioration along these same dimensions, consistent with their lower well-being.

6 Possible Channels and Further Discussion

We explore the channels through which automation affects SWB. For causal interpretation, we use 2SLS as our main specification; OLS gives similar or larger estimates and is reported in the Appendix. subsection 6.1 provides evidence on income changes, while subsection 6.2 suggests more leisure and health improvement as key channels. In subsection 6.3, we document self-identification as an important channel. We also provide evidence for the heterogeneous responses across groups in the above channels in subsection 6.4. As an extension, subsection 6.5 highlights the transformation from collectivist to individualistic well-being, with ample evidence ranging from family involvement, self-fulfilling activities, kinship relations, to political attitudes.

6.1 Income Effects

There is extensive evidence that SWB rises with higher income (Frank, 2001; Tella et al., 2003; Stevenson and Wolfers, 2008, 2013). Thus, it is crucial to examine the impact of automation on income, which remains debated. A few studies highlight its unemployment effect, which leads to income decline; meanwhile, robot substitution may weaken workers' bargaining power and put downward pressure on wages (Autor et al., 2003; Acemoglu and Restrepo, 2020). Others support the positive effects of automation in creating new job opportunities and fostering inclusive growth (Graetz and Michaels, 2018; Mann and Püttmann, 2023). Below we provide suggestive evidence that automation may boost income in the context of China.

We test the relationship between robot exposure and individual income in Table 4. Columns (1) shows the results for the full sample, where robot exposure significantly increases individual income. One more s.d. of robot exposure is predicted to raise income by 20.8%. To account for changes in price levels, we adjust income using prefecture-level CPI, and obtain consistent results in column (2). As shown in Table A24 (column (1) and (5)), robot exposure positively predicts CPI, yet even after controlling for CPI, the effect on individual income remains positive and statistically significant. We then restrict to individuals that always remain in the labor market in columns (3)-(4), and to the "stayers" in columns (5)-(6). The results are consistent, with lower significance but greater magnitude.

To further corroborate our findings, we use prefecture-level data from China Urban Statistical Yearbook to examine automation's regional economic impact. As shown in columns (2)-(4) of Table A24, robot penetration positively predicts regional wage per capita. The results remain robust when using 2SLS estimation and adjusting for price levels (prefectural or provincial CPI). Given that regional population may bias wage per capita, we estimate a weighted regression (population weights) in columns (6)-(8), with similar findings. In sum, higher robot exposure is associated with higher individual incomes and regional wages, which can translate into higher SWB.

6.2 Leisure and Health Effects

Aside from rising income, robots may enhance SWB by increasing leisure time. As noted by Frey and Osborne (2017), automation can boost labor productivity, allowing the same output to be achieved in less time, thus reducing working hours. Robots also reduce work intensity and improve workplace safety (Luo et al., 2025). Furthermore, they facilitate flexible arrangements like remote work or flexible hours, further shortening work duration (Autor and Dorn, 2013; Bloom et al., 2015). Below we show that automation can reduce working

hours, increase leisure time, and improve workers' general health conditions.

We test its impact on working hours in Table 5, which shows that automation is associated with fewer working hours. As shown in columns (1)-(2), one s.d. more robot exposure rate can reduce 0.207 hours of work per weekday, or about 4.66% of the average weekday. For the whole week, the effect amounts to 1.037 working hours. We then restrict to individuals who always remain in the labor market in columns (3)-(4). As expected, the effect becomes larger in magnitude, with one s.d. more robot exposure leading to 0.319 fewer hours of work. Similar results are obtained using the "stayers" in columns (5)-(6). To address the concern that the overall decline in working hours may reflect rising unemployment, we restrict the analysis to employed individuals and still get consistent results, as shown in columns (7)-(8). Overall, the findings suggest that automation can reduce working hours and increase leisure time, consistent with results from other countries (Bessen et al., 2023).

One may wonder how workers spend their "additional" leisure time. Based on their higher SWB, we expect that they may spend such time on self-fulfilling activities, like reading books, watching TV, exercising, or browsing the Internet. Table A25 shows that automation is associated with more time spent on these activities. For instance, one s.d. more robot exposure is associated with 8.8% more time on exercising and 11.2% more time on surfing the Internet. These results remain robust across various model specifications or using 2SLS estimation. Table A26 displays its effect on all activities available in CGSS, which shows that robot penetration fosters workers' engagement in a wide range of self-fulfilling activities, albeit to varying degrees.

However, more leisure time does not benefit everyone: the unemployed may suffer from spending more time idle at home. We examine how automation changes respondents' health and emotion in Table 6. Notably, robot exposure is positively associated with better health and more positive emotions. Similar findings are obtained when using the labor-market pool or stayer pool, as shown in columns (3)-(6). We explore its health outcomes in detail in Figure 6. Panel A shows the results for different emotions: robot exposure brings positive emotions but decreases negative ones. Similar effects are also observed for physical health (Panels B and C), where robot exposure predicts higher scores in both ADL tests and Physical health tests, consistent with Luo et al. (2025).

6.3 Self-identification Effects

Aside from the above objective factors, SWB is also shaped by social comparison, known as self-identification (Festinger, 1954). For the majority of individuals not replaced by robots, navigating automation successfully may strengthen their self-confidence. As shown by Yam

et al. (2023), stronger self-affirmation can reduce job insecurity caused by robot exposure. We examine the above self-identification effects in Table 7. We analyze the relationship between robot exposure and individuals' confidence in their future prospects, measured on a 1 to 5 scale. The results indicate that for each s.d. increase in robot exposure, individuals' confidence increases by 0.044 units, or 1% of the sample mean. Columns (2)-(3) show that robot penetration enhances workers' meritocratic beliefs (recognition on "working hard pays off") and self-reported social status. The findings remain robust when restricting to the labor-market pool or the stayer pool. Overall, robot exposure is positively associated with individuals' confidence and self-reported status, consistent with the self-identification channel.

6.4 Discussion: Decomposition and Heterogeneity

We decompose the effect of automation on SWB into its influence on the above channels. Conceptually, we follow a "predicted-change" approach. First (in the three subsections above), we estimate for each mechanism k a regression analogous to Equation 3:

$$M_{ipt}^{k} = \alpha_{0k} + \alpha_{1k} RobotExposure_{pt} + \gamma Control_{ipt} + \eta_k P_{p,t=2009} \# T_t + \mu_i^k + \delta_{mt}^k + u_{ipt}^k,$$

so that α_{1k} measures the partial effect of robot exposure on mechanism k. Second, we relate SWB to the mechanisms,

$$SWB_{ipt} = \theta_0 + \theta_{\text{inc}} M_{ipt}^{\text{inc}} + \theta_{\text{leis}} M_{ipt}^{\text{leis}} + \theta_{\text{heal}} M_{ipt}^{\text{heal}} + \theta_{\text{self}} M_{ipt}^{\text{self}} + \nu_{ipt},$$

and use the estimated θ_k to map changes in mechanisms into changes in SWB. The marginal effect of robot exposure on SWB is then

$$\begin{aligned}\beta_1 = \frac{\partial SWB_{ipt}}{\partial RobotExposure_{pt}} &= \sum_{k \in \{\text{inc,leis,heal,self}\}} \theta_k \frac{\partial M_{ipt}^k}{\partial RobotExposure_{pt}} + \frac{\partial \nu_{ipt}}{\partial RobotExposure_{pt}} \\ &= \underbrace{\theta_{\text{inc}}\alpha_{1,\text{inc}}}_{\text{Income channel}} + \underbrace{\theta_{\text{leis}}\alpha_{1,\text{leis}}}_{\text{Leisure channel}} + \underbrace{\theta_{\text{heal}}\alpha_{1,\text{heal}}}_{\text{Health channel}} + \underbrace{\theta_{\text{self}}\alpha_{1,\text{self}}}_{\text{Self-identification channel}} + \underbrace{\frac{\partial \nu_{ipt}}{\partial RobotExposure_{pt}}}_{\text{Residual component}}.\end{aligned}$$

The results from this decomposition analysis are shown in Table A27. The dependent variable is individual SWB, and the regressors are the four mechanisms. Columns (1)-(4) show the increase in SWB associated with movements across quantiles of the distribution of income, leisure, health, and self-identification levels, while column (5) summarizes the

residual effect that is not captured by the above channels. Together, the income, leisure, health, and self-identification effects account for 45.4%, 15.3%, 10.9%, and 13.8% of the total effects on SWB, respectively, with only 14.7% unexplained.

We then explore heterogeneity in the above channels to illustrate our findings in section 5. Figure 7 presents the effects of automation on income, leisure, health, and self-confidence across work status subgroups. The patterns for job finders and employed stayers are broadly similar (except for working hours): both groups experience moderate income gains, have more positive emotions, and exhibit increases in self-confidence and meritocratic beliefs. These trends suggest that the income, leisure (and health), and self-identification effects primarily benefit these groups, consistent with their rising SWB levels shown in Figure 5. By contrast, job losers experience income declines and diminished self-confidence, suggesting that they are excluded from the aforementioned channels and primarily affected by the displacement effect, which drives the observed decline in their well-being.

Panel C reveals a notable divergence between job finders and employed stayers in working hours. The substantial increase in hours among job finders, and corresponding decrease for job losers, reflect transitions in work status. However, the decline in working hours among employed stayers likely reflects productivity gains, which we refer to as the "leisure effect," as also shown in columns (7)-(8) of Table 5. For unemployed stayers, the effects of automation across all mechanisms appear statistically insignificant, likely due to their disengagement from the labor market.

Together, these heterogeneous patterns help explain the distributional effects documented in Figure 4 and Figure 5, underscoring the widening well-being gap between advantaged and disadvantaged groups.

6.5 Extension: Transformation towards Individualism

In addition to improving overall well-being, automation can shift the source of SWB from societal values toward individualism. First, as a form of skill-biased technological change, automation incentivizes individuals to invest in human capital to enhance labor market competitiveness, thereby fostering self-reliance (Autor et al., 2003). Second, it disrupts traditional modes of work by encouraging fragmented labor practices (Petriglieri et al., 2019). These changes weaken kinship-based networks and reinforce individualism, reshaping the foundations of well-being. Below we provide suggestive evidence that automation in China has not only increased average SWB but also transformed its underlying sources. This analysis serves as an extension and should be interpreted with caution.

Rising Independence. We begin by exploring the influence of robot penetration on independence. Table A28 documents a significant decline in children's household activities and a growing preference for living alone. This highlights that people become more independent in the face of automation. We then analyze shifts in views on elderly support, examining preferences for government assistance, self-care, child support, and joint efforts. Columns (3)-(6) show decreasing reliance on child support in response to automation. These trends reflect that people rely less on their children and depend more on themselves, signaling rising individualism.

Decaying Kindred Linkage. With growing marketization, more fragmented labor relations, and stronger self-identification, people would become more inclined to seek help from societal sources, such as news media and charity groups, rather than kinship relations like family or lineage groups. This shift reflects another form of individualism. Table A29 illustrates that in response to automation, people turn less to family for help and more to social support networks, such as charities and media. This generally implies rising self-consciousness and decaying kindred linkages. Meanwhile, individuals may pay less attention to maintaining social relationships. We examine how automation influenced the frequency of visits to relatives and neighbors.[19] Table A30 shows that robot exposure significantly reduced the frequency of visits to relatives, suggesting weakened kindred bonds. The effects on visiting neighbors are insignificant, serving as placebos. We also construct two relationship indexes to measure inter-personal relationships, both of which decline with increased robot exposure. Therefore, the above evidence implies a shift toward more individualistic orientations and weaker kinship linkages.

Increasing Political Apathy. Another crystallization of rising individualism is political apathy. In Table A31, we analyze the relation between automation and political engagement, including attention, awareness, and frequency of viewing political news. The results show a decline in all measures with increased robot exposure, suggesting that automation fuels political apathy. This aligns with global trends of growing disinterest in politics amid modernization.(Wildavsky, 1987; Goodin and Dryzek, 1980).[20]

19. In Chinese society, the practice of visiting each other is crucial for maintaining social ties, no matter between relatives, friends, or neighbors (Fei, Hamilton, and Zheng, 1992).

20. While political participation in authoritarian states is relatively low, opportunities for Chinese people to engage in politics have expanded during the past four decades (Chen et al., 2016; Martinez-Bravo et al., 2022). Also, we focus on participatory inclination instead of actual capability.

7 Conclusion

China has witnessed tremendous progress in robotics technology, transitioning from a manufacturing giant into a major technological power. Existing scholarship has raised concerns about its effect on individuals: from job displacement, rising economic vulnerability, to deteriorating health problems and declining political trust. This paper provides a systematic assessment of how automation relates to subjective well-being. Our baseline and instrumental-variables estimates indicate that greater robot exposure is associated with higher reported life satisfaction. Automation, in this setting, appears to improve the perceived quality of life for a large share of the population.

These gains, however, are highly uneven. Robot penetration disproportionately benefits individuals with higher SES, while those unemployed and low-status individuals experience reductions in SWB. The channels we document are consistent with this pattern: automation is associated with higher income, shorter working hours, better health, and stronger self-identification among the employed, whereas it is linked to declines along these same dimensions for those who lose jobs.

Such polarization effect is typical for technological transitions, like the impact of mechanical switching technology on telephone operators (Feigenbaum and Gross, 2024), yet the issue may become a political threat to the developmental state with performance-based legitimacy (Zhao, 2009; Lu et al., 2024). As emphasized by Lei (2023), automation could widen inequality between social groups without policy intervention. These findings highlight the need for targeted policies to mitigate the negative effects on vulnerable groups and to promote more inclusive improvements in well-being.

This result should be taken with caution, however, as it remains unresolved how to aggregate subjective well-being into an overall measure of social welfare. While we provide solid evidence that the positive effects of automation outweigh the negative effects, we refrain from making strong claims about a definitive net welfare impact of robotics technology. Instead, we focus on the distributional change in SWB and highlight the rise of "SWB inequality." On one hand, the normative assessment of its effect may vary depending on researchers' values or policy priorities, so whether or not the "net" effect is negative or positive hinges greatly on the research themes. On the other hand, the mapping from reported SWB to underlying utility is likely to be nonlinear and heterogeneous, and it is far beyond the scope of this paper to estimate the SWB function. One future pathway is to estimate the subjective gains and losses in the face of the automation process, which will surely bring about more fruitful research.

8 Tables

TABLE 1 Baseline results

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. Ordinal (scale 1-5)						
Robot exposure	0.878***	0.195***	0.202***	0.221***	0.326***	0.285***
	(0.051)	(0.073)	(0.069)	(0.069)	(0.094)	(0.106)
Bootstrap standard error	<0.015>***	<0.031>***	<0.035>***	<0.038>***	<0.068>***	<0.076>***
Standardized	[0.169]	[0.038]	[0.039]	[0.043]	[0.063]	[0.055]
Dependent-variable mean	3.642	3.645	3.645	3.645	3.645	3.650
Panel B. Binary (low SWB=1 & 2 & 3 & 4, high SWB=5)						
Robot exposure	0.318***	0.014	0.055*	0.063**	0.130***	0.106**
	(0.024)	(0.033)	(0.029)	(0.028)	(0.040)	(0.047)
Standardized	[0.061]	[0.003]	[0.011]	[0.012]	[0.025]	[0.020]
Dependent-variable mean	0.250	0.251	0.251	0.251	0.251	0.253
Panel C. Binary (low SWB=1 & 2 & 3, high SWB=4 & 5)						
Robot exposure	0.359***	0.091***	0.097***	0.104***	0.160***	0.155***
	(0.022)	(0.032)	(0.031)	(0.032)	(0.042)	(0.048)
Standardized	[0.069]	[0.018]	[0.019]	[0.020]	[0.031]	[0.030]
Dependent-variable mean	0.551	0.553	0.553	0.553	0.553	0.554
Panel D. Binary (low SWB=1 & 2, high SWB=3 & 4 & 5)						
Robot exposure	0.154***	0.056***	0.038**	0.038**	0.027	0.019
	(0.010)	(0.016)	(0.018)	(0.016)	(0.027)	(0.031)
Standardized	[0.030]	[0.011]	[0.007]	[0.007]	[0.005]	[0.004]
Dependent-variable mean	0.880	0.881	0.881	0.881	0.881	0.881
Panel E. Binary (low SWB=1, high SWB=2 & 3 & 4 & 5)						
Robot exposure	0.048***	0.033***	0.013	0.016*	0.009	0.005
	(0.005)	(0.008)	(0.009)	(0.008)	(0.015)	(0.017)
Standardized	[0.009]	[0.006]	[0.002]	[0.003]	[0.002]	[0.001]
Dependent-variable mean	0.961	0.961	0.961	0.961	0.961	0.962
Controls	✓	✓	✓	✓	✓	✓
Predetermined control # year		✓	✓	✓	✓	✓
Province FE			✓			
Prefecture FE					✓	
Individual FE						✓
Province-year FE				✓	✓	✓
Observations	123,349	118,142	118,142	118,142	118,142	110,495

Notes: Table 1 reports the baseline regression results using the CFPS dataset. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$. All the regressions use OLS specification in Equation 3. Standard errors in parentheses are two-way clustered at the prefecture-year level while those in angle brackets are from the wild cluster bootstrap (500 times). Standardized coefficients in brackets indicate the effect of a one-s.d. increase in the explanatory variable on the outcome. The dependent variable is individual SWB while the key explanatory variable is robot exposure. Columns (1) to (6) report the results at different controls and FEs. Panel A reports the results of the ordinal dependent variable while Panels B to E report the results of the binary dependent variable.

TABLE 2 IV estimation

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	First stage	Second stage					
Panel A. Ordinal (scale 1-5)							
Robot exposure		0.650***	0.243***	0.248***	0.260***	0.371***	0.315**
		(0.057)	(0.085)	(0.085)	(0.082)	(0.109)	(0.126)
Bootstrap standard error		<0.017>***	<0.034>***	<0.040>***	<0.045>***	<0.072>***	<0.085>***
Standardized		[0.125]	[0.047]	[0.048]	[0.050]	[0.072]	[0.061]
Robot exposure IV	3.164***						
	(0.111)						
Dependent-variable mean		3.642	3.645	3.645	3.645	3.645	3.650
KPrk Wald F		1014.246	1003.828	1144.078	1285.197	949.873	816.343
Panel B. Binary (low SWB=1 & 2 & 3 & 4, high SWB=5)							
Robot exposure		0.230***	0.004	0.053	0.057*	0.128***	0.099*
		(0.024)	(0.035)	(0.032)	(0.031)	(0.044)	(0.051)
Standardized		[0.044]	[0.001]	[0.010]	[0.011]	[0.025]	[0.019]
Panel C. Binary (low SWB=1 & 2 & 3, high SWB=4 & 5)							
Robot exposure		0.253***	0.114***	0.116***	0.121***	0.170***	0.151**
		(0.026)	(0.038)	(0.038)	(0.037)	(0.049)	(0.059)
Standardized		[0.049]	[0.022]	[0.022]	[0.023]	[0.033]	[0.029]
Panel D. Binary (low SWB=1 & 2, high SWB=3 & 4 & 5)							
Robot exposure		0.125***	0.079***	0.058***	0.059***	0.050	0.042
		(0.013)	(0.020)	(0.022)	(0.021)	(0.031)	(0.036)
Standardized		[0.024]	[0.015]	[0.011]	[0.011]	[0.010]	[0.008]
Panel E. Binary (low SWB=1, high SWB=2 & 3 & 4 & 5)							
Robot exposure		0.043***	0.046***	0.021*	0.022**	0.022	0.023
		(0.006)	(0.010)	(0.011)	(0.010)	(0.018)	(0.021)
Standardized		[0.008]	[0.009]	[0.004]	[0.004]	[0.004]	[0.004]
Controls	✓	✓	✓	✓	✓	✓	✓
Predetermined control # year	✓		✓	✓	✓	✓	✓
Province FE				✓			
Prefecture FE						✓	
Individual FE	✓						✓
Province-year FE	✓				✓	✓	✓
Observations	110,495	123,349	118,142	118,142	118,142	118,142	110,495

Notes: Table 2 presents the instrumental variable (IV) estimation results using the CFPS dataset. ***p < 0.01, **p < 0.05, *p < 0.1. All the regressions use 2SLS specification in Equation 4 and Equation 5. Standard errors in parentheses are two-way clustered at the prefecture-year level while those in angle brackets are from the wild cluster bootstrap (500 times). Standardized coefficients in brackets indicate the effect of a one-s.d. increase in the explanatory variable on the outcome. The dependent variable is individual SWB while the key explanatory variable is robot exposure. Column (1) reports the first-stage estimation results using US robot exposure as IV while columns (2) to (7) report the second-stage estimation results with different controls and FEs. Panel A reports the results of the ordinal dependent variable while Panels B to E report the results of the binary dependent variable.

TABLE 3 Heterogeneous effects of automation across different SES groups

X :	(1) Education level	(2) Urban	(3) Social status	(4) Employment	(5) AIOS (reverse)
Panel A. OLS					
Robot exposure × **X**	0.337***	0.113**	0.259***	0.647***	0.311**
	(0.049)	(0.053)	(0.053)	(0.181)	(0.138)
Bootstrap standard error	<0.042>***	<0.042>***	<0.044>***	<0.214>***	<0.145>**
Standardized	[0.065]	[0.022]	[0.050]	[0.126]	[0.061]
Robot exposure	0.146	0.203*	0.201**	-0.368*	-0.085
	(0.104)	(0.110)	(0.099)	(0.211)	(0.137)
Panel B. 2SLS					
Robot exposure × **X**	0.357***	0.122**	0.300***	0.698***	0.321**
	(0.051)	(0.060)	(0.057)	(0.182)	(0.144)
Bootstrap standard error	<0.043>***	<0.044>***	<0.047>***	<0.221>***	<0.158>**
Standardized	[0.069]	[0.024]	[0.058]	[0.135]	[0.062]
Robot exposure	0.133	0.213*	0.212**	-0.338	-0.100
	(0.124)	(0.111)	(0.103)	(0.215)	(0.151)
Controls	✓	✓	✓	✓	✓
Predetermined control # year	✓	✓	✓	✓	✓
Individual FE	✓	✓	✓	✓	✓
Province-year FE	✓	✓	✓	✓	✓
Dependent-variable mean	0.500	0.728	0.314	0.964	0.597
Observations	110,495	110,495	110,495	72,194	70,194

Notes: Table 3 presents the estimation results for the heterogeneous effects of automation across different SES groups using the CFPS dataset. ***p < 0.01, **p < 0.05, *p < 0.1. Panel A uses OLS specification in Equation 3 while Panel B applies 2SLS specification in Equation 4 and Equation 5. Standard errors in parentheses are two-way clustered at the prefecture-year level while those in angle brackets are from the wild cluster bootstrap (500 times). Standardized coefficients in brackets indicate the effect of a one-s.d. increase in the explanatory variable on the outcome. The dependent variable is individual SWB while the key explanatory variable is robot exposure. Columns (1)-(5) report the estimation results with an interaction term with high educated dummy (1 for senior high school education or above, 0 junior high school education or below), urban dummy (1 for urban, 0 for rural), high social status dummy (1 for SES score >3, 0 for SES score <=3, scale 1-5), and reverse AI-induced occupational substitutability (AIOS) (the reverse of probability of occupation being replaced by AI, with higher value indicating lower substitutability), respectively. All interacted variables are from the first wave of the survey for each respondent. All regressions include the same controls and FEs as the baseline.

TABLE 4 Mechanism: income effects

	(1)	(2)	(3)	(4)	(5)	(6)
	Full pool		Labor market pool		Stayer pool	
	Nominal	Deflated	Nominal	Deflated	Nominal	Deflated
Robot exposure	1.087**	1.080**	1.359**	1.352*	1.309*	1.302*
	(0.542)	(0.541)	(0.691)	(0.690)	(0.704)	(0.702)
Bootstrap standard error	<0.263>***	<0.257>***	<0.372>***	<0.380>***	<0.395>***	<0.400>***
Standardized	[0.208]	[0.207]	[0.265]	[0.263]	[0.255]	[0.254]
Controls	✓	✓	✓	✓	✓	✓
Predetermined control # year	✓	✓	✓	✓	✓	✓
Individual FE	✓	✓	✓	✓	✓	✓
Province-year FE	✓	✓	✓	✓	✓	✓
Dependent-variable mean	3.769	3.759	4.805	4.792	4.741	4.729
Observations	115,393	115,393	60,541	60,541	53,198	53,198

Notes: Table 4 presents the estimation results for the income effects of automation using the CFPS dataset. ***p < 0.01, **p < 0.05, *p < 0.1. All the regressions use 2SLS specification in Equation 4 and Equation 5 (all OLS estimations yield nearly consistent results). Standard errors in parentheses are two-way clustered at the prefecture-year level while those in angle brackets are from the wild cluster bootstrap (500 times). Standardized coefficients in brackets indicate the effect of a one-s.d. increase in the explanatory variable on the outcome. The explanatory variable is robot exposure while the dependent variable is individual annual income (nominal and deflated by CPI, logged, respectively). Income data is derived from self-reports, and all missing observations are excluded from the analysis. Columns (1) and (2) report the estimation with full pool while columns (3) and (4) exclude those that have already exited the labor market. Columns (5) and (6) only keep those with stable work status (employed stayers and unemployed stayers) compared to Panel B. All regressions include the same controls and FEs as the baseline.

TABLE 5 Mechanism: leisure effects

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Full pool		Labor market pool		Stayer pool		Stayer pool (employed)	
	Weekday	Week	Weekday	Week	Weekday	Week	Weekday	Week
Robot exposure	-1.094*	-5.469*	-1.659*	-8.295*	-1.404**	-7.018**	-1.442**	-7.209**
	(0.657)	(3.283)	(0.847)	(4.237)	(0.651)	(3.253)	(0.654)	(3.269)
Bootstrap standard error	<0.306>***	<1.597>***	<0.443>***	<2.185>***	<0.433>***	<2.007>***	<0.406>***	<2.184>***
Standardized	[-0.207]	[-1.037]	[-0.319]	[-1.597]	[-0.270]	[-1.351]	[-0.278]	[-1.388]
Controls	✓	✓	✓	✓	✓	✓	✓	✓
Predetermined control # year	✓	✓	✓	✓	✓	✓	✓	✓
Individual FE	✓	✓	✓	✓	✓	✓	✓	✓
Province-year FE	✓	✓	✓	✓	✓	✓	✓	✓
Dependent-variable mean	4.444	22.218	6.146	30.729	6.349	31.743	6.381	31.907
Observations	113,645	113,645	59,439	59,439	52,215	52,215	51,947	51,947

Notes: Table 5 presents the estimation results for the leisure effects of automation using the CFPS dataset. ***p < 0.01, **p < 0.05, *p < 0.1. All the regressions use 2SLS specification in Equation 4 and Equation 5(all OLS estimations yield nearly consistent results). Standard errors in parentheses are two-way clustered at the prefecture-year level while those in angle brackets are from the wild cluster bootstrap (500 times). Standardized coefficients in brackets indicate the effect of a one-s.d. increase in the explanatory variable on the outcome. The explanatory variable is robot exposure while the dependent variables are working hours (every weekday and every week, respectively). Working hour data is derived from self-reports, with zero imputed for individuals who have exited the labor market or are unemployed. Columns (1) and (2) report the estimation with full pool while columns (3) and (4) exclude those that have already exited the labor market. Columns (5) and (6) keep those with stable work status (employed stayers and unemployed stayers) compared to Panel B. Columns (7) and (8) only use employed stayers (with stable work status). All regressions include the same controls and FEs as the baseline.

TABLE 6 Mechanism: health effects

	(1)	(2)	(3)	(4)	(5)	(6)
	Full pool		Labor market pool		Stayer pool	
	General health	Mental health (emotion)	General health	Mental health (emotion)	General health	Mental health (emotion)
Robot exposure	0.625**	0.278***	0.558*	0.210**	0.617*	0.190**
	(0.315)	(0.073)	(0.299)	(0.085)	(0.320)	(0.086)
Bootstrap standard error	<0.087>***	<0.047>***	<0.108>***	<0.072>***	<0.125>***	<0.073>***
Standardized	[0.186]	[0.217]	[0.188]	[0.218]	[0.189]	[0.218]
Controls	✓	✓	✓	✓	✓	✓
Predetermined control # year	✓	✓	✓	✓	✓	✓
Individual FE	✓	✓	✓	✓	✓	✓
Province-year FE	✓	✓	✓	✓	✓	✓
Dependent-variable mean	5.357	3.404	5.535	3.417	5.505	3.419
Observations	104,753	60,075	53,471	29,571	47,365	26,552

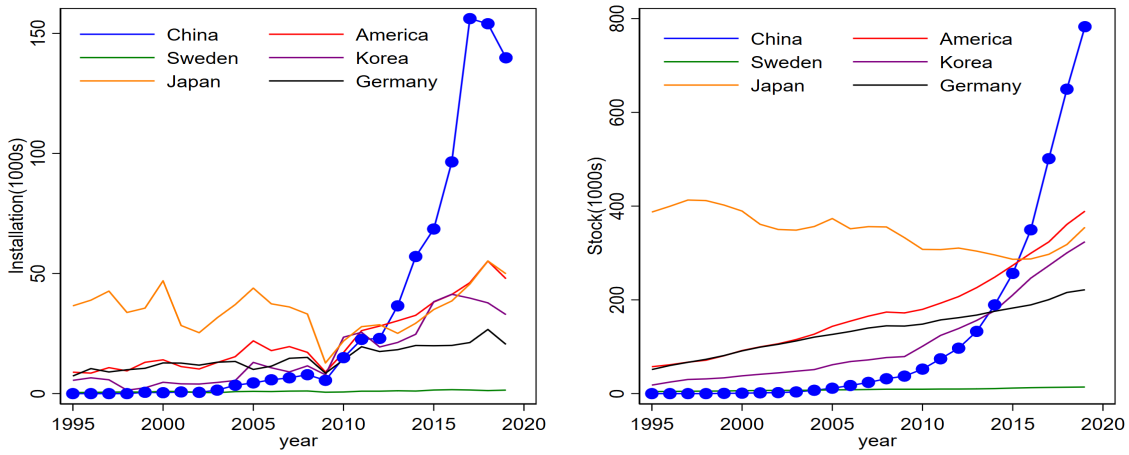
Notes: Table 6 presents the estimation results for the health effects of automation using the CFPS dataset. ***p < 0.01, **p < 0.05, *p < 0.1. All the regressions use 2SLS specification in Equation 4 and Equation 5 (all OLS estimations yield nearly consistent results). Standard errors in parentheses are two-way clustered at the prefecture-year level while those in angle brackets are from the wild cluster bootstrap (500 times). Standardized coefficients in brackets indicate the effect of a one-s.d. increase in the explanatory variable on the outcome. The explanatory variable is robot exposure while the dependent variables are interviewer-reported general health status (scale 1-7) and mental health (positive emotion index proxies). Columns (1) and (2) report the estimation with full pool while columns (3) and (4) exclude those that have already exited the labor market. Columns (5) and (6) only keep those with stable work status (employed stayers and unemployed stayers) compared to Panel B. All regressions include the same controls and FEs as the baseline. For more about positive emotion index, see subsubsection A.2.4.

TABLE 7 Mechanism: self-identification effects

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Full pool			Labor market pool			Stayer pool		
	Confidence	Status	Work pays off	Confidence	Status	Work pays off	Confidence	Status	Work pays off
Robot exposure	0.229**	0.226**	0.160*	0.347***	0.228*	0.240**	0.324**	0.183	0.284***
	(0.107)	(0.107)	(0.089)	(0.116)	(0.123)	(0.093)	(0.131)	(0.134)	(0.107)
Bootstrap standard error	<0.070>***	<0.068>***	<0.073>**	<0.091>***	<0.091>**	<0.096>**	<0.098>***	<0.094>*	<0.101>***
Standardized	[0.044]	[0.043]	[0.041]	[0.068]	[0.044]	[0.062]	[0.063]	[0.035]	[0.074]
Controls	✓	✓	✓	✓	✓	✓	✓	✓	✓
Predetermined control # year	✓	✓	✓	✓	✓	✓	✓	✓	✓
Individual FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Province-year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Dependent-variable mean	3.869	2.876	3.894	3.935	2.881	3.885	3.930	2.909	3.896
Observations	115,031	112,178	31,672	60,411	58,674	16,876	53,072	51,401	14,126

Notes: Table 7 presents the estimation results of the impact of automation on self-identification using the CFPS dataset. ***p < 0.01, **p < 0.05, *p < 0.1. All the regressions use 2SLS specification in Equation 4 and Equation 5 (all OLS estimations yield nearly consistent results). Standard errors in parentheses are two-way clustered at the prefecture-year level while those in angle brackets are from the wild cluster bootstrap (500 times). Standardized coefficients in brackets indicate the effect of a one-s.d. increase in the explanatory variable on the outcome. The explanatory variable is robot exposure while the dependent variables are self-confidence (scale 1-5), self-report social status (scale 1-5) and degree of recognition of "working hard pays off" (scale 1-5) respectively. Columns (1) and (2) report the estimation with full pool while columns (3) and (4) exclude those that have already exited the labor market. Columns (5) and (6) only keep those with stable work status (employed stayers and unemployed stayers) compared to Panel B. All regressions include the same controls and FEs as the baseline. For more about positive emotion index, see subsubsection A.2.4.

9 Figures



(A) **Robot installation of major economies.** (B) **Robot stocks of major economies.**

FIGURE 1 Robot units of major economies around the world.

Notes: Figure 1 plots the temporal trend of robots in major economies from 1995 to 2019. Data is obtained from the IFR. The horizontal axis measures year. while the vertical axis corresponds to robot installations and stocks. Panel A presents new robot installations whereas Panel B shows robot stocks.

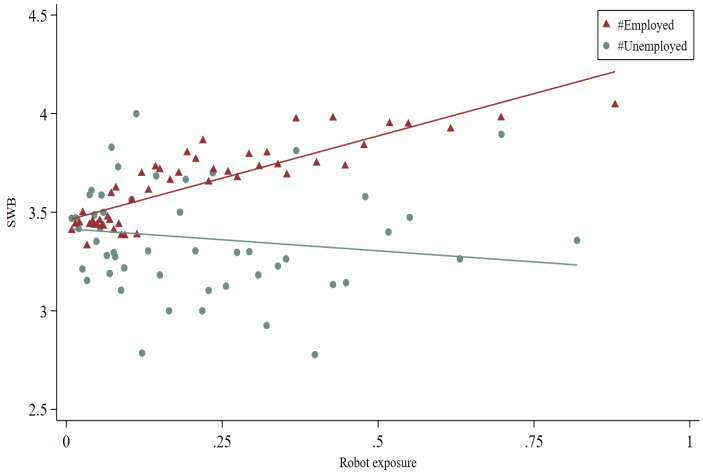
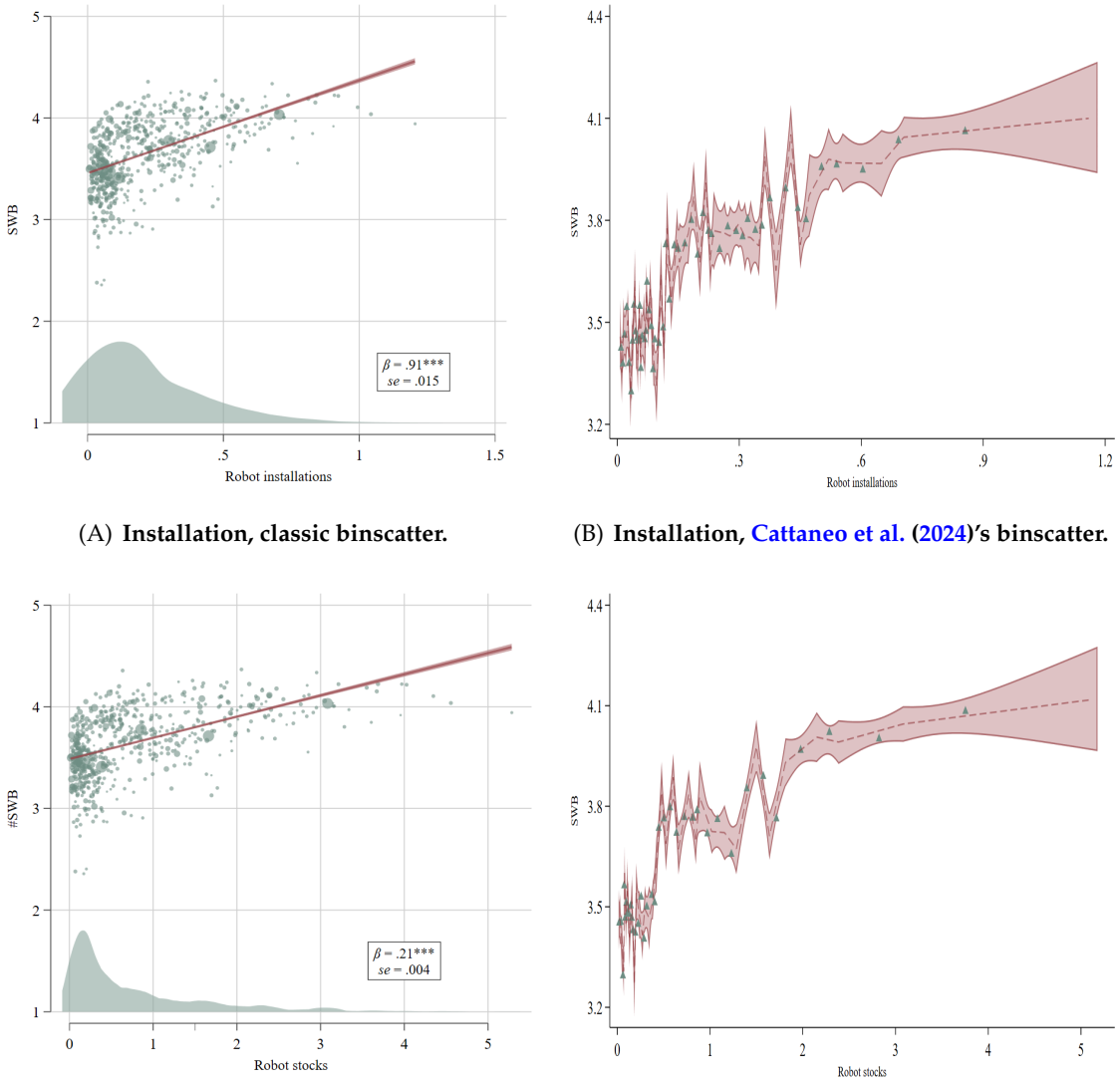


FIGURE 2 SWB and robot exposure across static work status.

Notes: Figure 2 plots the relationship between robot exposure and SWB across different static work status using the CFPS dataset. The horizontal axis corresponds to robot exposure, with the vertical axis measuring SWB. The maroon triangles and teal dots respectively show the y-means of the employed and the unemployed binned by 50 boxes evenly. The lines are estimated by OLS .



(A) **Installation, classic binscatter.**

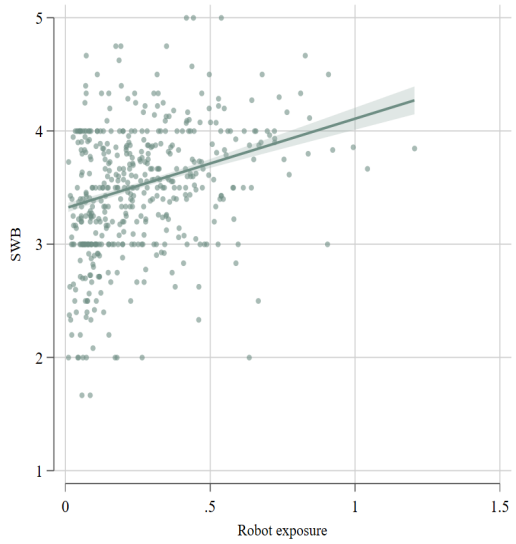
(B) **Installation, Cattaneo et al. (2024)'s binscatter.**

(C) **Stocks, classic binscatter.**

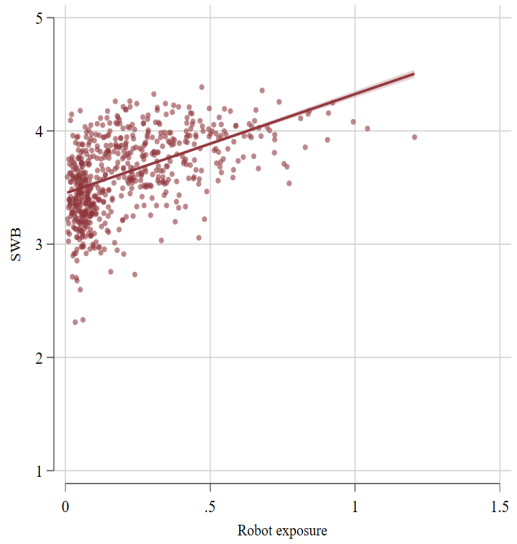
(D) **Stocks, Cattaneo et al. (2024)'s binscatter.**

FIGURE 3 SWB and robot exposure.

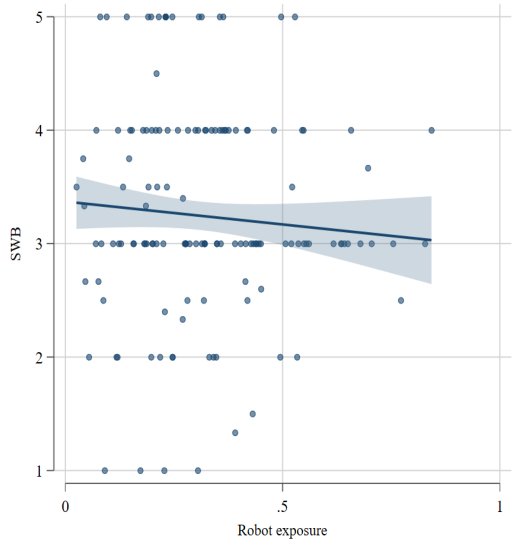
Notes: Figure 3 plots the relationship between robot exposure and SWB using the CFPS dataset. The horizontal axis corresponds to robot exposure, with the vertical axis measuring SWB. In Panels A and C, the dots show the y-means binned by robot exposure, with larger dots indicating more observations. In Panels B and D, the triangles show the y-means binned by 35 boxes evenly. The key explanatory variables in Panels A and B are exposure measured by robot installations while those in Panels C and D are measured by robot stocks. Panels A and C show the "classic" binscatters while Panels B and D apply the method used in Cattaneo et al. (2024). The lines are estimated by OLS and confidence interval is at 95% level.



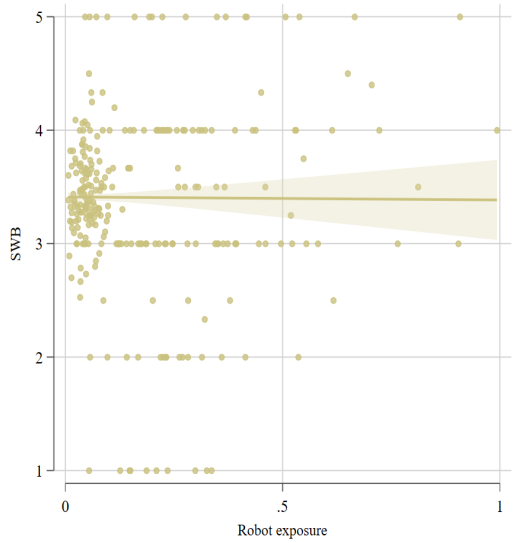
(A) **Job finders.**



(B) **Stayers (employed).**



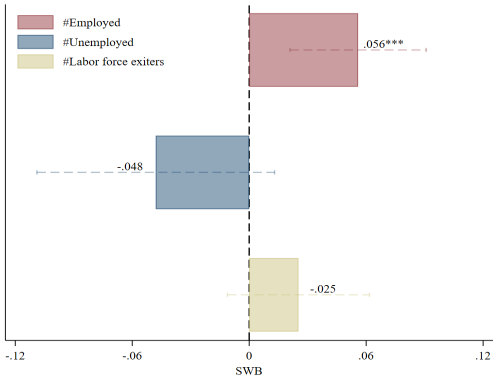
(C) **Job losers.**



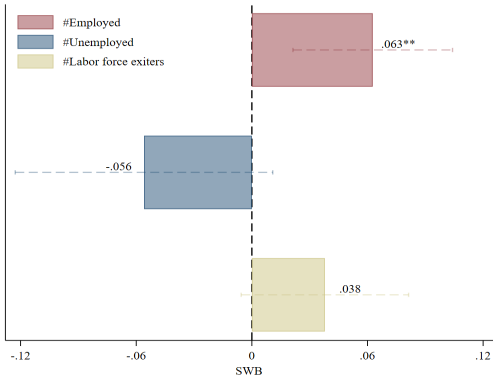
(D) **Stayers (unemployed).**

FIGURE 4 SWB and robot exposure across dynamic work status.

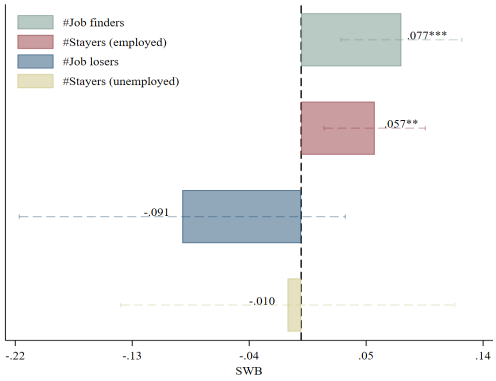
Notes: Figure 4 plots the relationship between robot exposure and SWB across different dynamic work status using the CFPS dataset. The horizontal axis corresponds to robot exposure, with the vertical axis measuring SWB. The dots show the y-means binned by robot exposure. Panels A, B, C, and D respectively plot the relationship across job finders, employed stayers, job losers, and unemployed stayers. The lines are estimated by OLS and confidence interval is at 95% level.



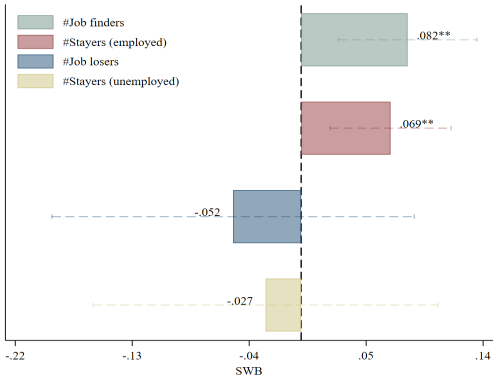
(A) **Static work status, OLS.**



(B) **Static work status, 2SLS.**



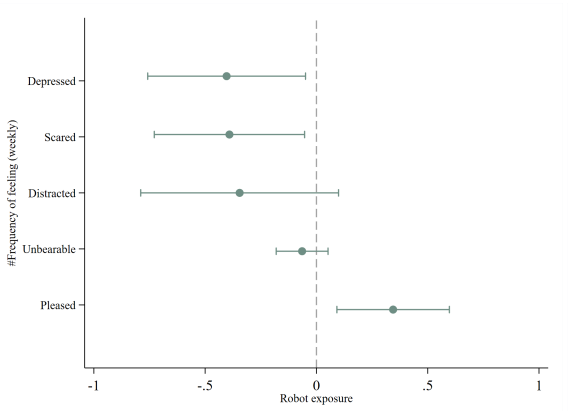
(C) **Dynamic work status, OLS.**



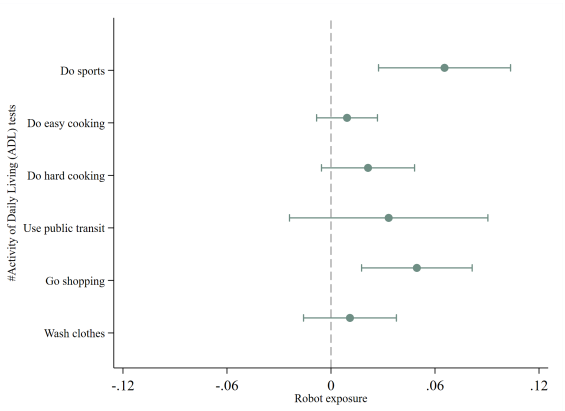
(D) **Dynamic work status, 2SLS.**

FIGURE 5 The effects of automation on SWB across work status.

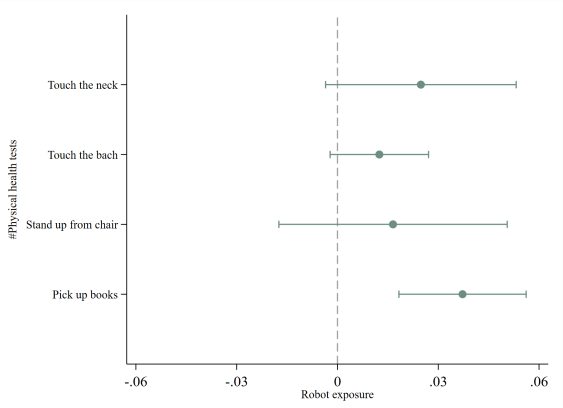
Notes: Figure 5 shows the effects of automation on SWB across work status using interaction term models. Data is derived from CFPS dataset. Numbers on CIs indicate the effect of a one-s.d. increase in robot exposure on the outcome. The dependent variable is SWB while the explanatory variable is robot exposure. In Panels A and B, the maroon, navy and khaki columns respectively show the standardized effects on the employed, the unemployed, and labor market exiters. The teal, maroon, navy and khaki columns in Panels C and D respectively show effects on job finders, employed stayers, job losers, and unemployed stayers. Panels A and C report the OLS estimation results while Panels B and D report the 2SLS estimation results. Confidence interval is at 95% level. The regression employs the same controls and FEs as the baseline.



(A) **Emotion.**



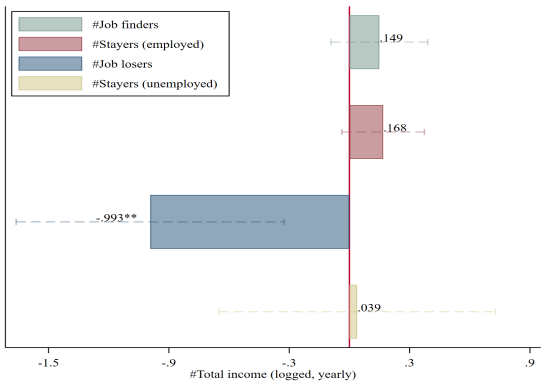
(B) **ADL test.**



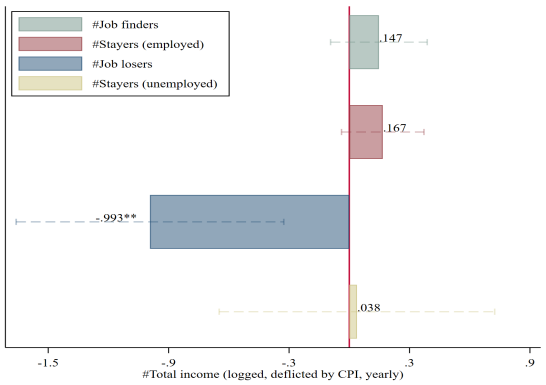
(C) **Physical health test.**

FIGURE 6 The effects of automation on mental and physical health.

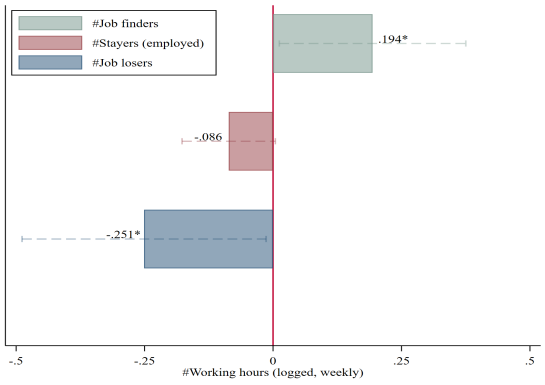
Notes: Figure 6 plots the regression coefficients of robot exposure on mental and physical health using the CFPS dataset. All the regressions use 2SLS specification in Equation 4 and Equation 5. Standard errors are two-way clustered at the prefecture-year level. The explanatory variable is robot exposure. The dependent variables in Panel A are the frequencies of feeling depressed, scared, distracted, unbearable, and pleased every week (scale 1-5). Panel B's variables are a series of dummies indicating whether respondents can complete these activities independently (including do sports, do easy cooking, do hard cooking, use public transportation, go shopping, and wash clothes). Those in Panel C are also dummies indicating whether respondents can touch the neck, touch the back, stand up from chair, and pick up books without help, respectively. The dotted teal lines show the 90% confidence interval. All regressions include the same controls and FEs as the baseline. More about ADL test and physical health test, see subsubsection A.2.2 and subsubsection A.2.3.



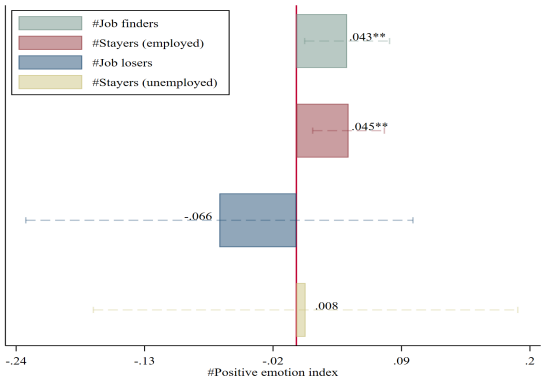
(A) **Income (nominal).**



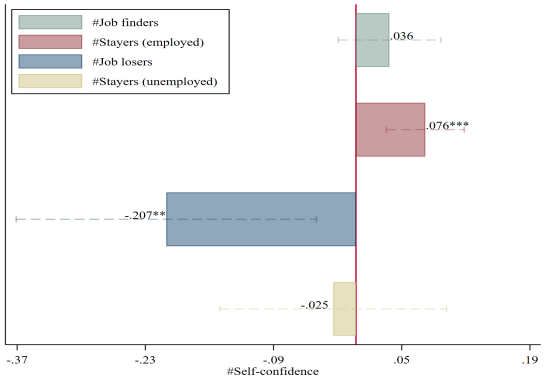
(B) **Income (deflated by CPI).**



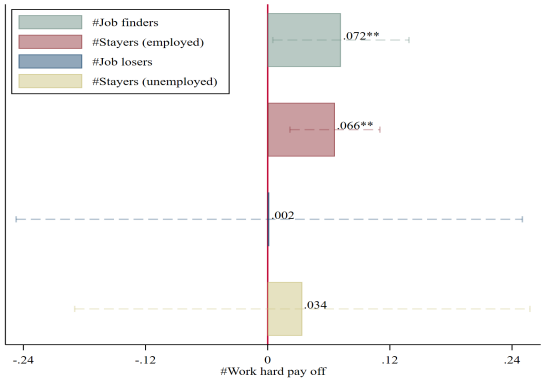
(C) **Working hours.**



(D) **Positive emotion index.**



(E) **Self-confidence.**



(F) **Working hard pays off.**

FIGURE 7 Mechanisms across work status.

Notes: Figure 7 shows the effects of automation on a series of mechanisms across work status using interaction term models. Data is derived from CFPS dataset. All the regressions use 2SLS specification in Equation 4 and Equation 5. Numbers on CIs indicate the effect of a one-s.d. increase in robot exposure on the outcome. The dependent variables are income (logged, respectively nominal and deflated by CPI), weekly working hours (logged), positive emotion index, self-confidence (scale 1-5), and redegree of belief that "working hard pays off" (scale 1-5). The explanatory variable is robot exposure. The teal, maroon, navy and khaki columns respectively show the standardized effects on job finders, employed stayers, job losers, and unemployed stayers. Confidence interval is at 95% level. All regressions include the same controls and FEs as the baseline.

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Appendix for "Robot and Happiness: Average Gains, Divergent Lives"

(For Online Publication)

Shangkun Xie[*] Siyuan Fan[†]

Contents

Appendix A: More on Data

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Appendix E: A Simple Model for Automation and Happiness

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Appendix A More on Data

A.1 More on IFR data and robot exposure

A.1.1 Facts

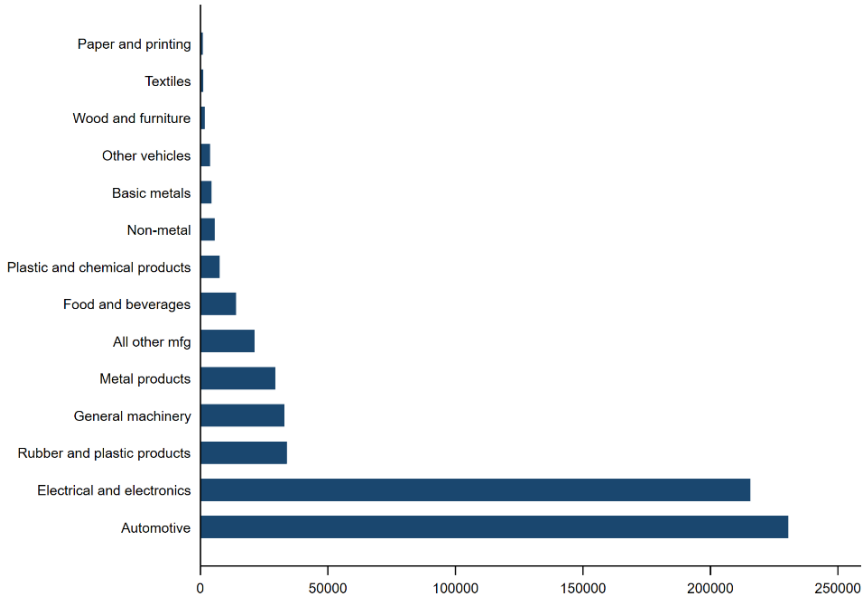


FIGURE A1 Total robot installations in 14 manufacturing sectors in China from 2005 to 2019.

A.1.2 Matching Methods for IFR Data and China's Sector

Based on classification criteria and sector names, we match and calculate the 31 manufacturing secondary industries in China **(GB/4754-2011)** with the 14 manufacturing secondary industries in the IFR (Industrial Classification of Manufacturing). The matching methods are labeled below, with the left representing sector categories in the IFR and the right being sectors in China.

1.**Food and beverages**: 13 - Agro-food processing sector+14 - Food Manufacturing+15 - Wine, Beverage and Refined Tea Manufacturing Sector

2.**Textiles**: 17 - Textile sector+18 - Textile, clothing and apparel sector+19 - Leather, fur, feather and their products and footwear sector

3.**Wood and furniture**: 20 - Wood processing and wood, bamboo, rattan, palm and straw products sector+21 - Furniture manufacturing

4.**Paper and printing**: 22 - Paper and paper products sector+23- Printing and Recording Media Reproduction

5.**Plastic and chemical products**: 26 - Chemical raw materials and chemical products manufacturing+27 - Pharmaceutical Manufacturing+28 - Chemical Fiber Manufacturing

6.**Rubber and plastic products**: 29 - Rubber and plastic products sector

7.**Non-metal**: 30 - Non-metallic mineral products

8.**Basic metals**: 31 - Ferrous metal smelting and rolling processing sector+32 - Non-ferrous metal smelting and rolling processing sector

9.**Metal products**: 33 - Metal products sector

10.**General machinery**: 34 - General Equipment Manufacturing+35 - Specialized equipment manufacturing

11.**Automotive**: 36 - Automobile manufacturing

12.**Other vehicles**: 37 - Manufacturing of railroad, ship, aerospace and other transportation equipment

13.**Electrical and electronics**: 38- Electrical (machinery and equipment manufacturing)+39 - Manufacturing of computer, communications and other electronic equipment+40 - Instrumentation Manufacturing

14.**All other mfg**: 16 - Tobacco products sector+24-Cultural, Educational, Industrial, Sports and Recreational Goods Manufacturing Sector+25-Petroleum Processing, Coking and Nuclear Fuel Processing Sector+41-Other Manufacturing Industries+42-Waste Resources Comprehensive Utilization Sector+43-Metal Products, Machinery and Equipment Repair Sector

A.1.3 Prefecture-level Characteristics

When examining the income effects, we utilize a range of prefecture-level characteristics, including the average absolute wage of labor, GDP, the proportion of primary sector output value, the proportion of secondary sector output value, administrative area land area, population size, employment size, number of high school students, expenditure on science and technology, education expenditure, foreign capital utilization amount, and public budget revenue. Additionally, we incorporate two CPI indices: the prefectural and provincial CPI. These data are sourced from the China City Statistical Yearbook and the China Provincial Statistical Yearbook.

In China, the wave of digitization goes hand in hand with the automation process. Therefore, we control for prefecture-level digital economy and financial development variables for robustness. Specifically, we obtain digital economy-related indicators such as the number of internet users per hundred people, the proportion of computer services and software employees, per capita telecommunications service volume, and the number of mobile phone users per hundred people from the China Urban Statistical Yearbook. We also obtain the "Digital Inclusive Finance Index of China," compiled jointly by Peking University Digital Finance Research Center and Ant Group, to obtain the "Digital Financial Inclusive Development Index" at the prefecture-level.

A.2 More on construction of indexes

A.2.1 AI-induced Occupational Substitutability (AIOS)

We further construct the AI-induced occupational substitutability (AIOS) probability at the individual level. We match the data of the probability of individual occupation being replaced by AI, calculated by Frey and Osborne (2017), with the CFPS database to construct the AIOS at the individual level. Frey and Osborne (2017) calculated the AIOS probability based on the information of each occupation from the O*NET data of the United States Department of Labor, including the cognitive and operational ability, creativity, and social capability. Using the U.S. Department of Labor's Standard Occupational Classification Code (SOC10), AIOS probabilities were calculated for 702 occupations. We utilize the 1988 and 2008 international Standard Occupational classification codes (ISC088 and ISC008) to match SOC10 with the Chinese National Standard Occupational Classification Code (CSCO), and then match it with the CFPS database.

A.2.2 Activity of Daily Living (ADL) Test

The Activities of Daily Living (ADL) scale provides a comprehensive, accurate, and efficient measure of an individual's capacity for daily functioning. The China Family Panel Studies (CFPS) administered the ADL assessment to respondents, including the following questions:

1. Are you able to independently do sports?
2. Are you able to independently perform simple kitchen tasks?
3. Are you able to independently perform complex kitchen tasks?
4. Are you able to independently use public transportation?
5. Are you able to independently go shopping?
6. Are you able to independently wash clothes?

A.2.3 Physical Health Test

The China Family Panel Studies (CFPS) includes four questions on the assessment of physical health conditions:

1. Are you able to touch the back of the neck with hand?
2. Are you able to touch the lower back with hand?
3. Are you able to quickly standing up from a chair after sitting for a period ?
4. Are you able to pick up a book from the floor?

A.2.4 Positive Emotion Index

The China Family Panel Studies (CFPS) includes five questions on the assessment of emotion:

1. How often do you feel depressed each week?
2. How often do you feel scared each week?
3. How often do you feel distracted each week?
4. How often do you feel unbearable each week?
5. How often do you feel pleased each week?

Each question is ranked with scores 1-4. We inverted the negative emotion scores and calculated the mean frequency of the above emotions as the positive emotion index.

A.2.5 Relationship Index

The 2010 wave of the China Family Panel Studies (CFPS) provides data on household interactions with neighbors and relatives. Specifically, respondents reported the frequency of activities with neighbors or relatives over the past month, including joint entertainment, sharing food, providing assistance, visiting, and chatting. Respondents could choose from the following frequency categories: never (0), once a month (1), two to three times a month (2), two to three times a week (3), and almost every day (4).

Using these data, we construct two relationship indices. Relationship index 1 sums the frequencies of the five activities, resulting in a measure ranging from 0 to 20, while relationship index 2 sums the occurrence of each activity (each a binary variable, defined as 1 if the activity occurred at least once in the past month, and 0 otherwise), yielding a measure ranging from 0 to 4.

A.3 More on Summary



(A) **Distribution of life satisfaction.** (B) **Distribution of happiness.**

(C) **Evolution of life satisfaction.** (D) **Evolution of happiness.**

FIGURE A2 Distribution and evolution of life satisfaction and happiness.

Notes: Figure A2 plots the distribution and evolution of life satisfaction and happiness using the CFPS dataset. Panels A and B present distribution of life satisfaction and happiness whereas Panels C and D show the evolution of them from 2010 to 2020.

TABLE A1 Data: descriptive statistics of robot exposure

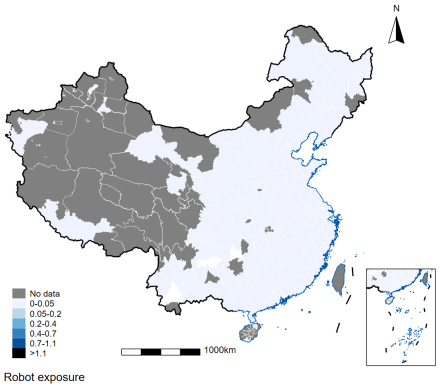
Notations	Definitions	N	Mean	SD	Min	Max
Independent variables:						
Robot exposure	Prefectural robot exposure	635	0.210	0.196	0.006	1.205
Robot exposure 2010	Robot exposure in 2010	127	0.048	0.025	0.006	0.131
Robot exposure 2012	Robot exposure in 2012	127	0.073	0.037	0.010	0.197
Robot exposure 2014	Robot exposure in 2014	127	0.189	0.097	0.025	0.513
Robot exposure 2016	Robot exposure in 2016	127	0.287	0.145	0.043	0.772
Robot exposure 2018	Robot exposure in 2018	127	0.454	0.223	0.080	1.205

TABLE A2 Data: descriptive statistics of individual variables

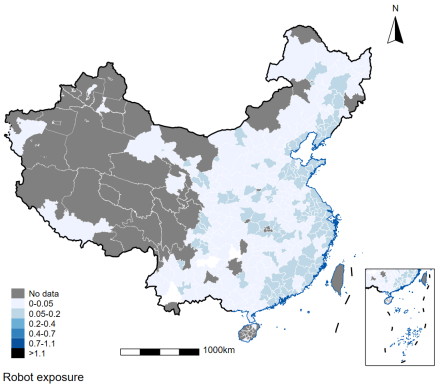
Notations	Definitions	N	Mean	SD	Min	Max
Dependent variables:						
Subjective well-being (SWB)	Life satisfaction (ordinal, 1 to 5)	123,349	3.642	1.062	1	5
Individual characteristics:						
Age	Age	123,349	47.569	15.749	16	108
Gender	1 for male, 0 for female	123,349	0.488	0.500	0	1
Edu	Education level (ordinal, 1 to 8)	123,349	2.584	1.353	1	8
Married	1 for married, 0 for unmarried	123,349	0.831	0.375	0	1
Hukou	household registration, 1 for urban, 0 for rural	123,355	0.718	0.450	0	1
Nationality	1 for Han ethnic group, 0 for others	123,349	0.918	0.275	0	1
Party	1 for CPC member, 0 for others	123,349	0.070	0.256	0	1
Familysize	Population in family	123,349	4.215	1.928	1	26
Mechanism variables:						
Income	Total annual income, CNY	123,349	9,283	22,866	0	1,800,000
Income_deflated	Total annual income deflated by prefectural CPI, CNY	123,349	9,064	22,329	0	1,750,462
Reverse_AIOS	Reverse of AI-induced occupational substitutability (AIOS) probability	77,115	0.596	0.138	0	1
Worktime_weekday	Working hour per weekday	121,643	4.497	5.218	0	21
Worktime_week	Average working hour per week	121,643	22.484	26.089	0	160
Health	Interviewer-reported health status (ordinal, 1 to 7)	111,808	5.354	1.281	1	7
Emotion	Average frequency of five positive emotions (ordinal, 1 to 4)	70,741	3.403	0.555	1	4
Confidence	Self-confidence in the future (ordinal, 1 to 5)	123,012	3.866	1.075	1	5
Status	Social status (ordinal, 1 to 5)	118,508	2.868	1.040	1	5
Workhard	Level of belief in working hard pays off (ordinal, 1 to 5)	51,750	3.867	0.811	1	5
Work status:						
Employed[a]	Those employed	120,313	0.666	0.472	0	1
Unemployed[a]	Those unemployed but still in the labor market	120,313	0.032	0.176	0	1
Dropout[a]	Those exited the labor market	120,313	0.302	0.459	0	1
Stayer_unemployed[b]	Those initially unemployed and currently still unemployed	22,153	0.003	0.057	0	1
Stayer_employed[b]	Those initially employed and currently still employed	22,153	0.874	0.331	0	1
Job_loser[b]	Those initially employed but currently unemployed	22,153	0.057	0.232	0	1
Job_finder[b]	Those initially unemployed but currently employed	22,153	0.065	0.247	0	1

[a] : These report the time-varying work status at the individual-year level.

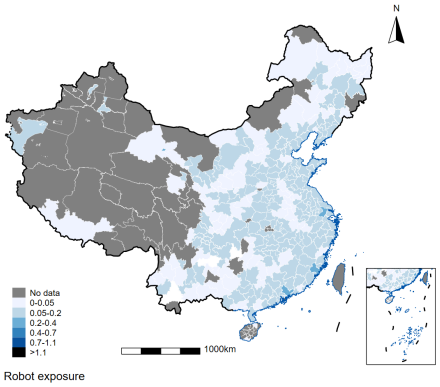
[b] : These present the individual-level work status across the entire waves, with individuals who have exited the labor market excluded.



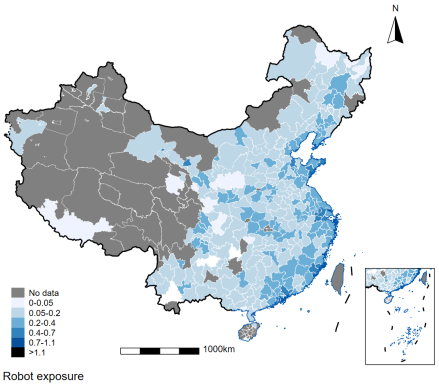
(A) **Robot exposure in 2006.**



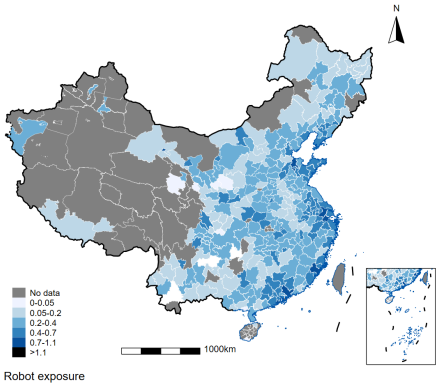
(B) **Robot exposure in 2010.**



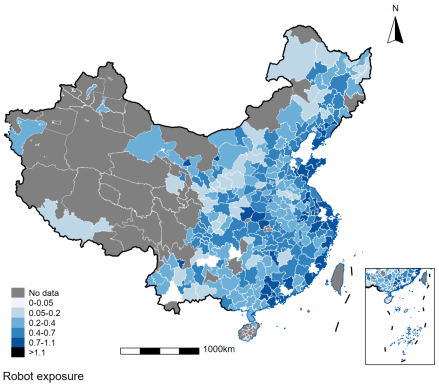
(C) **Robot exposure in 2012.**



(D) **Robot exposure in 2014.**



(E) **Robot exposure in 2016.**



(F) **Robot exposure in 2018.**

FIGURE A3 Spatial distribution of prefectural robot exposure.

Notes: Figure A3 shows the prefectural robot exposure distribution measured by installations in China from 2006 to 2018. Darker color represents higher exposure. The gray areas correspond to regions that are not included in the sample.

Appendix B More on Baseline

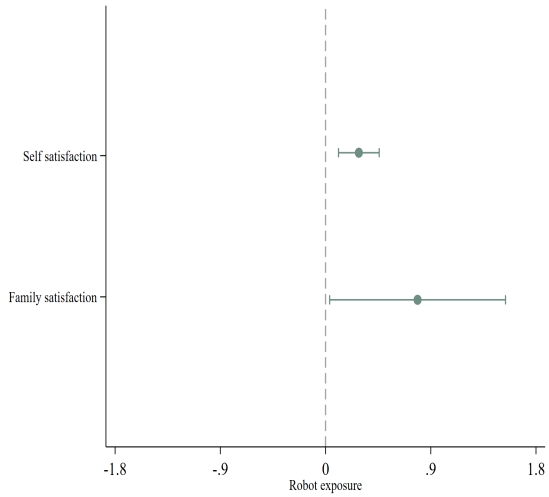
B.1 Alternative Sample Pool

TABLE A3 Baseline: baseline results across different pools

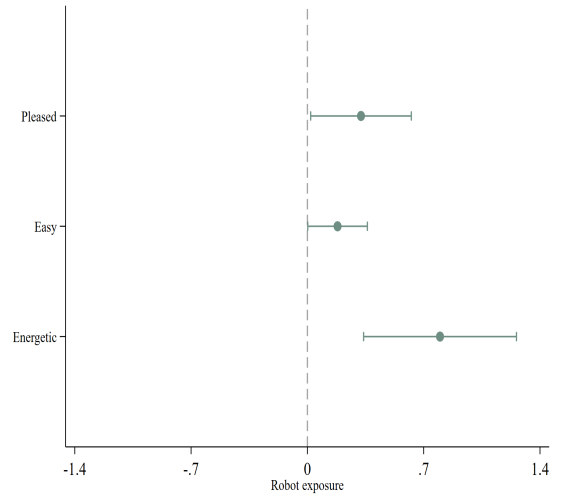
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. Full pool						
Robot exposure	0.878***	0.195***	0.202***	0.221***	0.326***	0.285***
	(0.051)	(0.073)	(0.069)	(0.069)	(0.094)	(0.106)
Standardized	[0.169]	[0.038]	[0.039]	[0.043]	[0.063]	[0.055]
Dependent-variable mean	3.642	3.645	3.645	3.645	3.645	3.650
Observations	123,349	118,142	118,142	118,142	118,142	110,495
Panel B. Labor market pool						
Robot exposure	0.835***	0.242***	0.248***	0.260***	0.335***	0.306**
	(0.053)	(0.088)	(0.078)	(0.076)	(0.108)	(0.119)
Standardized	[0.164]	[0.048]	[0.049]	[0.051]	[0.066]	[0.060]
Dependent-variable mean	3.613	3.619	3.619	3.619	3.619	3.625
Observations	67,030	64,342	64,342	64,342	64,342	58,091
Panel C. Stayer pool						
Robot exposure	0.858***	0.246***	0.284***	0.260***	0.372***	0.324**
	(0.054)	(0.094)	(0.079)	(0.076)	(0.110)	(0.127)
Standardized	[0.167]	[0.048]	[0.055]	[0.051]	[0.073]	[0.063]
Dependent-variable mean	3.621	3.626	3.626	3.619	3.626	3.643
Observations	61,923	59,544	59,544	64,342	59,544	51,185
Controls	✓	✓	✓	✓	✓	✓
Predetermined control # year		✓	✓	✓	✓	✓
Province FE			✓			
Prefecture FE					✓	
Individual FE						✓
Province-year FE				✓	✓	✓

Notes: Table A3 reports the baseline regression results across different pools using the CFPS dataset. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$. All the regressions use OLS specification in Equation 3. Standard errors in parentheses are two-way clustered at the prefecture-year level. Standardized coefficients in brackets indicate the effect of a one-s.d. increase in the explanatory variable on the outcome. The dependent variable is SWB while the key explanatory variable is robot exposure. Columns (1) to (6) report the results at different controls and FEs. Panel A reports the estimation with full pool. Panel B excludes those that have already exited the labor market. Panel C only keeps those with stable work status (employed stayers and unemployed stayers) compared to Panel B.

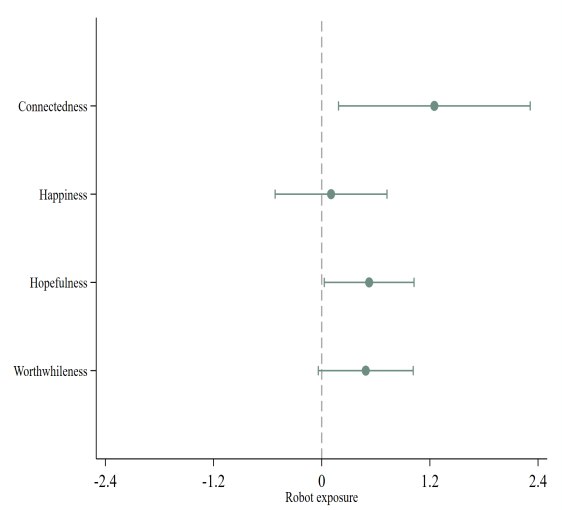
B.2 Alternative Measurement



(A) **Evaluative measures.**



(B) **Emotional measures.**



(C) **Eudaimonic measures.**

FIGURE A4 Alternative measurements of SWB.

Notes: Figure A4 plots the effects of automation on outcomes concerning subjective well-being following Li (2021). Data is derived from CFPS dataset. All the regressions use OLS specification in Equation 3. The explanatory variable is robot exposure. The dependent variables in Panel A are self-satisfaction (scale 1-5) and family life (scale 1-5) while those in Panel B are the frequency of feeling pleased, easy, and energetic every week (scale 1-4). Panel C shows results of eudaimonic measurement, including connectedness (scale 0-10), happiness (scale 0-10), hopefulness (scale 1-5) and worthwhileness (scale 1-5). The confidence intervals are at 95% level.

TABLE A4 Baseline: SWB transition matrix: 2×2, between low (1–3) and high (4–5)

	Final group		
Initial group	**Low (1–3)**	**High (4–5)**	**Total**
Low (1–3)	6,868 (21.7%)	9,152 (28.9%)	16,020 (50.6%)
High (4–5)	4,118 (13.0%)	11,528 (36.4%)	15,646 (49.4%)
Total	10,986 (34.7%)	20,680 (65.3%)	31,666 (100.0%)

Table A4 shows the SWB transition between high (scores 4–5) and low (scores 1–3) from the initial survey to the final survey. The analysis is at the individual level, with all respondents who participated in only a single survey wave excluded ($N = 31{,}666$). Value is the *share* of the full sample, with the *absolute count* in parentheses. Red indicates upward transition (final > initial), green indicates downward transition (final < initial), gray indicates no change (diagonal).

TABLE A5 Baseline: SWB transition matrix: 5×5

	Final SWB					
Initial SWB	**1**	**2**	**3**	**4**	**5**	**Total**
1	0.5% (171)	0.4% (138)	1.5% (467)	0.9% (270)	1.2% (394)	4.5% (1,440)
2	0.5% (154)	1.0% (305)	3.5% (1,097)	2.7% (842)	2.4% (772)	10.0% (3,170)
3	1.0% (311)	2.1% (660)	11.3% (3,565)	11.1% (3,525)	10.6% (3,349)	36.0% (11,410)
4	0.5% (174)	1.1% (355)	7.5% (2,370)	11.2% (3,541)	10.9% (3,452)	31.2% (9,892)
5	0.3% (101)	0.5% (151)	3.1% (967)	5.1% (1,617)	9.2% (2,918)	18.2% (5,754)
Total	2.9% (911)	5.1% (1,609)	26.7% (8,466)	30.9% (9,795)	34.4% (10,885)	100.0% (31,666)

Notes: Table A5 shows the SWB transition from the initial survey to the final survey. The analysis is at the individual level, with all respondents who participated in only a single survey wave excluded ($N = 31{,}666$). Value is the *share* of the full sample, with the *absolute count* in parentheses. Red colors indicates upward transition (final > initial), green indicates downward transition (final < initial), gray indicates no change (diagonal).

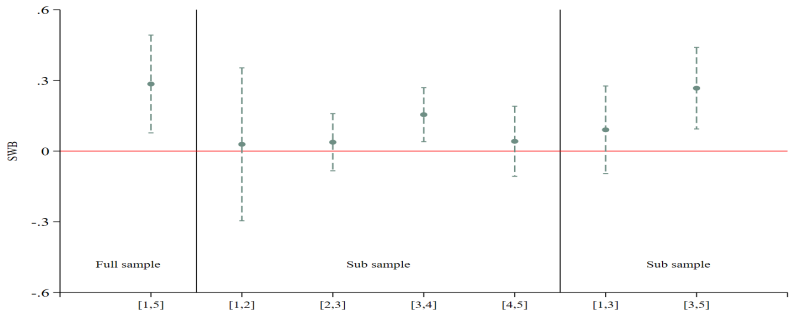


FIGURE A5 The impact of automation across subgroups.

Notes: Figure A5 plots the regression coefficients of automation on SWB in different satisfaction subgroups using the CFPS dataset. All the regressions use OLS specification in Equation 3. Standard errors are two-way clustered at the prefecture-year level. The explanatory variable is robot exposure while the dependent variable is SWB. We classify samples by SWB levels of 1 to 5, 1 and 2, 2 and 3, 3 and 4, 4 and 5, 1 to 3, 3 to 5, respectively. The dotted teal lines show the 95% confidence interval. All regressions include the same controls and FEs as the baseline.

TABLE A6 Baseline: order-logit model estimation results

	(1)	(2)	(3)
Panel A. OLS			
Robot exposure	2.866***	0.726***	0.706***
	(0.117)	(0.204)	(0.250)
Standardized	[0.548]	[0.139]	[0.135]
Standardized odds ratio	<72.94%>	<14.92%>	<14.46%>
Panel B. 2SLS			
Robot exposure	2.386***	0.662***	0.682**
	(0.108)	(0.250)	(0.336)
Standardized	[0.456]	[0.127]	[0.131]
Standardized odds ratio	<57.77%>	<13.51%>	<13.95%>
Dependent-variable mean	3.623	3.626	3.626
Observations	102,500	98,146	98,146
Individual FE	✓	✓	✓
Year FE			✓
Controls		✓	✓
Predetermined control # year		✓	✓

Notes: Table A6 reports the baseline regression results using order-logit model mentioned by Baetschmann et al. (2015). ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$. Data is derived from CFPS dataset. Standard errors in parentheses are two-way clustered at the prefecture-year level. Standardized coefficients in brackets indicate the effect of a one-s.d. increase in the explanatory variable on the outcome, and "standardized odds ratio" in angle brackets indicate the odds ratio effect ($\exp(\beta) - 1$) of a one-s.d. increase in the explanatory variable. The dependent variable is SWB and the key explanatory variable is robot exposure. Columns (1) to (3) report the results at different controls and fixed effects. Panel A reports the OLS estimation results while Panel B reports the 2SLS estimation results.

TABLE A7 Baseline: marginal effects of order-logit model

Row	SWB group	Marginal effect	Std. Error	p-value	Lower CI	Upper CI
1	Score 1	-0.0278***	0.0098	0.0050	-0.0471	-0.0085
2	Score 2	-0.0513***	0.0182	0.0050	-0.0869	-0.0157
3	Score 3	-0.0957***	0.0339	0.0050	-0.1622	-0.0292
4	Score 4	0.0432***	0.0153	0.0050	0.0132	0.0733
5	Score 5	0.1315***	0.0466	0.0050	0.0402	0.2229

Notes: Table A7 reports marginal effects of automation on SWB using order-logit model by Baetschmann et al. (2015). ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$. Data is derived from CFPS dataset. The dependent variable is SWB and the key explanatory variable is robot exposure. Rows (1) to (5) report the marginal effects of automation across different SWB groups. All the regressions include the same controls as the baseline, individual FE and year FE.

B.3 Alternative Specification

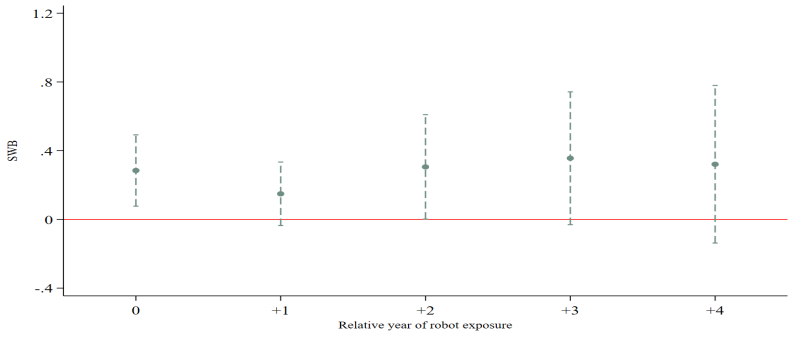


FIGURE A6 The dynamic impact of automation.

Notes: Figure A6 plots the regression coefficients of leading (1-4 years, respectively) automation on SWB using the CFPS dataset. The explanatory variable is robot exposure while the dependent variable is SWB. Standard errors are two-way clustered at the prefecture-year level. The solid teal lines show the 95% confidence interval. All regressions include the same controls and FEs as the baseline.

TABLE A8 Baseline: alternative IV using other country robot exposures

	(1)	(2)	(3)	(4)	(5)
			IV		
	Japan	Germany	Sweden	Korea	World
Robot exposure	0.204*	0.165	0.487***	0.376**	0.206**
	(0.112)	(0.115)	(0.179)	(0.148)	(0.104)
Bootstrap standard error	<0.076>***	<0.080>***	<0.117>***	<0.098>***	<0.077>***
Standardized	[0.039]	[0.032]	[0.094]	[0.072]	[0.104]
Dependent-variable mean	3.650	3.650	3.650	3.650	3.650
KPrk Wald F	3012.325	3059.568	337.020	534.777	4606.258
Controls	✓	✓	✓	✓	✓
Predetermined control # year	✓	✓	✓	✓	✓
Individual FE	✓	✓	✓	✓	✓
Province-year FE	✓	✓	✓	✓	✓
Observations	110,495	110,495	110,495	110,495	110,495

Notes: Table A8 presents the alternative IV estimation results using the CFPS dataset. ***p < 0.01, **p < 0.05, *p < 0.1. All the regressions use 2SLS specification in Equation 4 and Equation 5. Standard errors in parentheses are two-way clustered at the prefecture-year level while those in angle brackets are from the wild cluster bootstrap (500 times). Standardized coefficients in brackets indicate the effect of a one-s.d. increase in the explanatory variable on the outcome. The dependent variable is SWB while the key explanatory variable is robot exposure. Columns (2) to (5) report the second-stage estimation results using different country robot exposures as IV, respectively. All regressions include the same controls and FEs as the baseline.

TABLE A9 Baseline: long difference (2010-2018)

	(1)	(2)	(3)	(4)	(5)	(6)
	$\Delta Installation$			$\Delta Stock$		
	Unweighted	Weighted by base-year population	Weighted by survey size	Unweighted	Weighted by base-year population	Weighted by survey size
Panel A. OLS						
$\Delta Robot\ exposure$	0.280**	0.296*	0.344**	0.059**	0.063*	0.073**
	(0.139)	(0.167)	(0.140)	(0.029)	(0.035)	(0.030)
$\Delta Standardized$	[0.055]	[0.058]	[0.067]	[0.055]	[0.058]	[0.068]
Panel B. 2SLS						
$\Delta Robot\ exposure$	0.245*	0.286*	0.303**	0.052*	0.061*	0.064**
	(0.144)	(0.164)	(0.149)	(0.031)	(0.035)	(0.032)
$\Delta Standardized$	[0.048]	[0.056]	[0.060]	[0.048]	[0.056]	[0.060]
Predetermined control	✓	✓	✓	✓	✓	✓
Province FE	✓	✓	✓	✓	✓	✓
Dependent-variable mean	0.536	0.536	0.536	0.536	0.536	0.536
Observations	121	121	121	121	121	121

Notes: Table A9 reports the long difference regression results for the SWB effects of automation using CFPS prefecture-aggregated dataset. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$. Standard errors in parentheses are clustered at the prefecture level. Standardized coefficients in brackets indicate the effect of a one-s.d. increase in the explanatory variable on the outcome. The dependent variable is difference of average SWB between 2010 and 2018 while the key explanatory variable is the difference of robot exposure with installation and stock measures. Columns (1) to (6) are unweighted, weighted by base (2009) population and weighted by survey size, respectively. Panel A reports the OLS estimation results while Panel B reports the 2SLS estimation results. All regressions apply the same predetermined controls as baseline and province FE.

B.4 Checks for Shift-share Design

TABLE A10 Identification check: effects of automation at shock-level

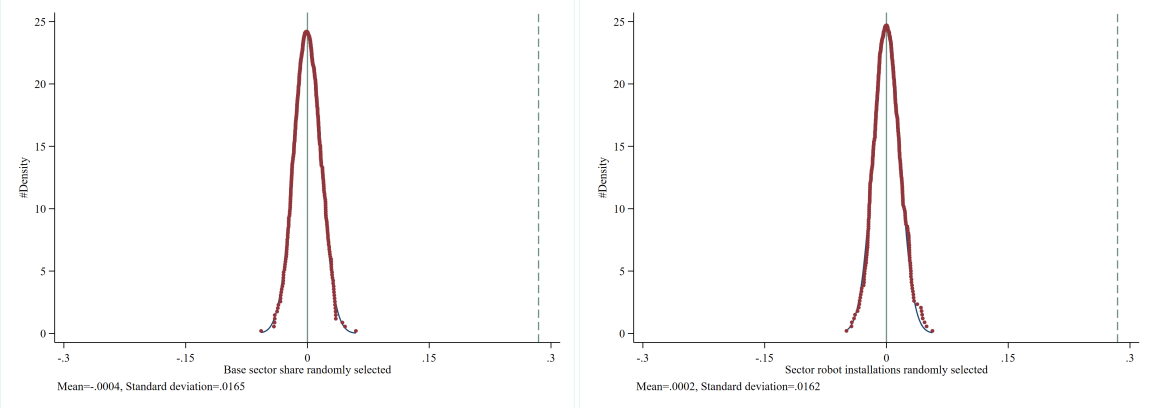
	(1)	(2)	(3)	(4)
	Robust SE		Sector clustered SE	
	OLS	2SLS	OLS	2SLS
Robot exposure	0.332***	0.284***	0.332**	0.284***
	(0.112)	(0.094)	(0.123)	(0.095)
Controls	✓	✓	✓	✓
Predetermined control # year	✓	✓	✓	✓
Prefecture FE	✓	✓	✓	✓
Province-year FE	✓	✓	✓	✓
Observations	30	30	30	30

Notes: Table A10 reports the baseline results at shock-level using CFPS prefecture-aggregated dataset. The estimates are based on 6 sectors in 5 years.***$p < 0.01$, **$p < 0.05$, *$p < 0.1$. The dependent variable is average SWB at prefecture level and the key explanatory variable is robot exposure. Columns (1) to (4) report the results with robust standard errors and clustered at the sector level following Borusyak et al. (2022), respectively. All the regressions include aggregated individual-level characteristics, predetermined prefecture controls, prefecture FE and province-year FE. All the regressions are weighted by survey sample size.

TABLE A11 Identification check: balance test of sector-level shocks

Variable	Coef.	SE	Variable	Coef.	SE
GDP per capita (logged)	0.0224	0.0275	Average wage (logged)	0.0881	0.0963
Unemployment ratio (%)	0.0420	0.0832	Fiscal expenditure per capita (logged)	0.0328	0.0636
Share of agriculture sector (%)	0.0359	0.0659	Share of industry sector (%)	0.0943	0.1856
Trade volume (logged)	0.0795	0.1343	Foreign investment (logged)	0.0537	0.1053
Share of college-educated population	0.0207	0.0264	Share of urban-working population	0.0798	0.0717
Joint significance test: χ^2=1.20, p-value=0.315					

Notes: Table A11 reports coefficients and standard errors from regressing sector-level automation shocks on each sector-specific weighted average of initial prefectural characteristics and year fixed effects. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$. All regressions are weighted by the simple average of the exposure to sector-level shock across prefectures. Standard errors are two-way clustered at prefecture-year level.



(A) **Base sector share randomly selected.** (B) **Sector robot installations randomly selected.**

FIGURE A7 Permutation-test of "share" and "shift".

Notes: Figure A7 demonstrates the estimate distributions for the pseudo robot exposure results using the CFPS dataset. All the regressions use OLS specification in Equation 3. Panel A randomly selects base sector share (share) 500 times while Panel B randomly selects robot installations (shift), to construct pseudo shift-share robot exposures. Standard errors are two-way clustered at the prefecture-year level. The dashed teal lines show the baseline effect. All regressions include the same controls and FEs as the baseline.

TABLE A12 Identification check: adjusted standard errors following Adao et al. (2019)

Row	Method	Coef	Std. Error	P-value	Lower CI	Upper CI	N
1	Prefecture clustered SE	0.2519***	0.0893	0.0057	0.0748	0.4290	555
2	Homoscedastic SE	0.2519***	0.0930	0.0070	0.0697	0.4341	555
3	EHW sector clustered SE	0.2519***	0.0769	0.0011	0.1012	0.4026	555
4	AKM0 sector clustered SE	0.2519***	0.0365	0.0000	0.1821	0.3250	555
5	AKM1 sector clustered SE	0.2519***	0.0353	0.0000	0.1826	0.3212	555

Notes: Table A12 reports the baseline results with adjusted standard errors using CFPS prefecture-aggregated dataset. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$. The dependent variable is average SWB at prefecture level and the key explanatory variable is robot exposure. Rows (1) to (5) report the results with different standard errors following Adao et al. (2019). All the regressions include aggregated individual-level characteristics, predetermined prefecture controls, prefecture FE and year FE. All the regressions are weighted by survey sample size.

TABLE A13 Identification check: HAC adjusted standard errors following Conley (1999)

	(1)	(2)	(3)	(4)	(5)
Panel A. Spatial adjusted standard errors					
	No adjust	50 Km	100 Km	300 Km	500 Km
Robot exposure	0.285***	0.285***	0.285***	0.285**	0.285***
	(0.090)	(0.092)	(0.097)	(0.117)	(0.106)
Panel B. Time adjusted standard errors					
	No adjust	1 Wave	2 Waves	3 Waves	4 Waves
Robot exposure	0.285***	0.285***	0.285***	0.285***	0.285***
	(0.090)	(0.070)	(0.075)	(0.085)	(0.089)
Controls	✓	✓	✓	✓	✓
Predetermined control # year	✓	✓	✓	✓	✓
Individual FE	✓	✓	✓	✓	✓
Province-year FE	✓	✓	✓	✓	✓
Dependent-variable mean	3.650	3.650	3.650	3.650	3.650
Observations	110,495	110,495	110,495	110,495	110,495

Notes: Table A13 reports the baseline results after adjusting for the heteroskedasticity-and-autocorrelation-consistent (HAC) standard errors following Conley (1999) using the CFPS dataset. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$. All the regressions use OLS specification in Equation 3. Standard errors are clustered as described in each respective column. Panel A reports the spatial adjusted standard errors to allow for spatial correlation and spillover effects while Panel B reports the wave adjusted standard errors to allow for correlation between waves and dynamic effects. All regressions include the same controls and FEs as the baseline.

TABLE A14 Identification check: pre-trend test using the CFPS dataset

	(1)	(2)	(3)	(4)	(5)	(6)
	Current robot exposure	Lagged robot exposure				
	Baseline	2014-2016 replace 2010-2012	2014-2016 replace 2012-2014	2016-2018 replace 2010-2012	2016-2018 replace 2012-2014	2016-2018 replace 2014-2016
Panel A. OLS						
Robot exposure	0.285***	0.014	0.074	0.008	0.045	0.031
	(0.106)	(0.066)	(0.062)	(0.040)	(0.037)	(0.029)
Standardized	[0.055]	[0.019]	[0.097]	[0.017]	[0.092]	[0.063]
Panel B. 2SLS						
Robot exposure	0.315**	0.010	0.073	0.010	0.040	0.027
	(0.126)	(0.066)	(0.061)	(0.040)	(0.037)	(0.030)
Standardized	[0.061]	[0.013]	[0.096]	[0.022]	[0.082]	[0.030]
Controls	✓	✓	✓	✓	✓	✓
Predetermined control # year	✓	✓	✓	✓	✓	✓
Individual FE	✓	✓	✓	✓	✓	✓
Province-year FE	✓	✓	✓	✓	✓	✓
Dependent-variable mean	3.650	3.416	3.581	3.416	3.581	3.735
Observations	110,495	36,430	31,758	36,430	31,758	34,664

Notes: Table A14 reports the results for pre-trend tests using the CFPS dataset. ***p < 0.01, **p < 0.05, *p < 0.1. Standard errors in parentheses are two-way clustered at the prefecture-year level. Standardized coefficients in brackets indicate the effect of a one-s.d. increase in the explanatory variable on the outcome. The dependent variable is SWB. Column (1) reports the baseline results and the key explanatory variables from columns (2) to (6) are lagged robot exposures (where the 2014-2016 period replaces 2010-2012, the 2014-2016 period replaces 2012-2014, the 2016-2018 period replaces 2010-2012, the 2016-2018 period replaces 2012-2014, and the 2016-2018 period replaces 2014-2016). Panel A reports the OLS estimation results while Panel B reports the 2SLS estimation results. All regressions include the same controls and FEs as the baseline.

TABLE A15 Identification check: pre-trend test before the surge of robot adoption (2007)

	(1)	(2)	(3)	(4)
Dataset:	CLHLS	CGSS	CHIP	CSS
Survey year:	1998-2005	2003-2005	2002	2005
Robot exposure$_{t+10}$	0.038	0.095	0.101	0.055
	(0.056)	(0.125)	(0.083)	(0.039)
Standardized	[0.008]	[0.025]	[0.038]	[0.015]
Controls	✓	✓	✓	✓
Predetermined control # year	✓	✓	✓	✓
Prefecture FE	✓	✓	✓	✓
Province-year FE	✓	✓	✓	✓
Observations	31,231	12,372	30,523	5,622

Notes: Table A15 reports the results for pre-trend tests using earlier alternative datasets before the surge of robot adoption in China (2007). ***p < 0.01, **p < 0.05, *p < 0.1. Standard errors in parentheses are two-way clustered at the prefecture-year level. Standardized coefficients in brackets indicate the effect of a one-s.d. increase in the explanatory variable on the outcome. The dependent variable is SWB with normalization for comparison across different datasets. The key independent variable is constructed as the ten-year lag of robot exposure, relative to the survey year. Columns (1) to (4) report the pre-trend test results using the following datasets, respectively: the Chinese Longitudinal Healthy Longevity Survey (CLHLS) 1998-2005, the Chinese General Social Survey (CGSS) 2003-2005, the Chinese Household Income Project (CHIP) 2002 , and the Chinese Social Survey (CSS) 2005. All regressions include the same controls as the baseline, prefecture FE and province-year FE.

TABLE A16 Identification check: controlling for sector-specific base share

	(1) Baseline	(2)	(3)	(4)	(5)	(6)	(7)	(8)
		Controlling for the prefecture's 2000 share of						
		Agriculture	Mining	Manufacturing	Gas	Construction	Education	All
Panel A. OLS								
Robot exposure	0.285***	0.286***	0.284***	0.293***	0.286***	0.283***	0.291***	0.287***
	(0.106)	(0.106)	(0.106)	(0.106)	(0.106)	(0.106)	(0.106)	(0.106)
Standardized	[0.055]	[0.056]	[0.055]	[0.056]	[0.055]	[0.054]	[0.056]	[0.056]
Panel B. 2SLS								
Robot exposure	0.315**	0.317**	0.315**	0.332***	0.319**	0.312**	0.329***	0.320**
	(0.126)	(0.126)	(0.126)	(0.127)	(0.126)	(0.126)	(0.126)	(0.126)
Standardized	[0.061]	[0.061]	[0.060]	[0.064]	[0.061]	[0.060]	[0.063]	[0.061]
Controls	✓	✓	✓	✓	✓	✓	✓	✓
Predetermined control # year	✓	✓	✓	✓	✓	✓	✓	✓
Individual FE	✓	✓	✓	✓	✓	✓	✓	✓
Province-year FE	✓	✓	✓	✓	✓	✓	✓	✓
Dependent-variable mean	3.650	3.650	3.650	3.650	3.650	3.650	3.650	3.650
Observations	110,495	110,495	110,495	110,495	110,495	110,495	110,495	110,495

Notes: Table A16 reports estimation results after controlling for the sector-specific base share using the CFPS dataset. ***p < 0.01, **p < 0.05, *p < 0.1. Robust standard errors two-way clustered at the prefecture-year level are reported in parentheses. Standardized coefficients in brackets indicate the effect of a one-s.d. increase in the explanatory variable on the outcome. The dependent variable is SWB while the key explanatory variable is robot exposure. Column (1) reports baseline results while column (2) to (8) respectively control for the base (2000) shares of the agriculture, mining, manufacturing, gas, construction, education sector and all of the above. Panel A reports the OLS estimation results while Panel B reports the 2SLS estimation results. All regressions include the same controls and FEs as the baseline.

TABLE A17 Identification check: controlling for linear trend

	(1) Baseline	(2)	(3)	(4)	(5)	(6)	(7)	(8) Prefecture	(9) Pre-control
		Base-sector-share linear trend							
		Agriculture	Mining	Manufacturing	Gas	Construction	Education	trend	trend
Panel A. OLS									
Robot exposure	0.285***	0.286***	0.284***	0.296***	0.286***	0.282***	0.292***	0.239*	0.229**
	(0.106)	(0.106)	(0.106)	(0.106)	(0.106)	(0.106)	(0.106)	(0.143)	(0.090)
Standardized	[0.055]	[0.055]	[0.055]	[0.057]	[0.055]	[0.054]	[0.056]	[0.046]	[0.044]
Panel B. 2SLS									
Robot exposure	0.315**	0.318**	0.315**	0.336***	0.320**	0.311**	0.330***	0.337*	0.242**
	(0.126)	(0.126)	(0.126)	(0.127)	(0.126)	(0.126)	(0.126)	(0.177)	(0.102)
Standardized	[0.061]	[0.061]	[0.060]	[0.065]	[0.061]	[0.060]	[0.063]	[0.065]	[0.046]
Controls	✓	✓	✓	✓	✓	✓	✓	✓	✓
Predetermined control # year	✓	✓	✓	✓	✓	✓	✓	✓	
Individual FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Province-year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Predetermined control linear trend									✓
Dependent-variable mean	3.650	3.650	3.650	3.650	3.650	3.650	3.650	3.650	3.650
Observations	110,495	110,495	110,495	110,495	110,495	110,495	110,495	110,495	110,495

Notes: Table A17 reports results after controlling for the linear trend using the CFPS dataset. ***p < 0.01, **p < 0.05, *p < 0.1. Robust standard errors two-way clustered at the prefecture-year level are reported in parentheses. Standardized coefficients in brackets indicate the effect of a one-s.d. increase in the explanatory variable on the outcome. The dependent variable is SWB while the key explanatory variable is robot exposure. Column (1) reports baseline results while columns (2) to (7) control for agriculture, mining, manufacturing, gas, construction, and education sector base share linear trend, respectively. Column (8) additionally adds a prefecture-specific linear trend and column (9) replaces the interaction terms between prefectural predetermined control and year dummies with those between control and the year linear trend. Panel A reports the OLS estimation results while Panel B reports the 2SLS estimation results. All regressions besides column (9) include the same controls and FEs as the baseline.

TABLE A18 Identification check: controlling for predetermined (2000) demographic characteristics

	(1) Baseline	(2)	(3)	(4)	(5)	(6)
		Controlling for the interaction terms between year dummy and				
		Share of population in agriculture sector	Share of population in sector & service sector	Urban-working population	College-educated population	All
Panel A. OLS						
Robot exposure	0.285***	0.241**	0.240**	0.236**	0.244**	0.273**
	(0.106)	(0.108)	(0.108)	(0.106)	(0.105)	(0.108)
Standardized	[0.055]	[0.047]	[0.047]	[0.046]	[0.048]	[0.053]
Panel B. 2SLS						
Robot exposure	0.315**	0.278**	0.277**	0.266**	0.269**	0.316**
	(0.126)	(0.122)	(0.122)	(0.120)	(0.119)	(0.122)
Standardized	[0.061]	[0.054]	[0.054]	[0.052]	[0.053]	[0.062]
Controls	✓	✓	✓	✓	✓	✓
Predetermined control # year	✓	✓	✓	✓	✓	✓
Individual FE	✓	✓	✓	✓	✓	✓
Province-year FE	✓	✓	✓	✓	✓	✓
Dependent-variable mean	3.650	3.653	3.653	3.653	3.653	3.653
Observations	110,495	100,057	100,057	100,057	100,057	100,057

Notes: Table A18 reports estimation results after controlling for the interaction terms between prefectural predetermined (2000) demographic characteristics and year dummies using the CFPS dataset. ***p < 0.01, **p < 0.05, *p < 0.1. Robust standard errors two-way clustered at the prefecture-year level are reported in parentheses. Standardized coefficients in brackets indicate the effect of a one-s.d. increase in the explanatory variable on the outcome. The dependent variable is SWB while the key explanatory variable is robot exposure. Column (1) reports baseline results while columns (2) to (6) control for a series of predetermined demographic characteristics. Panel A reports the OLS estimation results while Panel B reports the 2SLS estimation results. All regressions include the same controls and FEs as the baseline.

TABLE A19 Identification check: controlling for predetermined (2009) trade and offshoring

	(1) Baseline	(2) Trade volume	(3) Foreign investment	(4) Foreign investment use	(5) Foreign enterprise	(6) Foreign enterprise total output
Panel A. OLS						
Robot exposure	0.285***	0.264**	0.261**	0.269**	0.293***	0.278***
	(0.106)	(0.111)	(0.105)	(0.108)	(0.106)	(0.106)
Standardized	[0.055]	[0.051]	[0.050]	[0.052]	[0.056]	[0.053]
Panel B. 2SLS						
Robot exposure	0.315**	0.290**	0.291**	0.291**	0.315**	0.303**
	(0.126)	(0.136)	(0.123)	(0.130)	(0.126)	(0.125)
Standardized	[0.061]	[0.056]	[0.056]	[0.056]	[0.060]	[0.058]
Controls	✓	✓	✓	✓	✓	✓
Predetermined control # year	✓	✓	✓	✓	✓	✓
Individual FE	✓	✓	✓	✓	✓	✓
Province-year FE	✓	✓	✓	✓	✓	✓
Dependent-variable mean	3.650	3.650	3.650	3.650	3.650	3.650
Observations	110,495	110,495	110,495	110,495	110,495	110,495

Notes: Table A19 presents the estimation results after controlling for prefectural predetermined (2009) trade and offshoring using the CFPS dataset. ***p < 0.01, **p < 0.05, *p < 0.1. Standard errors in parentheses are two-way clustered at the prefecture-year level. Standardized coefficients in brackets indicate the effect of a one-s.d. increase in the explanatory variable on the outcome. The dependent variable is SWB while the key explanatory variable is robot exposure. Column (1) reports the baseline estimation results. Columns (2)-(6) report the results controlling for the trade volume (logged), foreign investment volume (logged), foreign investment use (logged), the number of foreign enterprises (logged), foreign enterprise total output (logged), and all of the above, respectively. Panel A reports the OLS estimation results while Panel B reports the 2SLS estimation results. All regressions include the same controls and FEs as the baseline.

Appendix C More on Robustness Checks and Heterogeneity

C.1 The Influence of Digital Technology

Over the past decade, China's Internet and digital technologies have undergone rapid development alongside its vast automation process. Digital technologies have not only propelled productivity growth and transformed production methods (Brynjolfsson and McAfee, 2014), but also provide unprecedented convenience for accessing resources, strengthening social connections, and facilitating interpersonal interactions (Turkle, 2011; Sunstein, 2018). Hence, to examine which factors play the most important role, we use a horse-race empirical strategy by adding some variables relevant to digital technologies at the prefecture level in Table A20. The results indicate that after controlling for confounding digital technology factors, the estimated coefficient for robot exposure exhibits minimal variation, suggesting robustness in estimation.

C.2 The Influence of Migration and Attrition

Since the relaxation of the household registration (*hukou*) system in China, there has been a great migration from rural to urban areas, driven by rapid industrialization and urbanization. However, due to the swift pace of automation, respondents relocating from one area to another may introduce serious self-selection biases to our estimation. To address this concern, we first exclude migration and *hukou* change samples and re-estimate in the columns (1) to (3) in Table A21. Moreover, to directly check whether there is a significant difference between the migration cohort and the non-migration cohort, we add an interaction term to the regression. As expected, we did not find any differences between the two cohorts. It is also worth noting that the proportion of CFPS respondents who migrated during the survey period is extremely low (less than 1%). This is because the CFPS survey locates respondents based on their current residence rather than their registered household (*hukou*) location[1]. As a result, the impact of migration on the estimates is negligible.

We also check the impact of sample attrition on our baseline estimation results. Similar to the above check, we first exclude attrition samples and then check the differences between the two cohorts, yielding similar results as the baseline, shown in columns (1)-(4) of Table A22. We then construct an attrition dummy indicating whether an individual who was in the first wave is no longer in the data later and directly estimate its relationship with automation. Columns (5)-(6) show little correlation between the two, suggesting that automation did not cause severe sample losses. In summary, our findings remain robust after dealing with sample attrition issues.

C.3 Alternative Clustering and Winsorization

We estimate the happiness effect using a variety of models and the results remain very robust. We explore the extent to which the baseline results might be sensitive to alternative clustering choices. As shown in Table A23, all coefficients remain statistically significant, confirming the robustness of our results. China's vast regional economic disparities also result in significant spatial heterogeneity in robot exposure. To mitigate the disturbance of outliers on the estimation results, we conduct sample screening for the top 1% and bottom 1%,

1. Although approximately one-quarter of the Chinese population (the floating population) holds a household registration (*hukou*) that differs from their current residence, the proportion of individuals who move between different non-hukou regions is quite small.

as well as the top 5% and bottom 5%. The results in Table A23 indicate that after controlling for outliers, our estimation results remain robust and become more significant both economically and statistically.

TABLE A20 Robustness check: controlling for digital technology

	(1)	(2)	(3)	(4)	(5)
		Digital technology			
	Baseline	Internet users per 100 people	Telecommunication per capita	Telephone users per 100 people	Digital finance index
Panel A. OLS					
Robot exposure	0.285***	0.277***	0.287***	0.284***	0.277**
	(0.106)	(0.106)	(0.106)	(0.106)	(0.108)
Standardized	[0.055]	[0.053]	[0.055]	[0.055]	[0.053]
Digital Technology		0.040	-0.011	0.019	0.018
		(0.032)	(0.024)	(0.030)	(0.035)
Panel B. 2SLS					
Robot exposure	0.315**	0.312**	0.317**	0.315**	0.310**
	(0.126)	(0.127)	(0.126)	(0.126)	(0.129)
Standardized	0.061	0.060	0.061	0.060	0.059
Digital technology		0.039	-0.011	0.019	0.016
		(0.032)	(0.024)	(0.030)	(0.035)
Controls	✓	✓	✓	✓	✓
Predetermined control # year	✓	✓	✓	✓	✓
Individual FE	✓	✓	✓	✓	✓
Province-year FE	✓	✓	✓	✓	✓
Dependent-variable mean	3.650	3.650	3.650	3.650	3.650
Observations	110,495	110,495	110,495	110,495	110,495

Notes: Table A20 presents the horse-race estimation results between digital technology and robot exposure using the CFPS dataset. ***p < 0.01, **p < 0.05, *p < 0.1. Standard errors in parentheses are two-way clustered at the prefecture-year level. Standardized coefficients in brackets indicate the effect of a one-s.d. increase in the explanatory variable on the outcome. The dependent variable is SWB while the key explanatory variable is robot exposure. Column (1) reports the baseline estimates, while columns (2)-(6) respectively add a series of variables concerning digital technology (including the number of internet users (per hundred people), telecommunication services per capita, mobile phone users (per hundred people), and the digital finance index). Panel A reports the OLS estimation results while Panel B reports the 2SLS estimation results. All regressions include the same controls and FEs as the baseline.

TABLE A21 Robustness check: migration

	(1)	(2)	(3)	(4)	(5)	(6)
	Exclude migration and *hukou* change samples			Check the difference between two cohorts		
	Prefecture migration	Province migration	*hukou* change	Prefecture migration	Province migration	*hukou* change
Panel A. OLS						
Robot exposure	0.303***	0.295***	0.240**	0.285***	0.284***	0.293***
	(0.106)	(0.106)	(0.108)	(0.106)	(0.106)	(0.106)
Standardized	[0.058]	[0.057]	[0.046]	[0.055]	[0.055]	[0.056]
Robot exposure × migration				-0.120	0.398	-0.109
(or *hukou*) change dummy				(0.240)	(0.290)	(0.068)
Standardized				[-0.023]	[0.076]	[-0.021]
Panel B. 2SLS						
Robot exposure	0.343***	0.330***	0.260**	0.317**	0.316**	0.319**
	(0.127)	(0.126)	(0.129)	(0.126)	(0.126)	(0.126)
Standardized	[0.066]	[0.063]	[0.050]	[0.061]	[0.061]	[0.061]
Robot exposure × migration				-0.286	0.240	-0.049
(or *hukou*) change dummy				(0.278)	(0.342)	(0.079)
Standardized				[-0.055]	[0.046]	[-0.009]
Controls	✓	✓	✓	✓	✓	✓
Predetermined control # year	✓	✓	✓	✓	✓	✓
Individual FE	✓	✓	✓	✓	✓	✓
Province-year FE	✓	✓	✓	✓	✓	✓
Dependent-variable mean	3.651	3.651	3.646	3.650	3.650	3.650
Observations	109,758	109,972	101,705	110,495	110,495	110,495

Notes: Table A21 reports the regression results controlling for migration using the CFPS dataset. ***p < 0.01, **p < 0.05, *p < 0.1. Robust standard errors two-way clustered at the prefecture-year level are reported in parentheses. Standardized coefficients in brackets indicate the effect of a one-s.d. increase in the explanatory variable on the outcome. The dependent variable is SWB, with the explanatory variable being robot exposure. Columns (1) to (3) respectively exclude individuals who migrate between provinces, migrate between prefectures, and change *hukou* during the survey. Columns (4) to (6) add an interaction term to check whether there is a significant difference between migration group and stable group. Panel A reports the OLS estimation results while Panel B reports the 2SLS estimation results. All regressions include the same controls and FEs as the baseline.

TABLE A22 Robustness check: attrition

	(1)	(2)	(3)	(4)	(5)	(6)
	Keep those who participated in all waves		Keep those who participated in at least 4 waves		Attrition (yes=1)	
	OLS	2SLS	OLS	2SLS	OLS	2SLS
Robot exposure	0.316**	0.397***	0.278**	0.344**	-0.010	0.008
	(0.124)	(0.143)	(0.116)	(0.135)	(0.034)	(0.035)
Standardized	[0.062]	[0.078]	[0.054]	[0.067]	[-0.002]	[0.001]
Controls	✓	✓	✓	✓	✓	✓
Predetermined control # year	✓	✓	✓	✓	✓	✓
Individual FE	✓	✓	✓	✓		
Prefecture FE					✓	✓
Province-year FE	✓	✓	✓	✓	✓	✓
Dependent-variable mean	3.687	3.687	3.676	3.676	0.400	0.400
Observations	47,247	47,247	77,881	77,881	118,142	118,142

Notes: Table A22 reports the regression results controlling for sample attrition using the CFPS dataset. ***p < 0.01, **p < 0.05, *p < 0.1. Robust standard errors two-way clustered at the prefecture-year level are reported in parentheses. Standardized coefficients in brackets indicate the effect of a one-s.d. increase in the explanatory variable on the outcome. The dependent variable is SWB, with the explanatory variable being robot exposure. Columns (1) to (4) respectively report the OLS and 2SLS estimation results keeping those participated in all waves or at least 4 waves. Columns (5) and (6) directly check the impact of automation on sample attrition using OLS and 2SLS models. Columns (1) to (4) include the same controls and FEs as the baseline while columns (5) and (6) include same controls as the baseline and prefecture FE, province-year FE.

TABLE A23 Robustness check: alternative clustering and winsorization

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. replace cluster hierarchy (OLS)	*Individual*	*County – year*	*County*	*Prefecture – year*	*Province – year*	*Province*
Robot exposure	0.285***	0.285***	0.285**	0.285***	0.285**	0.285**
	(0.069)	(0.108)	(0.111)	(0.107)	(0.124)	(0.117)
Standardized	[0.055]	[0.055]	[0.055]	[0.055]	[0.055]	[0.055]
Dependent-variable mean	3.650	3.650	3.650	3.650	3.650	3.650
Panel B. replace cluster hierarchy (2SLS)	*Individual*	*County – year*	*County*	*Prefecture – year*	*Province – year*	*Province*
Robot exposure	0.315***	0.315**	0.315**	0.315**	0.315**	0.315*
	(0.076)	(0.127)	(0.137)	(0.133)	(0.150)	(0.163)
Standardized	[0.061]	[0.061]	[0.061]	[0.061]	[0.061]	[0.061]
Panel C. winsorization	*Winsorize 1%*		*Winsorize 5%*		*Winsorize 10%*	
	OLS	2SLS	OLS	2SLS	OLS	2SLS
Robot exposure	0.320***	0.329**	0.327***	0.374**	0.326***	0.399***
	(0.109)	(0.130)	(0.118)	(0.146)	(0.120)	(0.153)
Standardized	[0.061]	[0.062]	[0.060]	[0.068]	[0.055]	[0.068]
Dependent-variable mean	3.650	3.650	3.650	3.650	3.688	3.688
Controls	✓	✓	✓	✓	✓	✓
Predetermined control # year dummy	✓	✓	✓	✓	✓	✓
Individual FE	✓	✓	✓	✓	✓	✓
Province-year FE	✓	✓	✓	✓	✓	✓
Observations	110,495	110,495	110,495	110,495	110,495	110,495

Notes: Table A23 reports the regression results after replacing cluster hierarchy and excluding outliers using the CFPS dataset. ***p < 0.01, **p < 0.05, *p < 0.1. Standardized coefficients in brackets indicate the effect of a one-s.d. increase in the explanatory variable on the outcome. The dependent variable is SWB, with the key explanatory variable being robot exposure. Panels A and B respectively report the results using different cluster hierarchies with OLS regression and 2SLS regression. Panel C reports the results after excluding outliers. All regressions include the same controls and FEs as the baseline.

C.4 More on Heterogeneity

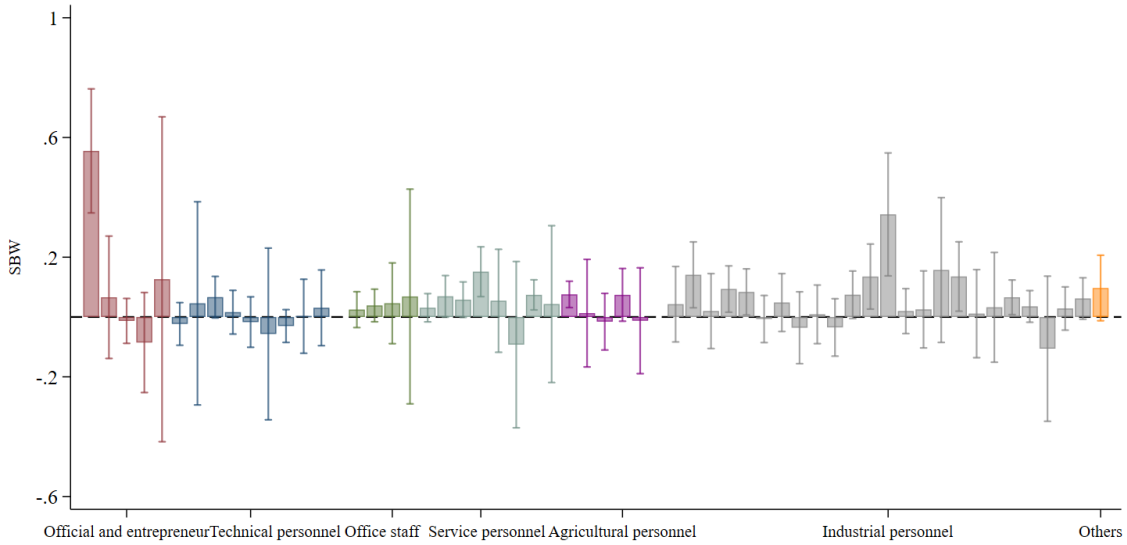


FIGURE A8 The impact of automation on SWB across occupations (second category).

Notes: Figure A8 plots the impact of automation on SWB across occupations (second category). All the regressions use 2SLS specification in Equation 4 and Equation 5. Standard errors in parentheses are two-way clustered at the prefecture-year level. Columns indicate the effect of a one-s.d. increase in the explanatory variable on the outcome. From left to right, the categories are officials and entrepreneurs, technical personnel, office staff, service personnel, agricultural personnel, industrial personnel, and others. The dependent variable is SWB while the key explanatory variable is robot exposure. Confidence interval is at 90% level. All regressions include the same controls and FEs as the baseline.

Appendix D More on Mechanism

D.1 Mechanisms and Happiness

D.2 Income Effects

TABLE A24 Mechanism: income effects–impact of automation on price level and income

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Unweighted				Weighted by population			
	Price level	Wage per capita			Price level	Wage per capita		
	Prefecture CPI	Raw	Adjusted by Prefecture CPI	Adjusted by Province CPI	Prefecture CPI	Raw	Adjusted by Prefecture CPI	Adjusted by Province CPI
Panel A. OLS								
Robot exposure	0.374**	25017.949***	23792.450***	24953.578***	0.393**	27207.317***	25790.982***	27089.093***
	(0.158)	(5475.149)	(5537.460)	(5400.279)	(0.175)	(5202.771)	(5228.748)	(5128.929)
Standardized	[0.073]	[4309.311]	[4177.860]	[4302.614]	[0.077]	[4686.427]	[4528.794]	[4670.829]
Panel B. 2SLS								
Robot exposure	0.446**	28925.895***	27189.557***	28475.578***	0.506**	31105.676***	29304.888***	30625.764***
	(0.191)	(6109.825)	(6163.561)	(6007.580)	(0.212)	(5814.672)	(5845.919)	(5730.260)
Standardized	[0.087]	[4982.451]	[4774.378]	[4909.893]	[0.099]	[5357.915]	[5145.822]	[5280.638]
Predetermined control # year	✓	✓	✓	✓	✓	✓	✓	✓
Prefecture FE	✓	✓	✓	✓	✓	✓	✓	✓
Province-year FE	✓	✓	✓	✓	✓	✓	✓	✓
Dependent-variable mean	102.653	39386.817	39841.157	38492.631	102.653	39386.817	39841.157	38492.631
Observations	3,176	3,127	2,919	3,116	3,176	3,127	2,919	3,116

Notes: Table A24 presents estimation results of the impact of automation on price level and income using prefecture-year panel data. ***p < 0.01, **p < 0.05, *p < 0.1. Standard errors in parentheses are clustered at the prefecture level. Standardized coefficients in brackets indicate the effect of a one-s.d. increase in the explanatory variable on the outcome. The dependent variables from columns (1) to (8) are prefecture CPI, wage per capita with different adjustments, respectively. The explanatory variable is robot exposure. Panel A reports the OLS estimation results while Panel B reports the 2SLS estimation results. All regressions apply the same predetermined controls as baseline, prefecture FE and province-year FE.

D.3 Leisure and Health Effects

TABLE A25 Mechanism: leisure and health effects–self-fulfilling activity 1

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Read books			Watch TV			Exercise			Surf the internet		
	Yes=1	Raw	Logged	Yes=1	Raw	Logged	Yes=1	Raw	Logged	Yes=1	Raw	Logged
Panel A. OLS												
Robot exposure	0.116***	0.118	0.156***	0.083**	1.955	0.227*	0.317***	1.435***	0.451***	0.073**	4.158***	0.559***
	(0.025)	(0.474)	(0.041)	(0.034)	(1.234)	(0.126)	(0.065)	(0.382)	(0.112)	(0.035)	(0.773)	(0.102)
Standardized	[0.023]	[0.024]	[0.031]	[0.017]	[0.392]	[0.046]	[0.062]	[0.280]	[0.088]	[0.015]	[0.830]	[0.112]
Panel B. 2SLS												
Robot exposure	0.139***	0.483	0.199***	0.080**	2.201	0.222	0.348***	1.611***	0.507***	0.095***	4.691***	0.642***
	(0.028)	(0.394)	(0.042)	(0.040)	(1.493)	(0.149)	(0.068)	(0.394)	(0.116)	(0.035)	(0.810)	(0.108)
Standardized	[0.028]	[0.097]	[0.040]	[0.016]	[0.441]	[0.044]	[0.068]	[0.315]	[0.099]	[0.019]	[0.937]	[0.128]
Controls	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Predetermined control # year	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Individual FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Province-year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Dependent-variable mean	0.154	1.071	0.238	0.900	11.731	2.155	0.558	2.317	0.829	0.302	3.257	0.618
Observations	80,250	80,250	80,250	90,006	90,006	90,006	83,110	83,110	83,110	87,671	87,536	87,536

Notes: Table A25 presents the impact of automation on various self-fulfilling activities using the CFPS dataset. ***p < 0.01, **p < 0.05, *p < 0.1. Standard errors in parentheses are two-way clustered at the prefecture-year level. Standardized coefficients in brackets indicate the effect of a one-s.d. increase in the explanatory variable on the outcome. From columns (1) to (12), dependent variables are the number of books read per year (binary, raw and logged), hours spent watching TV per week (binary, raw and logged), hours spent exercising per week (binary, raw and logged), and hours spent online per day (binary, raw and logged), respectively. The explanatory variable is robot exposure. Panel A reports the OLS estimation results while Panel B reports the 2SLS estimation results. All regressions include the same controls and FEs as the baseline.

TABLE A26 Mechanism: leisure and health effects–self-fulfilling activity 2

	(1) Watch TV	(2) Watch Movies	(3) Go Shopping	(4) Read books	(5) Watch shows	(6) Meet with friends	(7) Listen to musics	(8) Do exercise	(9) Watch sports games	(10) Do handicrafts	(11) Surf the Internet
Panel A. OLS											
Robot exposure	0.261	0.147	0.819*	0.687**	0.004	0.896***	0.016	1.217***	0.064	0.431*	0.583**
	(0.302)	(0.236)	(0.428)	(0.307)	(0.230)	(0.343)	(0.394)	(0.410)	(0.235)	(0.261)	(0.278)
Standardized	[0.024]	[0.014]	[0.077]	[0.064]	[0.000]	[0.084]	[0.002]	[0.114]	[0.006]	[0.040]	[0.055]
Panel B. 2SLS											
Robot exposure	0.383	0.083	0.764*	0.485	-0.168	0.768**	-0.274	1.130***	0.101	0.635**	0.611**
	(0.303)	(0.227)	(0.446)	(0.312)	(0.247)	(0.360)	(0.399)	(0.427)	(0.284)	(0.268)	(0.285)
Standardized	[0.036]	[0.008]	[0.071]	[0.045]	[-0.016]	[0.072]	[-0.026]	[0.106]	[0.009]	[0.059]	0.057]
Controls	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
FEs	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Dependent-variable mean	4.432	1.362	2.605	2.279	1.425	2.338	2.326	2.169	1.398	1.423	2.229
Observations	47,667	47,578	47,627	47,526	47,548	47,636	47,550	47,565	47,527	47,583	47,623

Notes: Table A26 presents the regression results of the impact of automation on self-fulfilling activities in leisure time using the Chinese General Social Survey (CGSS) dataset. ***p < 0.01, **p < 0.05, *p < 0.1. Standard errors in parentheses are two-way clustered at the prefecture-year level. Standardized coefficients in brackets indicate the effect of a one-s.d. increase in the explanatory variable on the outcome. The dependent variables are the frequencies of a series of activities (scale 1-5), while the explanatory variable is robot exposure. Panel A reports the OLS estimation results while Panel B reports the 2SLS estimation results. All the regressions include the same controls as baseline, prefecture FE, and province-year FE.

D.4 Discussion: Decomposition and Heterogeneity

TABLE A27 Mechanism: decomposition of mechanisms

Dependent variable:	(1) Across income: Mean SWB	(2) Across leisure: Mean SWB	(3) Across health: Mean SWB	(4) Across self-identification: Mean SWB	(5) Within all categories: Mean SWB
Robot exposure	0.142***	0.048***	0.034**	0.043*	0.046
	(0.055)	(0.016)	(0.016)	(0.022)	(0.091)
Bootstrap standard error	<0.037>***	<0.010>***	<0.018>***	<0.018>**	<0.075>
Share of the effect	45.3%	15.3%	10.9%	13.8%	14.7%
Observations	52,444	52,444	52,444	52,444	52,444
Controls	✓	✓	✓	✓	✓
Predetermined control × year	✓	✓	✓	✓	✓
Individual FE	✓	✓	✓	✓	✓
Province-year FE	✓	✓	✓	✓	✓

Notes: Table A27 shows the decomposition of the total effect of automation on SWB. The data is drawn from CFPS 2010-2018 and no outcome variable exhibits any missing values. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$. All the regressions use 2SLS specification in Equation 4 and Equation 5 (all OLS estimations yield nearly consistent results). Standard errors in parentheses are two-way clustered at the prefecture-year level while those in angle brackets are from the wild cluster bootstrap (500 times). The dependent variable is individual SWB across different mechanisms while the key explanatory variable is robot exposure. Column 1 shows the effect of automation in each income level, which measures the increase in SWB associated with movements across quantiles of the distribution of annual income. Column 2 shows the effect in each level of weekly leisure time, which measures the increase in SWB associated with movements across quantiles of the distribution of weekly leisure hours. Column 3 shows the effect in each level of health status (ranked with 1-7), measuring the increase in SWB associated with movements across septiles of the general health status. Column 4 shows the effect for different degrees of self-identification (self-confidence, ranked with 1-5), measuring the increase in SWB associated with movements across quantiles of self-identification. Column 5 shows the effect of automation on the distance between individual SWB and the average SWB within all the previous categories, which measures the residual component of the increase in SWB generated by automation that is not explained by variation in the previous categories. All regressions include the same controls and FEs as the baseline.

D.5 Extension: Transformation towards Individualism

TABLE A28 Mechanism: individualism–independence

	(1) Things children do	(2) Live alone	(3)	(4)	(5)	(6)
			Child maintenance concept			
			Elderly self-care	Government care	Child care	Joint care
Panel A. OLS						
Robot exposure	-0.202***	1.013***	0.123**	-0.005	-0.166	0.076
	(0.069)	(0.294)	(0.058)	(0.066)	(0.176)	(0.187)
Standardized	[-0.044]	[0.034]	[0.012]	[-0.000]	[-0.016]	[0.007]
Panel B. 2SLS						
Robot exposure	-0.123*	1.012***	0.103*	0.028	-0.149	0.046
	(0.059)	(0.068)	(0.059)	(0.067)	(0.187)	(0.194)
Standardized	[-0.027]	[0.034]	[0.010]	[0.003]	[-0.014]	[0.004]
Controls	✓	✓	✓	✓	✓	✓
FEs	✓	✓	✓	✓	✓	✓
Dependent-variable mean	0.320	0.728	0.045	0.081	0.459	0.293
Observations	18,660	7,031	47,766	47,766	47,766	47,766
Dataset	CFPS	CSS	CGSS	CGSS	CGSS	CGSS

Notes: Table A28 presents the results of the impact of automation on parent-child relationship using CFPS, China Social Survey (CSS) dataset (2011), and Chinese General Social Survey (CGSS) dataset. ***p < 0.01, **p < 0.05, *p < 0.1. Standard errors in parentheses are two-way clustered at the prefecture-year level. Standardized coefficients in brackets indicate the effect of a one-s.d. increase in the explanatory variable on the outcome. The dependent variables from columns (1) to (6) are things children do for parents (scale 0-4), willingness to live alone (binary), and a series of dummies indicating the child's choice of maintenance to parents (elderly self-care, government care, child care, and joint care), respectively. The key explanatory variable is robot exposure. Panel A reports the OLS estimation results while Panel B reports the 2SLS estimation results. All the regressions include the same controls as baseline. Column (1) controls individual and province-year FE while column (2) controls province FE. Columns (3) to (6) include prefecture and province-year FE.

TABLE A29 Mechanism: individualism–who to ask for help?

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Kindred Support		Social Support				
	Family	Clan	Government	Workplace	Friend	Charity	Media
Panel A. OLS							
Robot exposure	-0.107	-0.107	0.215	0.159	0.349*	0.105***	0.160***
	(0.117)	(0.257)	(0.180)	(0.096)	(0.187)	(0.039)	(0.060)
Standardized	[-0.006]	[-0.006]	[0.012]	[0.009]	[0.020]	[0.006]	[0.009]
Panel B. 2SLS							
Robot exposure	-0.108	-0.107	0.216	0.159*	0.350*	0.105***	0.159***
	(0.117)	(0.257)	(0.180)	(0.096)	(0.187)	(0.039)	(0.060)
Standardized	[-0.006]	[-0.006]	[0.012]	[0.009]	[0.020]	[0.006]	[0.009]
Controls	✓	✓	✓	✓	✓	✓	✓
FEs	✓	✓	✓	✓	✓	✓	✓
Dependent-variable mean	0.859	0.409	0.153	0.103	0.674	0.020	0.051
Observations	10,148	10,128	10,121	10,117	10,142	10,110	10,112

Notes: Table A29 presents the estimation results of the impact of automation on who to turn to for help when encountering trouble using China Social Survey (CSS) dataset (2013). ***p < 0.01, **p < 0.05, *p < 0.1. Standard errors in parentheses are clustered at the prefecture level. Standardized coefficients in brackets indicate the effect of a one-s.d. increase in the explanatory variable on the outcome. The dependent variables are a series of objective dummies including family, clan, government, workplace, friend, charity, and media, respectively, with the key explanatory variable being robot exposure. Panel A reports the OLS estimation results while Panel B reports the 2SLS estimation results. All the regressions include the same controls as baseline and province FE.

TABLE A30 Mechanism: individualism–kindred and social linkage

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Frequency of visits				Relationship index			
	Binary		Continuous		Ordinal		Binary	
	Relative	Neighbor	Relative	Neighbor	Relative	Neighbor	Relative	Neighbor
Panel A. OLS								
Robot exposure	-3.624***	-1.188	-1.581**	-0.295	-12.827*	-8.381	-4.101	-2.346
	(1.372)	(2.089)	(0.630)	(0.757)	(6.580)	(6.814)	(2.796)	(2.447)
Standardized	[-0.091]	[-0.030]	[-0.040]	[-0.007]	[-0.324]	[-0.212]	[-0.104]	[-0.059]
Panel B. 2SLS								
Robot exposure	-3.295**	-0.639	-1.453**	-0.153	-11.824*	-6.512	-3.825	-1.852
	(1.425)	(2.126)	(0.661)	(0.765)	(6.648)	(6.853)	(2.857)	(2.441)
Standardized	[-0.083]	[-0.016]	[-0.037]	[-0.004]	[-0.298]	[-0.164]	[-0.097]	[-0.047]
Controls	✓	✓	✓	✓	✓	✓	✓	✓
FEs	✓	✓	✓	✓	✓	✓	✓	✓
Dependent-variable mean	0.790	0.653	0.417	0.265	3.320	4.291	1.639	1.555
Observations	28,022	28,033	28,040	28040	27,997	27,993	28,040	28,040

Notes: Table A30 presents the estimation results of the impact of automation on kindred and social linkage using the CFPS dataset (2010). ***p < 0.01, **p < 0.05, *p < 0.1. Standard errors in parentheses are clustered at the prefecture level. Standardized coefficients in brackets indicate the effect of a one-s.d. increase in the explanatory variable on the outcome. The dependent variables from columns (1) to (8) are frequency of visits (scale 0-4), relationship index (ordinal setting, scale 0-20; binary setting, scale 0-5), respectively for relatives and neighbors. The explanatory variable is robot exposure. Panel A reports OLS results while Panel B reports 2SLS results. All the regressions include the same controls as baseline and province FE. More on the measurement about relationship index, see subsubsection A.2.5.

TABLE A31 Mechanism: individualism– political apathy

	(1)	(2)	(3)	(4)	(5)	(6)
	Interest in politics		View political news		Political Awareness	
	OLS	2SLS	OLS	2SLS	OLS	2SLS
Robot exposure	-0.285***	-0.285***	-0.139***	-0.138***	-0.424	-0.425
	(0.060)	(0.060)	(0.048)	(0.048)	(0.373)	(0.372)
Standardized	[-0.069]	[-0.069]	[-0.034]	[-0.033]	[-0.102]	[-0.103]
Controls	✓	✓	✓	✓	✓	✓
FEs	✓	✓	✓	✓	✓	✓
Dependent-variable mean	3.565	3.565	3.006	3.006	4.280	4.280
Observations	2363	2363	2363	2363	2363	2363

Notes: Table A31 presents the estimation results of the impact of automation on political apathy using Ideology Survey of Chinese Internet Users (ISCIU) dataset (2017). ***p < 0.01, **p < 0.05, *p < 0.1. Standard errors in parentheses are clustered at the prefecture level. Standardized coefficients in brackets indicate the effect of a one-s.d. increase in the explanatory variable on the outcome. The dependent variables are interest in politics (scale 1-5), frequency of viewing political news (scale 1-4), and political participation awareness (scale 0-10), respectively. Columns (1), (3), (5) show OLS results while others present 2SLS estimate results. The explanatory variable is robot exposure. All the regressions include the same controls as baseline and province FE.

Appendix E Model: Automation and SWB

E.1 Settings

Consider a closed economy, with preferences defined over an aggregate of the output of $|\mathcal{I}|$ industries, given by:

$$Y = \left(\sum_{i \in \mathcal{I}} \alpha_i Y_i^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}}, \tag{A1}$$

where $\sigma > 0$ denotes the elasticity of substitution across goods and α_i is the share parameter designating the importance of sector i in the economy (with $\sum_{i \in \mathcal{I}} \alpha_i = 1$).

In the autarky equilibrium, the economy consumes its own production of each good, denoted by X_i. Hence, we have $Y_{ci} = X_{ci}, \forall i \in \mathcal{I}$. We choose the consumption aggregate as numeraire (with price normalized to one) and denote the price of the output of sector i by P_{X_i}. Each sector produces output by a continuum of tasks indexed by $s \in [0, 1]$, each of which can be produced using industrial robots or human labor. We use $x_i(s)$ to denote the quantity of task s utilized in the production of X_i, which produces X_i in fixed proportions so that:

$$X_i = A_i \min_{s \in [0,1]} \{x_i(s)\}, \tag{A2}$$

where A_i represents the productivity of sector i.

Following Acemoglu and Restrepo (2020); Beraja and Zorzi (2024), we consider two types of tasks. The first task can be automated (e.g., a low-skilled, routine-intensive occupation, $s \in [0, \theta_i]$) and can be performed by robots, whereas the second cannot ($s \in (\theta_i, 1]$). Industrial robots replace workers in some of the tasks that they were previously performing. Specifically, in sector i, tasks are technologically automated and can be performed by robots. We assume that all commuting zones have access to the same technology-that is, the same v_i in sector i. Denoting the productivity of labor by g_L and the productivity of robots by $g_M > 0$, we have:

$$x_i(s) = \begin{cases} g_M M_i(s) + g_L L_i(s) & \text{if } s \leq \theta_i, \\ g_L L_i(s) & \text{if } s > \theta_i, \end{cases} \tag{A3}$$

where $L_i(s)$ and $M_i(s)$ represent, respectively, the numbers of workers and robots used in task s. Because tasks above θ_i have not yet been technologically automated, they must be performed by labor. Therefore, the demands for labor and robots in task s is given by $L_i(s), M_i(s)$ respectively.

Each consumer j consumes product $C_j = C(X_{1j}, ..., X_{Ij})$ and supply labor L_j with preferences

$$U(C_j, L_j) = \frac{C_j^{1-\omega}}{1-\omega} - \frac{B L_j^{1+\epsilon}}{1+\epsilon}, \tag{A4}$$

where X_{ij} denotes consumer j's consumption in output X_i, C_j is the aggregate consumption, L_j represents its labor supply, B is a constant, ω determines the income elasticity of labor supply, and ϵ is the inverse of the wage elasticity of labor supply. Finally, household consumption is bounded by the budget constraint $P^c C_j \leq P^l L_j$, where P^c is the hypothetical price of the aggregate consumption (e.g., the Consumer Pricing Index). For all good X_i, holding other $P_{X_j}, j \neq i$ fixed, P^c should be increasing in P_{X_i}. Household optimization yields

$$L_j = p^{\frac{1-\omega}{\omega+\epsilon}} / B^{\frac{1}{\omega+\epsilon}}, \quad C_j = p^{\frac{1+\epsilon}{\omega+\epsilon}} / B^{\frac{1}{\omega+\epsilon}}, \quad U_j = p^{\nu} / \nu B^{\frac{\nu}{1+\epsilon}}, \tag{A5}$$

where $\nu = \frac{(1+\epsilon)(1-\omega)}{\omega+\epsilon}$ is a constant, $p = P^l/P^c$ is the relative wage.

As for the supply of robot units, we just assume a supply curve $M^k = m(P^m)^{1/\eta}$. The upward sloping comes from the fact that robots are produced using both scarce skills and materials, which causes increasing marginal cost. An equilibrium is defined as a set of prices P^c, P^l, P^m and quantities L, M, Y such that firms maximize profits, labor and robot supplies are given by , and the markets for labor, robots, and goods clear, i.e.,

$$\sum_{i\in\mathcal{I}}\int_0^1 L_i(s)ds = L = \sum_{j\in\mathcal{J}} L_j, \quad \sum_{i\in\mathcal{I}}\int_0^1 M_i(s)ds = M = M^k, \quad \sum_{i\in\mathcal{I}} X_i = Y = \sum_{j\in\mathcal{J}} C_j. \tag{A6}$$

The existence and uniqueness of the equilibrium are given by Acemoglu and Restrepo (2020).

E.2 Partial Equilibrium Analysis

To analyze the equilibrium impact of robots, we define cost savings from using robots as:

$$\pi = 1 - \frac{g_L P^m}{g_M P^l}. \tag{A7}$$

Robots will not be adopted when $\pi < 0$, so we focus on the case where $\pi > 0$.

Cost minimization for the final product implies that, for each $i \in \mathcal{I}$,

$$X_i = Y_i = (\alpha_i/P_{X_i})^\sigma Y. \tag{A8}$$

In turn, cost minimization for the production of X_i yields the demands for labor and robots as

$$L_i(s) = \begin{cases} 0 & s \le \theta_i \\ \frac{X_i}{A_i g_L} & s > \theta_i \end{cases}, \quad M_i(s) = \begin{cases} \frac{X_i}{A_i g_M} & s \le \theta_i \\ 0 & s > \theta_i \end{cases}. \tag{A9}$$

After aggregation across tasks, the demand for labor and robots in sector i are

$$L_i = \frac{(1-\theta_i)X_i}{A_i g_L}, \quad M_i = \frac{\theta_i X_i}{A_i g_M}. \tag{A10}$$

After aggregating across all industries yields the total labor and robot demand

$$L^d = \sum_{i\in\mathcal{I}} \frac{1-\theta_i}{A_i g_L}(\alpha_i/P_{X_i})^\sigma Y, \quad M_d = \sum_{i\in\mathcal{I}} \frac{\theta_i}{A_i g_M}(\alpha_i/P_{X_i})^\sigma Y. \tag{A11}$$

We could directly derive the partial equilibrium impact of an advance in automation/robotics technology for sector i, denoted by $d\theta_i$, on labor demand.

$$d\ln L^d = -\sum_{i\in\mathcal{I}} l_i \frac{d\theta_i}{1-\theta_i} - \sigma \sum_{i\in\mathcal{I}} l_i d\ln P_{X_i} + d\ln Y, \tag{A12}$$

where l_i refers to the employment ratio of sector i. Thus, $\frac{\partial \ln L^d}{\partial \theta_i} < 0$, summarized in the following proposition.

Proposition A1 *In partial equilibrium, robot penetration may reduce labor demand and give rise to unemployment.*

E.3 General Equilibrium Analysis

Since the equilibrium prices should equal unit costs, we have

$$P_{X_i} = \frac{(1-\theta_i)P^l}{A_i g_L} + \frac{\theta_i P^m}{A_i g_M} = \frac{(1-\theta_i)pP^c}{A_i g_L} + \frac{\theta_i P^m}{A_i g_M}. \tag{A13}$$

Combined with Equation A6, we could derive the full relationship between the prices.

$$\begin{cases} \sum_{i\in\mathcal{I}} \frac{1-\theta_i}{A_i g_L}(\alpha_i/P_{X_i})^\sigma Y & = Jp^{\frac{1-\omega}{\omega+\epsilon}}/B^{\frac{1}{\omega+\epsilon}} \\ \sum_{i\in\mathcal{I}} \frac{\theta_i}{A_i g_M}(\alpha_i/P_{X_i})^\sigma Y & = M^k \\ Y & = Jp^{\frac{1+\epsilon}{\omega+\epsilon}}/B^{\frac{1}{\omega+\epsilon}} \\ P_{X_i} & = \frac{(1-\theta_i)pP^c}{A_i g_L} + \frac{\theta_i P^m}{A_i g_M}. \end{cases} \tag{A14}$$

Hence, we have the following relation between the relative wage and robot penetration.

$$\begin{cases} \sum_{i\in\mathcal{I}} \frac{-d\theta_i}{A_i g_L}(\alpha_i/P_{X_i})^\sigma - \frac{\sigma(1-\theta_i)}{A_i g_L}\frac{(\alpha_i/P_{X_i})^\sigma dP_{X_i}}{P_{X_i}} & = \frac{-dp}{p^2} \\ -d\theta_i pP^c + (1-\theta_i)(P^c dp + p\beta_i dP_{X_i}) & = A_i g_L dP_{X_i} \end{cases} \tag{A15}$$

Solving the equations, we have

$$\frac{dp}{d\theta_i} = \frac{\sum_i \left(\frac{\kappa_i}{A_i g_L} - \frac{\sigma pP^c(1-\theta_i)\kappa_i}{A_i g_L P_{X_i}\Omega_i}\right)}{\frac{1}{p^2} - \sum_i \frac{\sigma P^c(1-\theta_i)^2\kappa_i}{A_i g_L P_{X_i}\Omega_i}} = \frac{\sum_i \left(\frac{\kappa_i}{A_i g_L} - \frac{\sigma pP^c(1-\theta_i)\kappa_i}{A_i g_L P_{X_i}\Omega_i}\right)}{(\sum_i \frac{1-\theta_i}{A_i g_L}\kappa_i)^2 - \sum_i \frac{\sigma P^c(1-\theta_i)^2\kappa_i}{A_i g_L P_{X_i}\Omega_i}}, \tag{A16}$$

where $\Omega_i = A_i g_L - p\beta_i(1-\theta_i) = A_i g_L - \frac{\beta_i(1-\theta_i)}{\sum_{i\in\mathcal{I}}\frac{1-\theta_i}{A_i g_L}\kappa_i}$ denotes the technological advantage of sector i, $\kappa_i = (\alpha_i/P_{X_i})^\sigma < 1$ denotes the relative weight of product Y_i in total production Y. Generically, $\frac{dp}{d\theta_i} > 0$, which means more robot penetration brings higher relative wages.[2]

From Equation A5, we have $\frac{dU_j}{dp} = p^{\nu-1}/B^{\frac{\nu}{1+\epsilon}} > 0$. Thus, $\frac{dU_j}{d\theta_i} > 0$, which shows that automation improves welfare. The following proposition sums up our findings.

Proposition A2 *Under generic conditions, robot penetration can raise wages and income, thus improving individual welfare.*

2. The condition holds as long as $\Omega_i < 0$ or $\Omega_i > \bar{K}$. When $|\mathcal{I}| = 1$ e.g., $\Omega_i = \frac{(\kappa_i-1)A_i g_L}{\kappa_i} < 0$.