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# **ROBOTS, LABOR MARKET OUTCOMES AND LIFE SATISFACTION: EVIDENCE FROM SOUTH KOREA**

Joop Adema, Jae Cho, and Nourhan Hashish

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**SCIENCES PO ECONOMICS DISCUSSION PAPER**

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No. 2025-03

# Robots, Labor Market Outcomes and Life Satisfaction: Evidence from South Korea <sup>\*</sup>

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March 26, 2025

## Abstract

This paper investigates the impact of South Korea’s rapid robotization, driven by the country’s proactive robotization policies, on subjective well-being using individual and household-level panel data. We measure individual exposure to robotization by estimating the probability that individuals work in occupations susceptible to robotization. This approach allows us to study the effect of robotization at the individual level, including the unemployed and indirectly affected workers. Our findings indicate that the initial phase of automation adversely affected workers. However, this negative impact diminished during the subsequent phase of automation. This suggests that once workers adapt to an environment integrated with robots, they begin to experience the benefits of automation.

*Keywords:* Robot adoption, job displacement, life satisfaction, industrial policy

*JEL:* D10, I31, J01, 014

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<sup>\*</sup>We would like to thank Nadzeya Laurentsyeva for valuable comments. All remaining errors are our own.

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# 1 Introduction

Robot adoption is expected to significantly enhance firms productivity because they can perform increasingly complex tasks efficiently and at a rapid pace compared with human workers (Bonfiglioli et al., 2024). On the other hand, workplace robotization could raise concerns about the quality of lives of the workers manifested in their life satisfaction. Considering that a strong positive relationship between life satisfaction and job experience has been found (Heller et al., 2002), increasing robot adoption at work is expected to have an effect on workers' life satisfaction. For example, a worker's life satisfaction could be changed as a result of robotization directly impacting their labor market outcomes (e.g., workers may lose their jobs to robots and this loss can significantly impact their life satisfaction). Furthermore, due to the subjective nature of life satisfaction, the psychological effects of robotization (e.g., fear of losing their jobs in the future, feelings of incompetence when compared to robots, etc.) could also reduce a worker's life satisfaction even if there is no actual impact on the workers wages or employment status.<sup>1</sup>

With the rise of automation technologies, previous studies have extensively explored the changes in the labor market outcomes due to robotization. Economists have assessed the effects of robot technologies on labor market outcomes in a variety of settings and found evidence for two countervailing effects: a displacement effect and a productivity effect. Acemoglu and Restrepo (2020) confirm that as specific tasks are transferred from workers to industrial robots, part of the workforce is displaced from their job. On the other hand, robotization enables workers who are not displaced to be more productive, or to produce novel products (Hirvonen et al., 2022). Furthermore, re-allocation of workers at the manufacturing sectors is witnessed in the case of Germany as the number of routine jobs in manufacturing sector decreases (Dauth et al., 2021). While evidence shows that there are pros and cons to robotization that can impact anyone (Acemoglu and Restrepo, 2020), multiple papers document that negative effects are more pronounced for young workers (Chiacchio et al., 2018) and labor market entrants (Dauth et al., 2021).

Amongst numerous studies evaluating the effect of robots on labor market outcomes, only a few of them were able to expand their scope of study to explore the effect of robotization on life satisfaction. This is primarily due to data limitations since the robot data sources used in previous studies are only defined at the sector or country level.<sup>2</sup> In addition, most of the literature examining the relationship between robotization and life satisfaction do not provide causal evidence. Instead, they rather focus their studies on countries with a relatively low density of industrial robots and much lower adoption rates (in terms of per 1000 workers) than South Korea (Gihleb et al., 2020; Schwabe and Castellacci, 2020).

In an attempt to overcome previous data limitations, we construct an individual-level exposure to robot, based on Anelli et al. (2021) and Graetz and Michaels (2018). Our exposure to robots measure is a proxy measure for distance to replaceable occupations. This proxy measure was chosen because both individuals working directly in replaceable occupations and those who are likely (based on demographic characteristics) to work in replaceable occupations may be affected by robotization. Additionally, we make a methodological contribution by adjusting the approach of Anelli (2019) to predict individual-level *replaceability* of employees in the base period, using occupation-level replaceability as is done in Graetz and Michaels (2018). This

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<sup>1</sup>If the displacement effect is stronger than the productivity effect then workers will lose their jobs and therefore life satisfaction will be negatively correlated with robotization.

<sup>2</sup>As the exposure measures are defined in the sector or country level, the previous studies, therefore, present the life satisfaction changes in an aggregated level. (Gihleb et al., 2020; Schwabe and Castellacci, 2020; Hinks, 2021)

measure of replaceability is based on the overlap between occupational titles and robot application as defined by the International Federation of Robotics (IFR). Although it is a very simple approach, it predicts robot adoption well.<sup>3</sup> Naturally, our robot exposure indicator allows us to investigate the life satisfaction of an individual by virtue of measuring robot exposure in an individual-occupation level.<sup>4</sup>

Information on individual’s life satisfaction is collected from the Korean Labor Income and Panel Study (KLIPS, hereafter). KLIPS provides us not only with individual level labor market outcomes, including employment and wage which allows us to observe the potential channels of the effect of robotization on worker’s life satisfaction, but also with the survey inquiring about individuals’ life satisfaction during our observation period. A linking of our exposure measure to the detailed individual level information from KLIPS, allows us to finally be able to provide a causal evidence of the effect of robotization on life satisfaction.

Our empirical strategy extends to the potentially most affected workers. Prior literature confirmed that the manufacturing sector is an industry that has the highest robot adoption rate as well as the highest male labor force participation rate; this is also applicable to the South Korean case.<sup>5</sup> As robotization primarily affects the earnings and job security of the (male) household head, this in turn may affect the labour supply decisions made by the spouse. Therefore, we also study the labor market position and life satisfaction of spouses. These spouses are typically out of the labor force, work in part-time jobs, or work in low-paid occupations in South Korea. This is of particular interest, as previous work has shown that robots strengthen the position of incumbent laborers in firms (household heads or males in our study) (Dauth et al., 2021), and weakens that of potential entrants (spouses or females).<sup>6</sup> Therefore, we believe we are the first to find to demonstrate the indirect effect of household head’s exposure to robotization on their spouse’s life satisfaction as well as economic activities.

The current research explores the South Korean case. In previous studies, the government’s role in fostering/controlling investments in robot-producing and robot-adopting industries was overlooked. This is simply because governments did not actively pursue policies specifically oriented towards industrial robots until recently. In 2005 the South Korean government launched the official support for intelligent and industrial robot industry, creating the systematic base for the industry in South Korea. The *Intelligent Robots Development and Distribution Promotion Act* introduced in 2009 gave the government wide-reaching abilities to spur robot development and adoption. The law aims at improving work conditions, increasing productivity and ultimately raising individuals’ life satisfaction. The statement of purpose of this law reads: “The purpose of this Act is to contribute to enhancing the quality of life of citizens and the national economy by establishing and promoting a policy on the sustainable development of the intelligent robot industry to facilitate the development and distribution of intelligent robots and lay down the foundation therefore.”<sup>7</sup> This law entailed a wide set of measure, aimed at extending the use of robots in various industries. Therefore, the Korean government policies successfully led to the strong adoption of industrial robots over the past 15 years. In 2019, the number of industrial robots per thousand workers exceeded 10, which makes South Korea

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<sup>3</sup>Graetz and Michaels (2018) map the share of employment replaceable by robots to the country-industry level and use it as an Instrumental Variable for robot adoption across countries.

<sup>4</sup>For a detailed explanation, please refer to Section 4.

<sup>5</sup>See appendix

<sup>6</sup>Although a household head could be also female, in this paper we refer to the household head as male and the spouse as female, as coded in the Korean labor force survey which reflects the secondary position of women in the labor market. For a characterization of the South Korean labor market, see section 4

<sup>7</sup>For more on this law, we refer the reader to section 3 and the Act itself available at Center (2024).

the country with the highest level of robot adoption in the world.<sup>8</sup> In light of all these facts, we focus on two distinct time periods as our two exogenous shocks: between 2005 and 2009, when robot innovation (as measured by the number of patents) was strong and a new legislation was announced and after 2009, when the rate of robot adoption increased strongly due to the legislation.

Along with the fact that South Korea is a front-runner in robot adoption policy, the strong labor market challenges facing South Korea make the country an interesting set-up for the unprecedented adoption of robots during the past 15 years. South Korea has a rapidly declining workforce<sup>9</sup>, as strong increase in educational attainment of the available workforce<sup>10</sup>, an increase in flexible work arrangements<sup>11</sup>, and a large gap in pay between men and women<sup>12</sup> which are the challenges that other developed countries also face (to a lesser extent).<sup>13</sup> Considering that other countries followed the example of South Korea recently, strongly investing in automation technologies<sup>14</sup>, we expect that studying the South Korean case will teach the countries whose governments begin to allocate their investments in the field of robotics.

We find that the strong robotization of South Korea’s industries improved life satisfaction for workers at the aggregate level due to improvements in their employment status while it had no impact on their wages. The effect size we find between 2009 and 2019 is modest and statistically significant: a one standard deviation in individual-level robot exposure decreased life satisfaction by -0.04 points (on a scale of -1 to 1). This result is equivalent to that of a percentage increase in log wage that leads to a 0.023 unit increase in life satisfaction. We investigate heterogeneous labor market outcomes and work conditions channels conducive to the main results. We find that males aged 20-29 who have a tertiary education and above are the ones driving our main results. We disentangle the mechanisms further by education levels and find that the low and vocationally educated individuals are the ones prone to the displacement effect. This is due to the prevalence of part-time jobs (a proxy for low-quality jobs) and the firm switch variable respectively in the onset of robotization at work from 2005 to 2009.<sup>15</sup>

Since both the workers and their fellow household members are affected by robotization, we estimate the effect of the household head’s exposure to replaceable occupation on their spouse’s life satisfaction. In line with the individual-level findings, we find a negative effect on life satisfaction, but only in the period between 2005 and 2009. Importantly, we do not find a statistically significant effect on labor market outcomes for spouses. This incentivized us to explore two other potential channels 1) aggregated household wages and 2) the wage and working hours gap between household heads and spouses. We confirmed that the main

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<sup>8</sup>We elaborate on the adoption of robots in South Korea in section 3.

<sup>9</sup>The working age population in South Korea is expected to decrease by about 35% in the next 30 years ([Agency, 2022](#)).

<sup>10</sup>For further discussion, see section 3

<sup>11</sup>In South Korea, the share of part time workers rose from below 2% in 2005 to 8% in 2019

<sup>12</sup>South Korea has an unconditional gender pay gap of 32.5%, the highest amongst the OECD countries. For more statistics on the position of women in the South Korean labor market (“[Organisation for Economic Co-operation and Development \(OECD\)](#)”, 2025). As many jobs amenable to robots are male-dominated, automation of these jobs may put downward pressure on male wages. Furthermore, since these individuals are likely to be at the low end of the wage distribution, this can also increase earnings inequality.

<sup>13</sup>See [Lee \(2020\)](#)

<sup>14</sup>For an overview of recent government-backed investments in robotics R&D, see [International Federation of Robotics \(IFR\) \(2025\)](#).

<sup>15</sup>We constructed the firm switch variable as a dummy equals zero if the individual stays in the same firm where he started working for the past 12 month following the initial date of the start of his job.

negative effect of the household head’s vulnerability to robotization on their spouses’ life satisfaction is largely attributed to a decrease in the total household wage.

To explain our main findings, we dive into two main channels: labor market outcomes and psychological effects notably the fear of being replaced by robots at work. Specifically, we incorporate some fear of job loss mechanisms using a local labor market (LLM) approach that follows [Acemoglu and Restrepo \(2020\)](#) and [Dauth et al. \(2021\)](#). The local labor market approach accounts for broader productivity effects that are not related to one’s occupation. It also measures the local effects of robotization at the regional level rather than across the country. The local labor market approach can signal the psychological effect of robotization on life satisfaction. Unlike individual- and household-level results that show a decline in life satisfaction during the early phase of robotization, the LLM approach does not yield any positive or negative effects on life satisfaction. This is largely due to the productivity effects and the labor market improvements happening for all workers regardless of whether they work in a region likely to be replaced by a robot or not. Therefore, the fear mechanism is ruled out while labor market outcomes are the drivers of the decline in life satisfaction from 2005 to 2009 as well as its increase as of 2009.

This paper is structured as follows. Section 2 discusses the prior literature on the labor market effects of robotization and wellbeing and how we contribute to it. Section 3 discusses the South Korean governments’ policies to foster robots in the past two decades, and how this affected robotization in subsequent years. In section 4 we present the Korean labour force survey and how we construct a measure of robot exposure on an individual level. As we focus on both the effects of robotization on individuals as well as households we present comparable but distinct analyses in sections 5 and 6. Section 9 concludes.

## 2 Related Literature

Our work connects to several strands of literature. First of all, it relates to studies that aim to estimate the effects of robotization on labor markets. The workhorse of this literature is the data collected by the International Federation of Robots (IFR), which collects the number of robots installed in countries, by industry and by application. [Graetz and Michaels \(2018\)](#) use this data to document across industries in 17 countries that robots increased productivity between 1993 and 2007. Using the same data, [Acemoglu and Restrepo \(2020\)](#) study the labor market effects across US commuting zones between 1990 and 2007. By relying on sectoral robot adoption in more technologically advanced countries, they construct a shift-share IV to study causal effects. They find large negative effects on employment and wages, predominantly in manufacturing sectors. Similar approaches have been undertaken by [Chiacchio et al. \(2018\)](#) and [Dauth et al. \(2021\)](#), who particularly document heterogeneity across workers and firms. Despite the fact that many of these studies find strong negative effects, they may have limited relevance to contemporaneous robot adoption, as most of these studies focus on the (late) 90s and early 2000s. A set of related studies has found that robotization may have contributed to the decreasing labor share in national income ([Guimarães and Gil, 2022](#)), and could attract jobs by reshoring ([Faber, 2020](#)). Using a survey of firms from Spain, [Koch et al. \(2021\)](#) find that larger and more productive firms adopt robots. Importantly, they document that job losses materialize in firms that do not adopt robots. This is consistent with [Hirvonen et al. \(2022\)](#), who find that within firms, adopting automation technologies does not preclude negative effects on labor market entrants and on firms not adopting robots. [Pavez, Luis R. Díaz and Martínez-Zarzoso, Inmaculada \(2023\)](#) employ a

panel data of 16 economic sectors in 10 emerging countries from 2008 to 2014 to study the impact of foreign robot son labor market outcomes. They find that robot adoption has negatively impacted employment in sectors highly-exposed to robot adoption.

A key characteristic of whether industries expand employment depends on their exposure to international trade (Aghion et al., 2020). Firms can increase competitiveness by adopting robots, enabling the capture of larger shares of the world market. Moreover by performing a careful match of robot applications (as categorized by IFR) and occupations, Caselli et al. (2021) document positive employment effects on robot operators, but heterogeneous effects on other workers in Italy between 2011 and 2018. Specific to the South Korean context, Kim (2024) find that higher local concentration of industries suitable for robot adoption leads to a decrease in online job vacancies related to the manufacturing sector and routine occupations between 2010 and 2019.

We contribute to the literature on the labor market effects of robots, by studying the effects of robot adoption using a low-attrition longitudinal data representative of the South Korean labor force. The South Korean context is an important contribution to the literature that mostly focuses on automation and robot adoption either in Europe or in the United States. Unlike Europe and the United States, South Korea is characterized by very low inward migration flows coupled with an aging population, which explain their vital need for robots as means to compensate for the shortage in labor. The South Korean characteristics make it an ideal setting to study the effects of robot adoption on labor market outcomes and life satisfaction without the existence of any major confounders (notably having a large number of immigrants).

The second literature we contribute to is that on the relation between workplace and life satisfaction. First of all, employment, wages and job quality explain a large part of the variation in life satisfaction (Grün et al., 2010). Ochsens and Welsch (2012) show that labor market institutions with a positive effect on job security increase life satisfaction. Along similar lines, reduced job security by business cycle fluctuations reduce life satisfaction and impacts several mental health indicators (Avdic et al., 2020), even in the absence of actual effects of unemployment. Rose and Stavrova (2019) show that low levels of life satisfaction are correlated to lower re-employment probabilities, suggesting that there may be self-reinforcing effect. Furthermore, once in unemployment, the worse re-employment probabilities than before exacerbate the negative effects on life satisfaction (Green, 2011). Giuntella et al. (2024), using German data that spans 20 years in an event study and a difference-in-differences framework, find that workers exposed to artificial intelligence are less likely to be satisfied with their lives and jobs while they showed major concerns about their job security.

We contribute to this literature by showing that fear of job loss due to an important wave of automation may affect workers at risk of being affected by automation, directly or indirectly. Not only do we show this to be the case for workers directly exposed to robots through their current occupation, but also for workers likely to be substituted with those in exposed occupations. A related literature considers the dynamics of within-household life satisfaction: Powdthavee (2009) finds that there are strong spillover effects between partners. Therefore, we not only assess the effect on affected workers themselves, but also on the life satisfaction of their partners.

In this paper, we assess whether government’s policies achieved their ultimate objectives: improving well-being. We examine whether the life satisfaction of workers and their family members improved after robot

adoption. South Korea poses a relevant setting: robot adoption was strongly encouraged by the central government, leading to an unprecedented adoption of industrial robots.

### 3 Institutional Background

As mentioned previously, the rapid automation in South Korea has been spurred by the national government. To thoroughly comprehend the political implementation by the state and its consequences on the labor market outcomes and workers' life satisfaction, it is important to understand the impetus of the state's involvement. Therefore, we introduce the institutional background of automation in South Korea in this chapter.

After its history of colonization and Korean War (1950-1953), South Korea was not only suffering from drastic poverty but also lagged behind in terms of industrialization compared to developed countries. To avoid further recession, the government conducted an unprecedented process for improving its industrialization. According to Alice (1992), the process was “with subsidies to distort relative prices in order to stimulate economic activity.” Considering the high economic dependency of South Korea on the United States after World War II, the government's strategy is more comprehensible. Between 1953 and 1961, the financial aid from the United States consisted of 70 percent of total imports and 75 percent of total fixed capital formation (Haggard et al., 1991). After the military coup led by Park, import-substituting economic strategy was fiercely executed. Under the new regime, the export-promotion program in the form of heavily subsidized credit and various institutional support was pronounced as a massive support for industrialization especially for the manufacturing sector. Taking the strong economic growth between the early 1960s and the mid-1990s into account, we can confirm that the strategy indeed worked to improve the economic conditions in South Korea. Furthermore, the export-oriented economy has established the base for the government and firms to rely on the efficiency of the manufacturing sector in order to keep up the growth rate and international competitiveness.

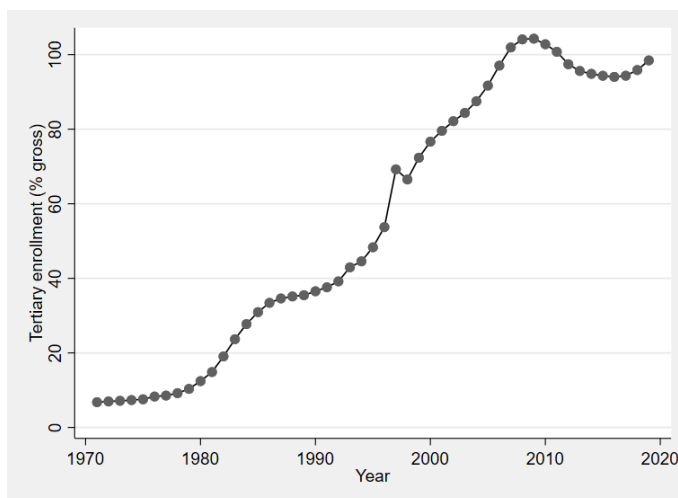


Figure 1: School enrollment at tertiary level, percentage of the population (World Bank 2021)

As Figure 1 illustrates, the population entering into tertiary education has been expanding since the mid 1980s; since higher education allows workers to have more bargaining power, it has led to an increase in

labor costs in South Korea by approximately 50% between 2000 and 2015 (Jin, 2015).

After the Asian financial crisis, the government used several methodical policies aimed at promoting robot adoption in the manufacturing sector even further. From 2000 onwards, the government gradually started to allocate investment directly into the robot industry to foster the production of domestic robots in 2005, the state launched the very first official support for the intelligent and industrial robot industry in order to create a systematic base for the industry.<sup>16</sup> After the introduction of these policies in 2005, approximately 486 million USD in government funds had flown into the robot related industry by 2007 (Yoon, 2016).

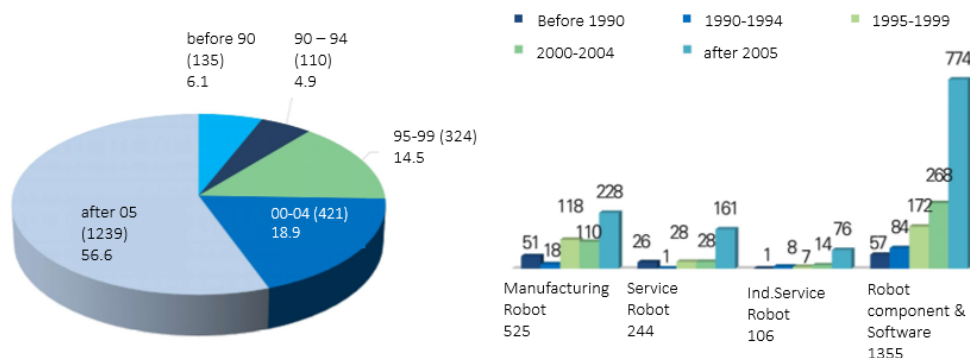


Figure 2: Number of newly added robot producers per year and per sector (Korea Robot Industry Promotion Institute 2011)

Between 2005 and 2019, 15.4% of all robotics patents were registered in South Korea, at the same time, South Korea contained less than 1% of the world’s population.<sup>17</sup> Prior to 2005, the share of robotics patents in South Korea was considerably smaller (Keisner et al., 2015).

Figure 2 demonstrates the number of robot related firms that were established after the 2005 policy. Approximately, 60 percent of robot enterprises were added after 2005. When we decompose the aggregated number of firms by sectors within the robot industry, we can confirm the conspicuous effect of the 2005 program. Furthermore, the effect of the state’s intervention in 2005 was visible in terms of robotics patents. South Korea occupied the third highest share of global robotics patents with 15.4% followed by the United States.<sup>18</sup> After the emergency in the early 2000s, South Korea’s robotics patents registered in the PATSTAT database accelerated and reached its peak in 2009.<sup>19</sup>

In 2008, the foundation for the Development and Distribution of Intelligent Robots Act was established in order to facilitate the development of intelligent robots and it finally led to the execution of the act from 2009.

<sup>16</sup>For more information on this law, see [Korea National Science and Technology Information Service \(2025\)](#).

<sup>17</sup>For an overview of robotics patents until 2019, see [Center for Security and Emerging Technology \(CSET\) \(2023\)](#).

<sup>18</sup>More detailed information can be found in [Asian Robotics Review \(2025\)](#).

<sup>19</sup>For more details, see [World Intellectual Property Organization \(WIPO\) \(2025\)](#), page 14.

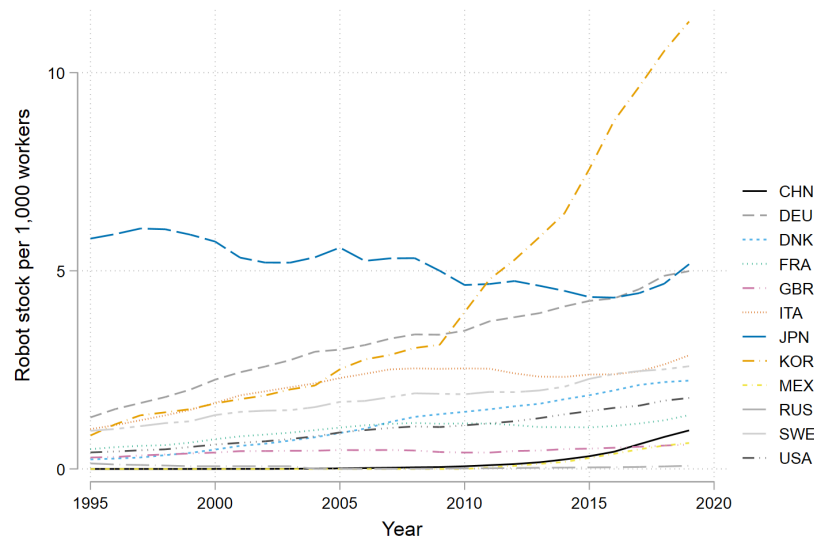


Figure 3: IFR (2020) and World Bank (2022)

The main difference between 2005 and 2009's policies is as follows. Previously, the government only supported the robot related industry; the *Development and Distribution of Intelligent Robots Act* was a package not only to promote the robot industry but also to encourage enterprises to adopt more automation in their production processes. Based on this act, a *Basic Robot Industry Plan* was and still is formulated every five years to stimulate the industrial robots market; for instance, according to article 24, firms investing in industry automation will obtain a tax deduction. As a result, from 2009 to 2018, the South Korean government invested over 17 billion US dollars to support the research and development of technologies related to the robotics industry.

To illustrate the massive adoption of rate robots in South Korea since 2009, the total number of industrial robots installed over time is shown in Figure 3. Specifically, Figure 3 shows the stock of robots as reported by IFR, divided by the total labor force, for a selected set of industrialized countries. Until 2009, South Korea's relative implementation of robots was comparable to Italy. In the period between 2005 and 2009, South Korea experienced the strongest increase in the number of robots per worker of all countries shown. After 2009, the number of robot installations in South Korea increased drastically. By 2019, the robot stock per worker exceeded 10, which trumps the countries with the next-highest stock of robots per worker (Germany and Japan) by more than a factor of two. In terms of net installations per worker (the slope in Figure 3), Korea exceeds all other countries shown. In the years between 2009 and 2019, South Korea installed on average 0.8 robots per 1,000 workers per year. In Germany, only 0.15 robots per 1,000 workers per years were installed.

## 4 Data Variable Description and Summary Statistics

### 4.1 KLIPS: a household-based labor force survey

Our main data provided by the Korean Labor Income and Panel Study (KLIPS). Conducted once a year, KLIPS is the only longitudinal income survey existing in South Korea. KLIPS collects information on consumption behavior, labor market participation, education, and social activities from about 5,000 households, including every member of these households. The data is available up to and including 2020. Our study observes the data from 1998 to 2020 based on the assumption that South Korea had a massive wave of automation during this period. We use an individual-level panel which is released for the annual conference held by KLIPS. The data contains information on gender; age; educational attainment; 3-digit occupation codes; 3-digit industrial affiliation codes; and labor market outcomes, such as employment, wages and working hours. The data contains the household's region of residence at an intermediate level of 225 divisions (these divisions comprise 3 types of units: Si (cities), Gun (counties) and Gu (districts)), which are nested in 17 larger geographic divisions (these divisions comprise 6 metropolitan cities, 1 special city, 1 special self-governing city, and 9 provinces). The comprehensive individual level information from KLIPS allows us to thoroughly understand the overall changes in average employment rate and the wage changes depending on workers' demographic information, occupations and working industry. Furthermore, KLIPS comprises detailed questions on workers' life quality, including their self-reported life satisfaction. Other information about the workers in the KLIPS include: Exposed rate of job training, job-status transition from permanent (regular) to temporary (part-time), preferred job training, reasons for leaving, smoking and drinking frequency, difficulties in obtaining a new job, etc. For the current study, we focus on the life satisfaction related questionnaire as a proxy of their life quality. KLIPS data provides us with the household identifier as well as each individual's relationship with the household head. This allows us to study the effects of robotization through the labor market position of individuals and their household members.

#### 4.1.1 KLIPS: Descriptive Statistics

The descriptive statistics in table 1 show the mean of the main variables of interest, their standard deviation in parentheses as well as the number of observations for the different samples used. Column (1) shows the main statistics for the overall sample of exposure used in the study while columns (2) and (3) represent the samples above and below the median exposure respectively. The median exposure of robotization is equal to 0.101. The above median exposure sample has a female mean of 0.38 which is much lower than that of the below median exposure of 0.68. The average age ranges between 40 and 45 years old in the three samples. The total number of observations for the above median exposure sample is 140,774 and the total number of observations for the below median exposure sample is 104,888. For the purpose of this study, the overall sample of exposure will be used in the main regression.

Table 1: Descriptives Statistics of the KLIPS Data

	(1) All	(2) Above Med. Exp.	(3) Below Med. Exp.
Life Satisfaction	0.32 (0.615)	0.28 (0.610)	0.37 (0.618)
Employed	0.66 (0.474)	0.68 (0.467)	0.63 (0.482)
Employed Manuf.	0.25 (0.432)	0.27 (0.446)	0.21 (0.408)
Log Monthly Wage	7.56 (0.668)	7.52 (0.620)	7.62 (0.730)
Log Hours	3.79 (0.380)	3.82 (0.369)	3.75 (0.391)
Work Satisfaction	3.33 (0.773)	3.27 (0.777)	3.42 (0.759)
Part-time	0.15 (0.356)	0.15 (0.361)	0.14 (0.348)
Log Hourly Wage	2.39 (0.677)	2.32 (0.632)	2.49 (0.728)
Education	3.79 (1.506)	3.40 (1.245)	4.31 (1.661)
Female	0.51 (0.500)	0.38 (0.486)	0.68 (0.465)
Age	42.53 (12.31)	40.44 (12.63)	45.35 (11.26)
5 years age bins	42.54 (12.43)	40.43 (12.75)	45.37 (11.39)
Observations	245 662	140 774	104 888

## 4.2 IFR: robot installations by industry and application

The International Federation of Robots (IFR) collects information on industrial robot adoption across countries, sectors, and applications. To harmonize the definition of a single robot across these dimensions, the following definition of a robot from IFR is used: a programmed actuated mechanism with a degree of autonomy to perform locomotion, manipulation or positioning. We use IFR data on the number of robots in use at the industry level in South Korea between 2004 and 2019. We merge the industry codes from IFR to the industry coding available throughout KLIPS (KSIC-8).

### 4.2.1 Local labor market approach

Using the distribution of industries across districts in 2004, as in [Acemoglu and Restrepo \(2020\)](#), we can proportionally distribute the adopted robots across the South Korean regions to generate a local exposure to robots. This regional-level robot exposure can be used to study the local labor market effects of robotization. One concern is that robot expansion within South Korea may be endogenous to local economic conditions. Therefore, our regional robot exposure is instrumented following [Acemoglu and Restrepo \(2020\)](#) using a shift-share instrument. In such a setting, the *shift* is robot adoption in more technologically advanced countries. Variation in temporal and regional robot exposure is driven by robot expansions in other countries, reflecting technological progress rather than local economic conditions in these countries.

## 4.3 Exposure Measure

Our exposure measure is a modification of the methodology of [Anelli \(2019\)](#). In this study, the authors constructed the exposure for 14 Western European countries from 1993 to 2016. Their measure enabled them to investigate the effect of robotization at an individual level. The measure is based on two main components: (i) an individual’s occupation is predicted using a multinomial logit (MNL) model (based on the following characteristics: age, gender, educational attainment and the district someone lives in) and (ii) an occupation’s exposure to robotization. Then, we can calculate an individual’s robot exposure in the following way by summing over all occupations:

$$Exposure_i = \sum_{k=1}^K \underbrace{Pr(o_i = k | age, \hat{gender}, edu, region)}_{\text{Obtained by multinomial logit}} \times \theta_k \quad (1)$$

Here,  $\theta_k$  is an occupation-level exposure to robots. [Anelli \(2019\)](#) use two distinct measures of robotization: the risk of computerization from [Frey and Osborne \(2017\)](#) and perceived threat (to workers) of automation from the International Social Survey Program in 1997. In our application, we use a different measure as we are interested in those most likely to be disadvantaged by robotization: low-skilled workers that are likely to work in occupations performing tasks that can be replaced by robots. Therefore, we use the simple occupation-level measure of [Graetz and Michaels \(2018\)](#). An occupation is coded as replaceable if the job title in the 1990 scheme contains a word that coincides with any of the applications mentioned in the IFR data. For example, welders are coded as replaceable because one of the applications of industrial robots is

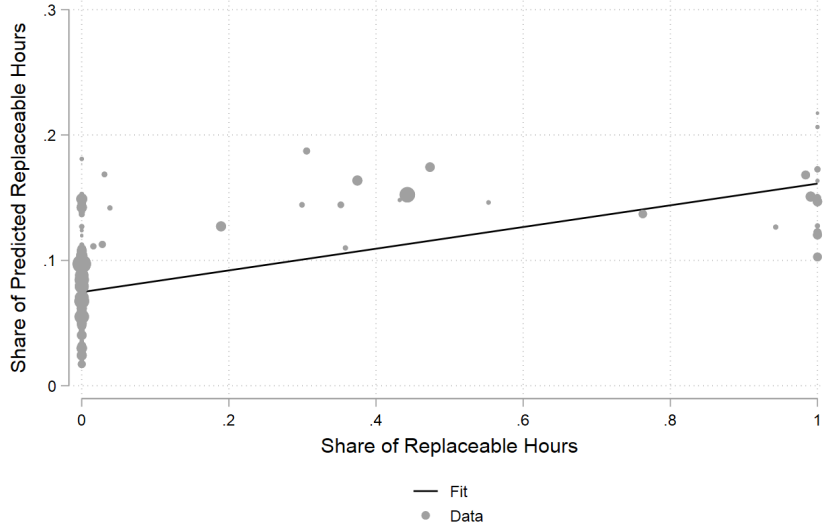


Figure 4: The Share of Replaceable Hours and the Predicted Share

Table 2: Average Characteristics By Quartiles of Robot Exposure

	(1)	(2)	(3)	(4)
	Quartiles of Exposure <sub>i</sub>			
	First	Second	Third	Fourth
Age	54.43	48.17	44.25	38.12
Share Female	0.81	0.51	0.59	0.18
Share High-skilled	0.61	0.44	0.06	0.00
Share in Seoul	0.21	0.27	0.22	0.12
Observations	81459	81123	81256	81274

welding. We match the occupations in the 1990 US Census to the KSCO-5 classification. As this merging is not one-to-one, some KSCO-5 occupations also have fractional replaceability. We restrict our sample to all individuals present in the data prior to 2005. For this sample, we perform the multinomial logit and calculate  $Exposure_i$  based on an individual's characteristics in the first available year. These results are robust to using earlier years, at the loss of precision.

Figure 4 shows that  $\theta_k$  and the average of  $Exposure_i$  by occupation are positively correlated, but show some variation. The size of each data point indicates the number of workers in that occupation in 2000. Notably, although some occupations are not replaceable (they lie on the y-axis), there is a strong residual variation in the predicted replaceability of the workers in some of these occupations. From Table 2, one can see that more exposed workers are likely to be low-skilled, male, young, and less likely to be located in the Seoul metropolitan region.

This exposure measures how exposed one is to occupations that can be replaced by robots. Therefore, this does not only measure direct effect through one's occupation, but also secondary labor market effects through

the labor market effects of other household members as well as regional transformation.

Importantly, individuals' exposure is correlated with the exposure of other household members, through assortative mating and cohabitation. Therefore, we do not only consider one's own exposure in section 5, but also the exposure of other household members in 6.

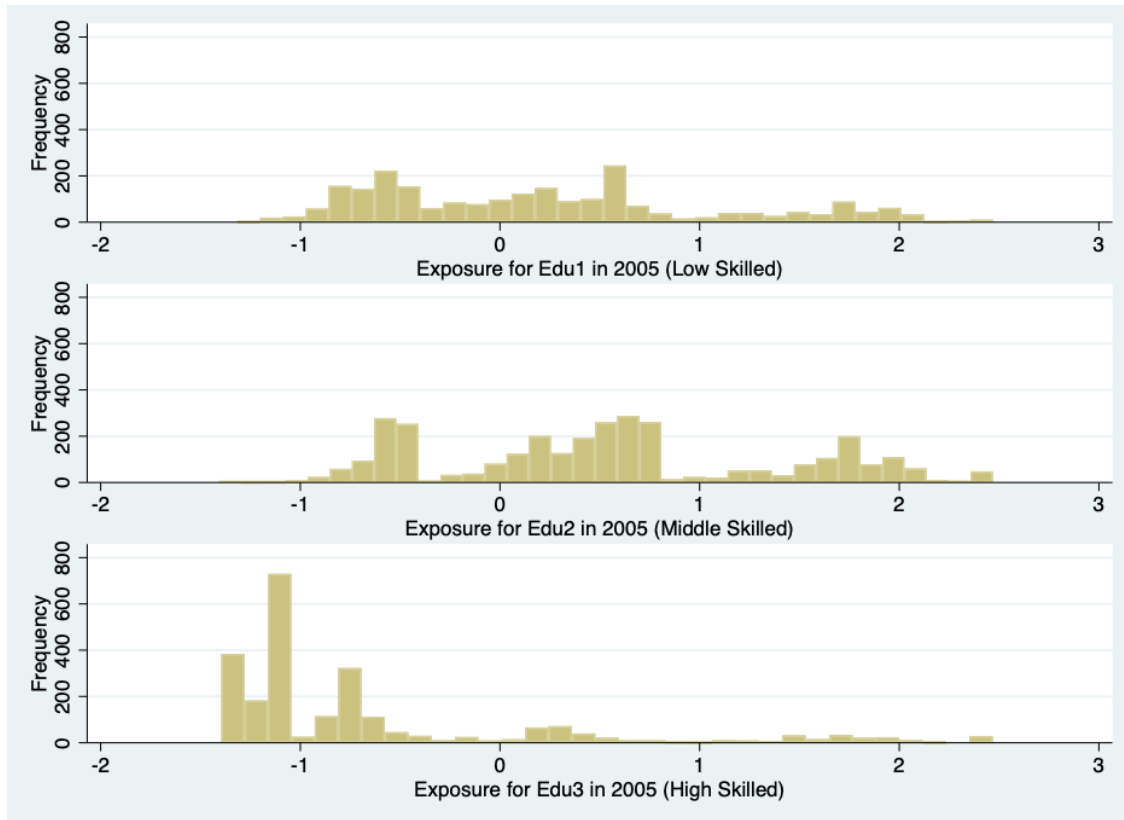


Figure 5: Histogram of the exposure variable by the three educational groups in 2005

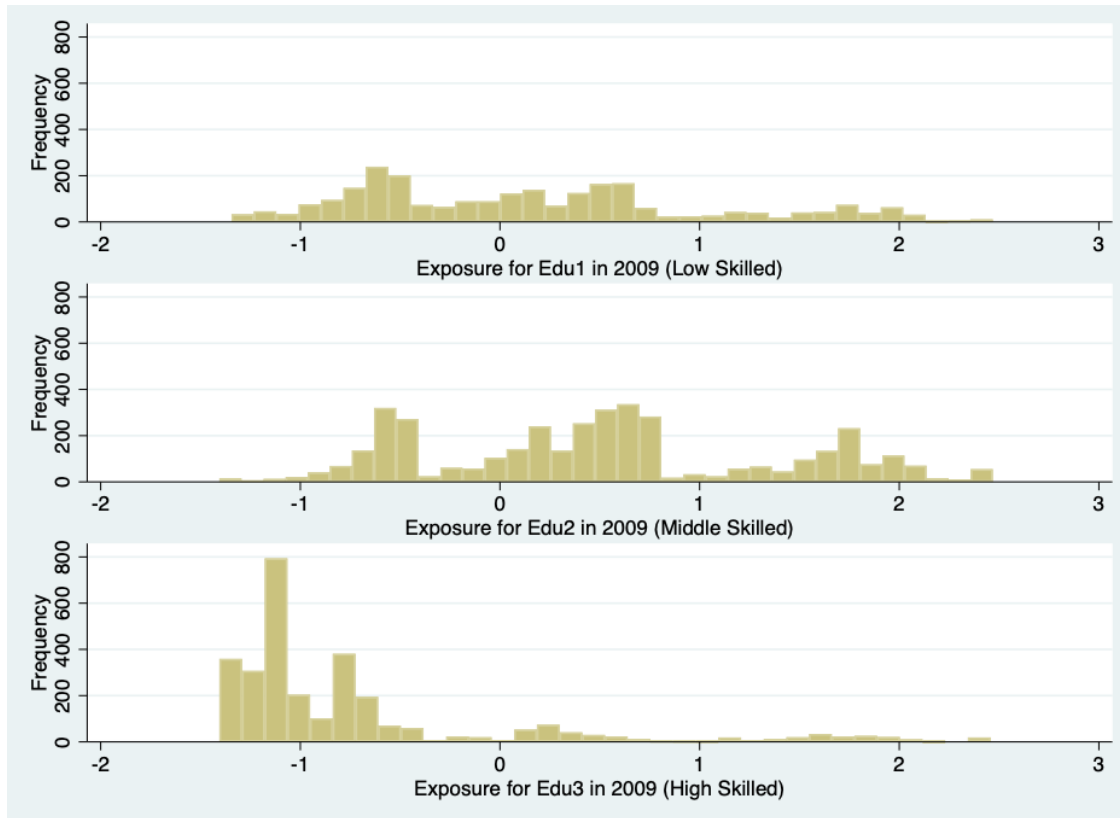


Figure 6: Histogram of the exposure variable by the three educational groups in 2009

Figure 5 and 6 show the distribution of the exposure to robotization measure in the years 2005 and 2009 respectively. According to the figures, there exists a lot of variation in the exposure measures to robots within the three education group.<sup>20</sup> The majority of the variation is coming from both the low education and the vocational education group. However, the high education group is the least varying of all the three. Exploring these within educational group exposure variation to robots is essential in further disentangling the results as well as the possible channels conducive to the main results.

## 5 Individual Level

### 5.1 Empirical Specification: An Event Study Approach

As individuals with different levels of exposure to robotization may be affected differentially by shocks in productivity or export demand, it is important to assess whether the parallel trends assumption of the untreated potential outcomes. The event study design serves two purposes: first, it serves as a test for the

<sup>20</sup>We divide these three education (skill) group based on their final education level. High education group includes the workers who have certificates higher than college or university; vocational education group consists of the workers who have graduated from the vocational school after their high school education. Low education group contains the information of workers who received education lower than high school.

parallel trend assumption prior to the widespread adoption of robotization, second, it sheds light on the dynamic path of outcomes.

$$Y_{idt} = \sum_k \beta_k 1(t = k) \times Exposure_i + \gamma X'_{it} + \phi_t + \theta_i + \epsilon_{idt} \quad (2)$$

Where  $Y_{idt}$  is the life satisfaction of individual  $i$  at time  $t$  in residential district  $d$ .<sup>21</sup>  $Exposure_i$  is the continuous measure of individual exposure level introduced in Equation 2.  $\gamma X'_{it}$  captures individual-level time varying controls: such as education levels, 5 years age bins interacted with a female dummy.  $\phi_t$  and  $\theta_i$  are year and individual fixed effects respectively. These individual fixed effects capture any differences that may arise due to sample composition, which enables us to estimate within-individual effects. Finally,  $\epsilon_{idt}$  is the error term. We cluster standard errors at the district and individual level.

$\beta_k$  measures the relationship between robot exposure in year  $k$  relative to the base year 2004, the year before the robotization policies commenced. By utilizing a panel of individuals, we are able to account for individual fixed effects and year fixed effects to account for nationwide shocks. This methodology allows us to identify the differential impact of increased robot exposure over time on changes in life satisfaction within the same individuals.

There are several potential threats to identifying the  $\beta_k$ 's as the time-dependent causal effect of robotization. First, as we use demographic factors to predict individuals' occupations, shocks to these demographic factors unrelated to Korea's robot policy and exposure to robotization may confound the causal effect. To alleviate this concern, we add interactions between the demographic information and year fixed effects in robustness tests.<sup>22</sup> Second, as the exposure of individuals within households may be positively correlated, we may capture the joint effect of exposure of both (or more) individuals in the household. By reverting to a household-level regression, we can separately identify the effect of one's own exposure and spousal exposure.

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<sup>21</sup>For the sake of simplicity, we construct a three-tier categorical variable to denote levels of life satisfaction: 1 for satisfied, 0 for neutral, and -1 for not satisfied.

<sup>22</sup>A more detailed analysis can be found in Appendix D.

## 5.2 Results

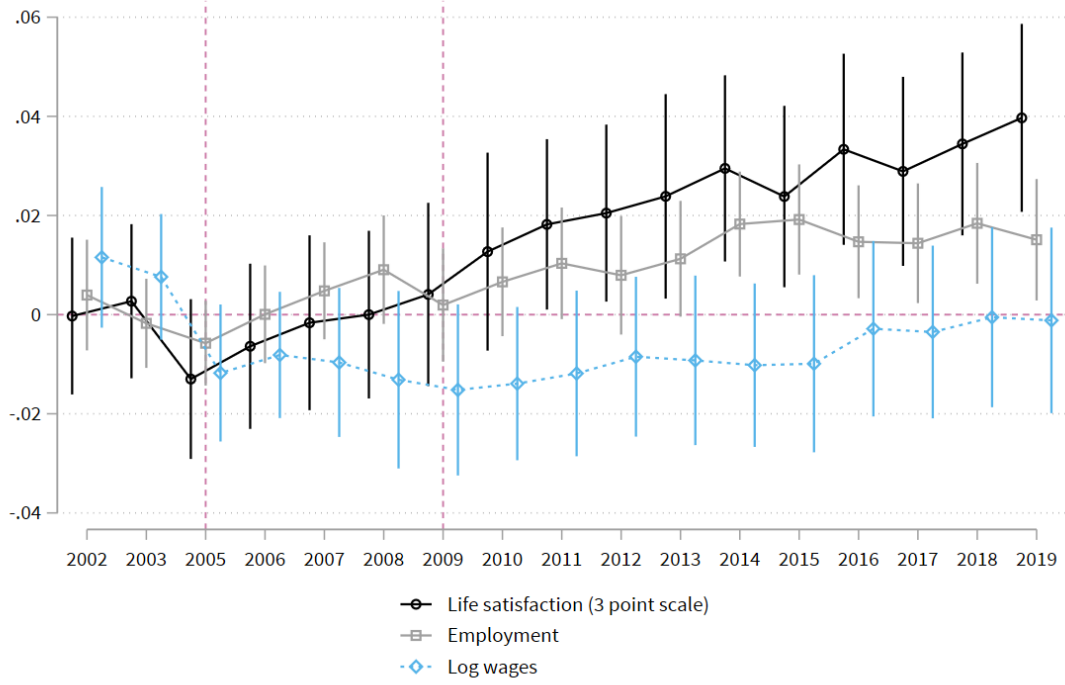
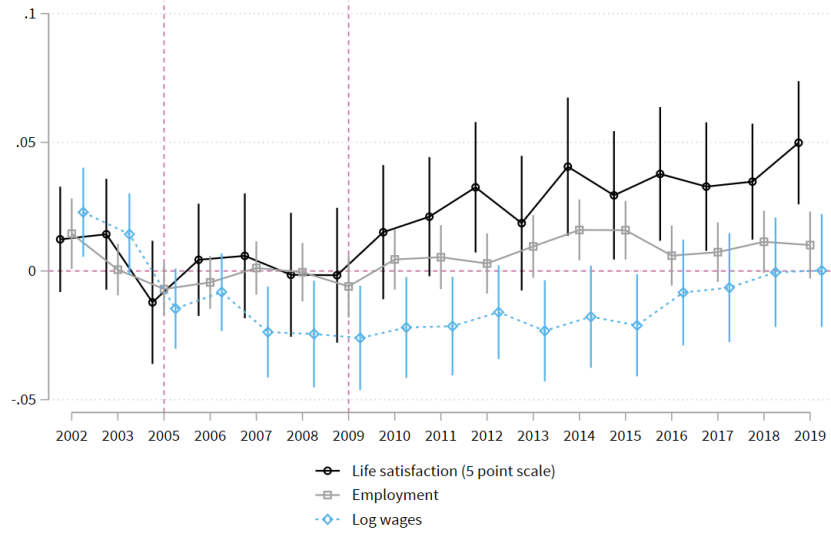
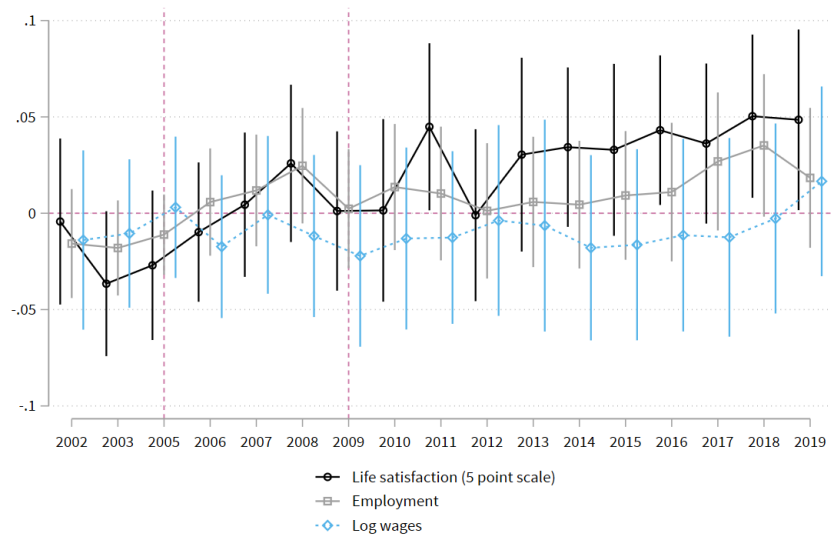


Figure 7: Event Study diagram of the effect of robotization exposure over time



(a) Male



(b) Female

Figure 8: Event Study diagram of the effect of robotization on life satisfaction by gender

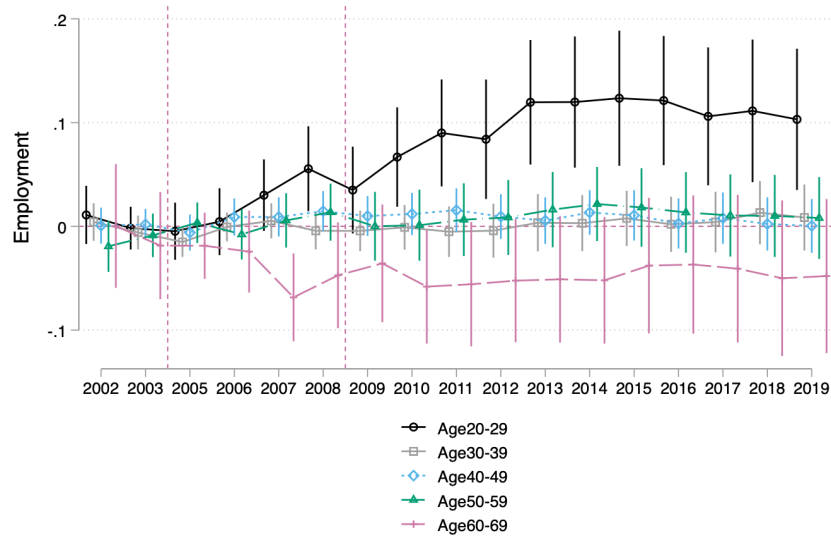


Figure 9: Event Study diagram of the effect of robotization exposure over time

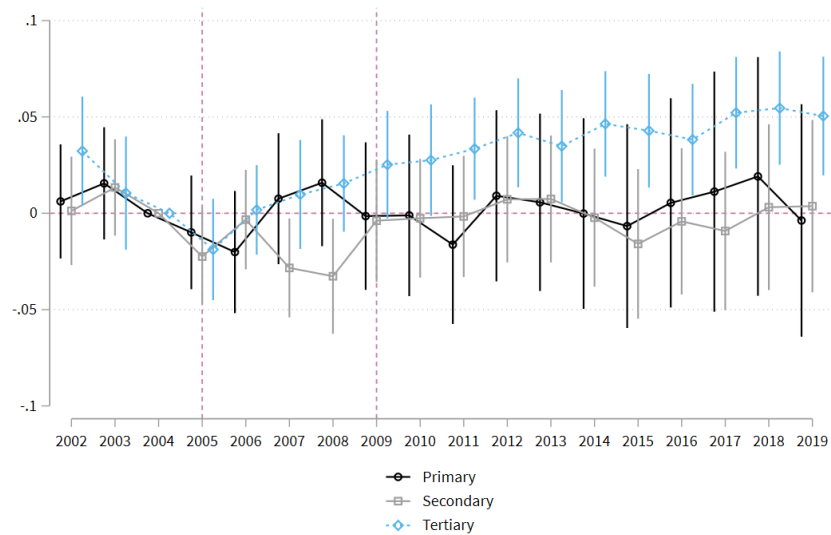


Figure 10: Event Study diagram of the effect of robotization on life satisfaction by the three main education levels

Figure 7 graphically shows the estimated  $\beta_k$ 's of equation 2.<sup>23</sup> We find that after the introduction of the 2005 reform, life satisfaction (black) gradually increased among more exposed individuals. At the same time, there is no effect on wages, but slightly positive effects on employment probabilities up to 2 percentage points. Figure 11 shows that this is driven primarily by decreases in level 2 at the expense of level 4 of life satisfaction. At the same time, job satisfaction increased considerably (Figure 12) after 2013.

<sup>23</sup>The full regression table can be seen in Appendix E, Table E.1

This implies that robotization generally has a favorable impact on life satisfaction, yet a comprehensive analysis is essential due to the observed varying effects of robotization, contingent upon the initial levels of life satisfaction experienced. Additionally, it appears that the predominant portion of the positive influence of robotization can be attributed to its impact on employment opportunities rather than the wage enhancements resulting from automation in the workplace.

Figure 8 presents the analyzes from the event study on life satisfaction, employment and wage levels differentiated by gender. Initially, during the era of the first robot adoption initiative, male life satisfaction reflected the trend observed in wage reductions; a notable decline in log wages was observed immediately following the government’s inaugural robot adoption incentive. However, after the implementation of the second robot policy, male life satisfaction began to align more closely with employment trends, which were on an upward trajectory. It is also important to note that after experiencing a decline post-2005, wages did not exhibit any signs of increase.

For females, our analysis does not reveal statistically significant reductions either in wages or in employment. In terms of life satisfaction, an upward trend is observed following the second wave of automation, although this increase is not statistically significant. When these findings are juxtaposed with outcomes for males, it becomes evident that exposure to robot has a more pronounced impact on males than on females. However, for both genders, life satisfaction appears to increase a few years after the second wave of robotization, suggesting an adjustment period to a new working environment characterized by greater reliance on robots. Additionally, it is observed that males, who have greater exposure to robotization, begin to experience a statistically significant improvement in life satisfaction after this adjustment period, in contrast to their female counterparts.

Our investigation extends to an analysis of heterogeneity in age, aiming to discern variations in life satisfaction following the implementation of both the initial and subsequent robot promotion policies. Figure 9 elucidates our main event study segmented by age cohort. Before the initial wave of robotization, the division of our sample according to birth year does not yield statistically significant differences. However, after the first wave of automation, we can see that the oldest cohort (Age 60 - 69) has the highest negative effect, compared to the younger cohorts, particularly after the 2005 wave of robot adoption. This supports previous findings that older workers nearing retirement often face greater challenges in acquiring skills that complement robotization (Fasbender and Gerpott, 2023; Asia et al., 2023). From around 2006 onward, the life satisfaction of the 60-69 age group seems to drop further, reaching the most negative levels between 2011 and 2015. The negative trend in life satisfaction among this older cohort suggests that the impact of robot adoption may have disproportionately affected workers nearing retirement, potentially due to the challenges they face in adaption new technologies, as seen in other studies on aging and automation (Asia et al., 2023).

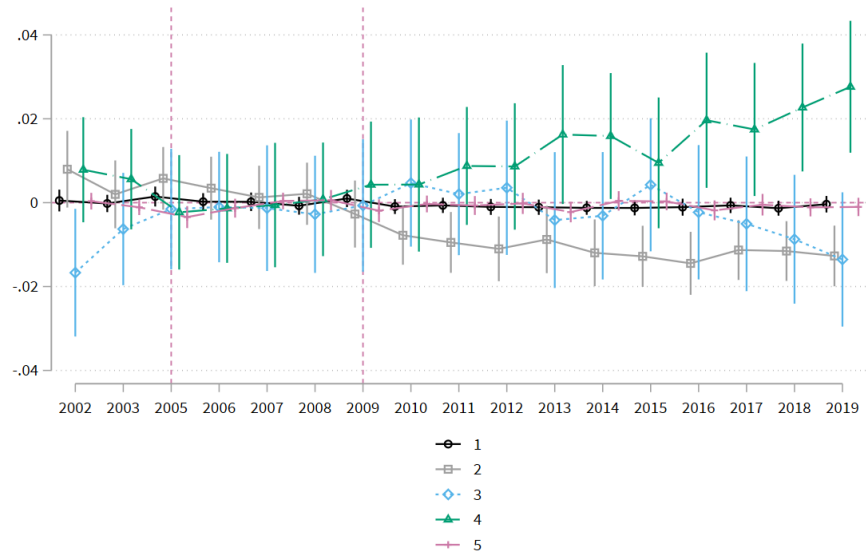


Figure 11: Levels of life satisfaction



Figure 12: Job satisfaction

### 5.3 Mechanisms

The econometric approach used for our mechanisms section consists of a difference-in-differences framework with multiple time periods, capturing the different stages of robot adoption in South Korea:

Table 3: Potential channels by Three education levels (individual level)

	Lower Educ.								Vocational Educ.								Tertiary							
	(1) Emp.	(2) Emp. Mandf.	(3) Log Wage.	(4) Firm Switch.	(5) Log Hours.	(6) Work Satisf.	(7) Part-time	(8) Log Hourly Wage.	(1) Emp.	(2) Emp. Mandf.	(3) Log Wage.	(4) Firm Switch.	(5) Log Hours.	(6) Work Satisf.	(7) Part-time	(8) Log Hourly Wage.	(1) Emp.	(2) Emp. Mandf.	(3) Log Wage.	(4) Firm Switch.	(5) Log Hours.	(6) Work Satisf.	(7) Part-time	(8) Log Hourly Wage.
Exposure × 2005-2009	-0.008 (0.006)	-0.004 (0.009)	0.013 (0.015)	0.000 (0.006)	-0.016 (0.011)	0.018 (0.024)	0.040* (0.011)	0.029* (0.015)	0.007 (0.006)	0.002 (0.007)	0.009 (0.011)	0.011** (0.004)	-0.007 (0.007)	0.011** (0.018)	-0.009 (0.010)	0.018 (0.012)	0.028** (0.009)	0.027** (0.011)	0.034** (0.010)	-0.002 (0.002)	-0.002 (0.006)	0.016 (0.021)	-0.007 (0.008)	0.037** (0.011)
Exposure × Post-2009	-0.013 (0.012)	-0.010 (0.014)	0.026 (0.022)	0.005 (0.009)	-0.009 (0.012)	0.035 (0.029)	0.041** (0.010)	0.027 (0.025)	0.012 (0.009)	0.003 (0.011)	0.011** (0.005)	0.000 (0.006)	-0.003 (0.009)	0.035** (0.025)	0.010 (0.012)	0.043** (0.015)	0.023** (0.011)	0.019** (0.014)	0.059** (0.012)	-0.001 (0.002)	-0.001 (0.010)	0.006 (0.022)	-0.018* (0.011)	0.052** (0.014)
Observations	4608	4648	2141	4648	28763	2118	4208	2187	7092	7092	4208	7092	4636	3718	27070	4230	5328	3940	5328	4065	3272	3102	3430	
Year DV	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	
Ind. FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	

Note: \*\*\* p<0.01, \*\* p<0.05, \* p<0.10. Standard errors are clustered at the district and individual level.

$$Y_{idt} = (\alpha + \delta Exposure_i) + \kappa Exposure_i \times 2005 - 2009 + \lambda Exposure_i \times Post_{2009} + \omega X'_{it} + \epsilon_{idt} \quad (3)$$

Where  $Y_{idt}$  is the life satisfaction of the individual  $i$  at time  $t$  in the residential district  $d$ .  $Post_{2009}$  is a dummy equal to 1 if post 2009 is the year of the major robotization shock. The dummy 2005 – 2009 equals 1 for the initial years 2005 and 2009,  $Exposure_i$  is a continuous treatment variable representing the individual exposure level standardized.  $Exposure_i \times 2005 - 2009$  captures the differential effect of high exposure between 2005 and 2009.  $Exposure_i \times Post_{2009}$  is a second interaction term between the continuous treatment variable and the post 2009 dummy. In our baseline specification, we include year and individual fixed effects, which nest the first four terms of equation 3. By including individual fixed effects, we partial out all variation due to time-independent characteristics of individuals.  $\omega X'_{it}$  captures time-varying individuals' characteristics such as education and gender interacted with 5 year age bins from 20 to 65 years old. This allows us to control for changes in outcomes over the life course for different demographic groups. Finally,  $\epsilon_{idt}$  is the error term. The remaining identifying variation originates from a within-individual variation in exposure to robotization between 2005 and 2009 and beyond 2009. As errors may be correlated within regions, we cluster standard errors at the district level.

Given the absence of significant pre-trend indicators in the two years preceding the 2005 wave of robotization, particularly among the vocational and lower education groups, we proceeded with our study. Table 3 shows the average effects over the two time periods of interest. The most pronounced adverse impact of automation is observed among the lower-educated group, with a decrease in life satisfaction by 0.028 standard deviations with a high probability of exposure to robot at work. The vocational education group also exhibited a decline in satisfaction, though to a lesser extent than that observed in the lower-educated cohort. No discernible effect was identified within the highly educated group.

Additional examination of Table 3 suggests that the diminished life satisfaction before 2009 among middle-educated workers could be linked to a shift from full-time to part-time employment. For those with secondary education, the increased frequency of changing employers post-robot adoption appears to be the primary factor contributing to their reduced life satisfaction. In contrast, the highly educated group experienced improvements in employment rates and wages.

The period from 2005 to 2009 marked a significant displacement of low and vocationally educated workers, driven by an increase in part-time work. Conversely, post-2009, vocational and highly educated individuals started to benefit from robotization through wage increments, a privilege not extended to their low-educated workers. This wage disparity underscored the varying capacities of these groups to adapt to the growing presence of robots. Furthermore, the analysis reveals that the negative implications of robot exposure are exacerbated for households with low or vocationally educated primary earners.

## 6 Household Level

In this chapter, we turn our focus to the effect of household heads' exposure to robots on their spouses' life satisfaction. Our main motivation of the current section is twofold. First, as we briefly mentioned above, manufacturing sector is the sector where robotization happens the most and is male dominated. As 90% of household heads in KLIPS are defined as males, we believe that if a household head has a high robot exposure, then this likely has certain effects on their spouses' life satisfaction. Second, according to the prior literature, there is a spillover effect in life satisfaction between household heads and their spouses (Powdthavee, 2009). Indeed, we also confirm it in our OLS regression 4. Based on this spillover effect, we posit that an exposure of household heads to robots at work could have a causal effect on the life satisfaction of their spouses. Drawing on our data construction, our conjecture is pertinent as we only sort couples who are not just married but also share their physical residential places. In other words, they interact with each other inevitably during our observation period; we believe this high intimacy will bring a high correlation between household heads' and spouses' life satisfaction. Table 4 validates our assumption.

Table 4: Spillover check: correlation between spouses' life satisfaction and husbands' life satisfaction

	(1)	(2)
Household head satisf.	0.617*** (0.006)	0.431*** (0.007)
Observations	59916.000	59540.000
Mean DV	0.31	0.31
sd DV	0.63	0.62
R <sup>2</sup>	0.38	0.51
Controls	Yes	Yes
Year FE	No	Yes
HH.ID FE	No	Yes

Note: \*\*\* p<0.01, \*\* p<0.05, \* p<0.10. Standard errors are clustered at the district level.

### 6.1 Empirical Specification

We examine the effect of automation within the household level. Our empirical specification for the household level follows the multiple time periods difference-in-differences framework as well.

$$Y_{s,d,t} = \alpha + \beta Exposure_h + \sigma Exposure_h \times 2005 - 2009 + \lambda Exposure_h \times Post_{2009} + FEs + \omega X'_{st} + \epsilon_{s,d,t} \quad (4)$$

$Y_{s,d,t}$  indicates life satisfaction of the spouse  $s$  at time  $t$  in district  $d$ . The time dummies are defined the same as with the individual specification. We have time dummies which are equal to 1 if the period is defined between 2005 and 2009; and 1 if it is any year beyond 2009. For the current specification, we employ the continuous treatment variable of household head's exposure to robotization to investigate the indirect effect within the household. Our variables of interest are the interaction terms of our exposure measure with time dummies, 2005 – 2009 and  $Post_{2009}$ . We control the education level of the spouse, the spouse's exposure to robotization and its interaction term with our time dummies. By including our control variables, we attempt to address a number of endogeneity issues in our model. First, the changes the labor supply of females which

might affect our results. During our observation periods, the Korean government executed two significant education reforms which affected the changes in workers' average skill levels (Lee, 2020).<sup>24</sup> As a consequence of those reforms, the female participation rate in the labor market increased; therefore, we expect changes in their life satisfaction. Furthermore, in order to attribute the results of our empirical specifications solely to robot exposure, we include a measure of spouses' exposure to robotization interacted with our time dummies. To allow our framework to capture the outcome changes of within-household variation in household head's exposure to robotization, we add the household identifier along with year fixed effects. Lastly, our error term is clustered at the district and household levels. To avoid confusion, the term household head is equivalent to husband; spouse indicates the household head (husband)'s wife.<sup>25</sup>

## 6.2 Results

Our analysis starts with the spouses' overall life satisfaction changes. Table 5 demonstrates the life satisfaction changes when we regress it on their household heads' exposure to robotization. As previously explained, the exposure measure interacts with our time dummy variables. According to column 5, we confirm the negative effect of our variable of interest. The coefficient exhibits a 0.022 decrease in life satisfaction of spouses with a 1 standard deviation increase in their household heads' exposure to robotization; it is equivalent to the impact of decrease in log wage of 1 that leads to 0.135 increase in spouses' life satisfaction<sup>26</sup>. This indicates that in the years between 2005 and 2009, the spouses became less satisfied than in the years before 2005 when their husbands had not yet been exposed to robotization. On the other hand, we don't confirm any compelling effect when we interact the exposure measure with Post 2009. The result is consistent regardless of the fixed effects and controls included.

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<sup>24</sup>The 6th (applied for the elementary and high school students who were registered in 1995-1998 school system) and 7th (applied for all primary and secondary students registered in 2000-2002 school system) reforms are conducted; one of the main consequences of those reforms was an increase in the female' entrance rate to tertiary education.

<sup>25</sup>In the KLIPS data, approximately 80% of household heads are defined as males. You can refer to the household descriptive statistics in the Appendix.

<sup>26</sup>The OLS regression is added our Appendix

Table 5: The impact of householders' exposure to robotization on spouses' life satisfaction

	(1)	(2)	(3)	(4)	(5)
Exposure $\times$ 2005-2009	-0.025** (0.012)	-0.024** (0.012)	-0.021* (0.012)	-0.022* (0.012)	-0.022* (0.012)
Exposure $\times$ Post 2009	0.007 (0.012)	0.010 (0.012)	0.005 (0.013)	0.010 (0.011)	0.002 (0.013)
Observations	47811.000	47810.000	47576.000	47811.000	47575.000
Mean DV	0.25	0.25	0.26	0.25	0.26
sd DV	0.63	0.63	0.63	0.63	0.63
R <sup>2</sup>	0.079	0.085	0.375	0.094	0.386
Controls	No	Yes	No	No	Yes
Year FE	No	No	No	Yes	Yes
HH.ID FE	No	No	Yes	No	Yes

Note: \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.10$ . Standard errors are clustered at the district and individual ID level. The exposure measure is standardized. Overall life satisfaction, the outcome of interest is a variable that has the following values: -1 indicating dissatisfaction, 0 indicating feeling neutral (neither satisfied nor dissatisfied) to 1 indicating feeling satisfied. The controls include education levels, and a female dummy interacted with 5 years age bins as well as spouses' exposure to robotization.

Table 6: The impact of household heads' exposure to robotization on life satisfaction of their spouses by three (household heads') education groups

	Lower Educ.		Vocational		High	
	(1)	(2)	(1)	(2)	(1)	(2)
Exposure $\times$ 2005-2009	-0.160*** (0.041)	-0.105*** (0.040)	-0.093*** (0.035)	-0.088** (0.037)	-0.090** (0.044)	-0.015 (0.043)
Exposure $\times$ Post 2009	-0.057 (0.044)	-0.011 (0.052)	-0.076* (0.042)	-0.070 (0.044)	-0.062 (0.050)	0.044 (0.051)
Observations	15754	15679	19788	19687	12266	12189
Mean DV	0.08	0.08	0.26	0.26	0.47	0.47
sd DV	0.62	0.62	0.62	0.62	0.59	0.59
R <sup>2</sup>	0.093	0.357	0.066	0.348	0.054	0.361
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	No	Yes	No	Yes	No	Yes
HH.ID FE	No	Yes	No	Yes	No	Yes

Note: \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.10$ . Standard errors are clustered at the district and individual ID level. The exposure measure is standardized. Overall life satisfaction, the outcome of interest is a variable that has the following values: -1 indicating dissatisfaction, 0 indicating feeling neutral (neither satisfied nor dissatisfied) to 1 indicating feeling satisfied. The controls include education levels, and a female dummy interacted with 5 years age bins as well as spouses' exposure to robotization.

We also look at the spouses' life satisfaction changes in the three education level categories of their household heads as in the previous chapter. According to Table 6, we can confirm that the negative effect of automation at the household heads' working place on their spouses is mainly driven by the lower educated and vocational groups. In other words, as a spouse whose husband is highly educated is less affected by changes in her husband's exposure to robotization compared to a spouse whose husband works in low educated or vocational related occupations.

### 6.3 Mechanisms

To understand our main result, we explore the same potential mechanisms with the three education levels as in individual specification: low, vocational and high. Similar to the individual case, we expect that the indirect effect of exposure to robots will have a heterogeneous effect depending on the education level of the household heads. Starting with the 2005-2009 period, we confirm that none of the labor market related variables have significant coefficients to explain our main results refer to Table 7. Furthermore, the Post 2009 years do not exhibit any significant results either, except for a weak negative effect on manufacturing employment of the spouses. Considering that our main results demonstrate a negative effect of household heads' exposure to robotization on their spouses' life satisfaction, the coefficients of potential channels in 2005-2009 and Post 2009 cases are unexpected.

Therefore, it motivates us to investigate further channels to explain our findings in Section 5.

We attribute the negative effect of household heads' exposure to robots on the spouses' life satisfaction to the indirect effect of exposure to robots on within-household economic dynamics. To shed more light on this aspect, we regress the within-household total wages, wage gap and working hours gap of a married couple on the robot exposure of the household heads. The results are summarized in the Table 8. The first column demonstrates how the total income of the household will change when the household heads are more exposed to robotization. The strong negative sign of the 2005 – 2009 case underpins our assumption that the decrease in spouses' life satisfaction is driven by the negative effect of within household outcome changes. Interestingly, we do not have a significant coefficient for the wage and working hour gap between the household heads and spouses.<sup>27</sup> Contrariwise, we can see the household head's exposure attributes to the change in wage gap between the household head and his spouse in *Post2009* case. Based on the definition of Log wage gap, the negative coefficient here indicates that the heads' exposure possibly affects the spouses' (heads') income positively (negatively); or simultaneously affects both of them.<sup>28</sup>

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<sup>27</sup>For variable construction, we put household heads' observation before the spouses'.

<sup>28</sup>For further analysis on the changes in household dynamics, see appendix Table A9

Table 7: Potential channels driving the spouse's result by education level

	Lower Educ.								Upper Educ./ Vocational								Tertiary								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	
Exposure × 2005-2009	Emp.	Changed Manuf.	Log Wage	Firm Switch	Log Hours	Work Satisf.	Part-time	Hourly Wage	Emp.	Changed Manuf.	Log Wage	Firm Switch	Log Hours	Work Satisf.	Part-time	Hourly Wage	Emp.	Changed Manuf.	Log Wage	Firm Switch	Log Hours	Work Satisf.	Part-time	Hourly Wage	
Exposure × Post 2009	0.018 (0.033)	0.007 (0.004)	0.026 (0.054)	-0.028 (0.038)	-0.043 (0.047)	-0.043 (0.071)	0.040 (0.078)	0.848 (0.971)	-0.001 (0.035)	-0.004 (0.003)	0.047 (0.080)	-0.002 (0.011)	-0.013 (0.041)	0.088 (0.073)	0.127 (0.081)	0.052 (0.758)	0.55 (0.933)	0.018 (0.008)	0.008 (0.012)	0.018 (0.022)	0.018 (0.053)	0.005 (0.022)	0.005 (0.091)	0.010 (0.071)	2.424 (1.719)
Observations	15712.000	15712.000	5640.000	8234.000	8450.000	6058.000	3417.000	5654.000	10727.000	10727.000	7306.000	9748.000	9820.000	7983.000	5005.000	7305.000	12218.000	12218.000	4515.000	5256.000	5205.000	4263.000	3332.000	4516.000	
Mean DV	0.55	0.01	0.50	2.61	3.85	-0.06	0.69	6.41	0.50	0.01	7.08	2.75	3.81	-0.21	0.72	8.25	0.44	0.00	0.00	7.50	3.69	-0.48	0.84	14.43	
sd DV	0.50	0.12	0.58	0.46	0.47	0.67	0.46	5.41	0.50	0.13	0.60	0.27	0.42	0.66	0.45	8.55	0.50	0.07	0.70	0.32	0.44	0.62	0.37	15.03	
R <sup>2</sup>	0.560	0.064	0.642	0.924	0.445	0.314	0.681	0.412	0.557	0.080	0.632	0.591	0.416	0.319	0.551	0.414	0.598	0.061	0.753	0.901	0.493	0.366	0.608	0.379	
Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	
District FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	
HHID FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	

Note: \*\*\* p<0.01, \*\* p<0.05, \* p<0.10. Standard errors are clustered at the district level.

Table 8: Effect of household exposure on the household dynamics

	Log Total Wage	Log Wage Gap	Log Hours Gap
Exposure $\times$ 2005-2009	-0.031*** (0.010)	-0.026 (0.029)	-0.004 (0.034)
Exposure $\times$ Post 2009	-0.039*** (0.014)	-0.074** (0.034)	-0.038 (0.040)
Observations	16318.000	12432.000	9829.000
Mean DV	8.22	6.99	7.08
sd DV	0.51	0.93	0.90
R <sup>2</sup>	0.780	0.585	0.411
Controls	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Household FE	Yes	Yes	Yes

Note: \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.10$ . Standard errors are clustered at the district level.

## 7 Local Labour Market Approach

In the previous sections, we document how the South Korean population is affected by robotization through a proxy measure for proximity to affected occupations. We find that after an initial decrease in life satisfaction for those exposed to robotization, the effect of automation on life satisfaction fades out in the following years thereafter. However, this method does not capture the productivity effects accruing in the region of residence as well as the fear mechanism<sup>29</sup>. In this section, therefore, we use two alternative approaches to shed light on labour market outcomes in the short and long run. This analysis is inspired by [Acemoglu and Restrepo \(2020\)](#), who posed the idea to use industry-level adoption of robots to predict robot adoption across regions in a country using the regional distribution of industries prior to the period of study. As robot adoption may be endogenous to local economic conditions, it can be instrumented with robot adoption in the same industries in another, ideally a technologically more advanced country. As robot adoption across industries over the world is ultimately driven by technological progress, this alleviates any remaining concerns about the measure of robot exposure being affected by the local economy.

This approach differs from our previous methods in two important ways. First, the local labor market approach takes into account broader productivity effects as well, which are not directly related to one's occupation. This is significant in explaining our main results since productivity effects possibly have a positive effect on the life satisfaction of workers in the long term.

Second, it measures the local effects of robotization, rather than the effects across the country. In other words, the variation in robot exposure is measured at the regional level. This enables us to demonstrate possible psychological effects of robotization on life satisfaction, by comparing the changes of aggregated life satisfaction between regions and the actual changes in employment and wage at the aggregate level.

<sup>29</sup>We will discuss further in the following.

## 7.1 Local Labour markets approach

As the approach in Section 3 employs a difference-in-differences with multiple time periods, we are interested in the long- and short-run response to robot adoption in the regions most exposed. To study this, we use the following empirical strategy:

$$\Delta Y_d = \alpha + \beta \Delta robot_{t_1,d}^{t_2} + \gamma X'_{t_1,d} + \epsilon_d \quad (5)$$

where  $d$  index the region (Si, Gun, Gu)<sup>30</sup>. The change in robot exposure  $\Delta robot_{d,t=t_1}^{t_2}$  is the long-term difference in the predicted number of robots installed in the region  $d$ .  $X'_d$  is a vector of controls that includes the cohorts of 20 to 50 years of age, as well as high education, vocational education and gender shares per region. As we do not observe the number of robots installed in a specific region, we calculate it as follows:

$$\Delta robot_{t_1,d}^{t_2} = 1000 \times \frac{\Delta robot_{t_1,j}^{t_2}}{L_{t_1,j}} \times \frac{L_{t_1,jd}}{L_{t_1,d}} \quad (6)$$

where  $\Delta robot_{t_1,j}^{t_2}$  denotes the total net installations in sector  $j$  between  $t_1$  and  $t_2$ .  $L_{t_1,j}$  denotes the total number of workers in  $t_1$  in sector  $j$ ,  $L_{t_1,d}$  in region  $d$  and  $L_{t_1,jd}$  in sector  $j$  and region  $d$ . We calculate the number of workers using KLIPS and the weights associated with each individual observation. We focus on the regions with at least 20 observations in the base year. This leaves us with 80 regions. For ease of interpretation, we multiply by 1000 to interpret  $\Delta robot_{t_1,d}^{t_2}$  as the number of robots per 1000 workers. The average number of robots installed per 1,000 workers is  $N$  between 2005 and 2009 and  $N$  between 2009 and 2019

## 7.2 Shift-share Instrumental Variable

As the regional-level robot exposure correlates with beneficial local economic conditions, driven by sectors well suited for robotization, the results of Equation 6 could be suffer from omitted variable bias. This cannot be solved by controlling for local economic conditions, as these could also mediate the effect of robot adoption on life satisfaction and relevant labor market conditions. Therefore, we resort to the shift-share IV approach commonplace in the literature dealing with labor market effects of robotization. The instrument is calculated as follows:

$$\Delta \hat{robot}_{t_1,dc}^{t_2} = 1000 \times \frac{\Delta robot_{t_1,j}^{t_2}}{L_{t_1,jc}} \times \frac{L_{t_1,jd}}{L_{t_1,d}} \quad (7)$$

where  $c$  indexes the country (set) used as a reference. In our subsequent analysis, we use Singapore as a reference country. The use of such instruments is typically supported by the assumption that the reference

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<sup>30</sup>South Korea consists of upper and lower level local autonomy. Si, Gun, Gu are the three main types that belong to the lower local autonomy. There are 60 of Si(equivalent to city), 15 of specific Si(city), 82 Gun(county), 69 Gu(district)

country  $c$  is more technologically advanced than the country of interest. If this would not be the case, robot adoption in the reference country could be driven by local conditions in the country of interest (e.g. through development of new technologies amenable to the country of interest). As South Korea is at the forefront of robot development and adoption, this assumption is strong. To the best of our knowledge of our knowledge, this IV approach has not been used in the literature.

### 7.3 Replaceability Instrumental Variable

An alternative IV can be based on the replaceability of occupations in a region in a specific base period. Using the measure of replaceability (the share of hours worked that is replaceable) developed by [Graetz and Michaels \(2018\)](#),  $\theta_k$  (as discussed in Section 4.3), we construct a region-based measure of replaceability:

$$\hat{\theta}_d = \frac{\sum L_{dk}\theta_k}{\sum L_{dk}} \quad (8)$$

$L_{dk}$  corresponds to the number of workers by occupation. This instrument, contrary to the shift-share instrument based on robot adoption in other countries, has no specific time dimension. However, the measure of replaceable hours from [Graetz and Michaels \(2018\)](#) is based on the matching of IFR applications and occupational titles in year  $t$ . Therefore, it is plausible that [Graetz and Michaels \(2018\)](#) find that this instrument is a strong predictor of subsequent robot adoption. This may suggest the matching of occupational titles to the functions of robots may generate a useful source of plausible exogenous variation ([Caselli et al., 2021](#)).

### 7.4 Results

To match our main empirical strategy temporally, we use long differences for two distinct time periods: 2005 to 2009 and 2009 to 2019. Table 9 shows the regression table of Equation 6.

We find that life satisfaction is unaffected by the local adoption of robots in both time periods. This can be reconciled with the negative initial and insignificant subsequent effects found in Section 5 in the following way. Our baseline result measures individuals' direct exposure to the jobs likely to be replaced by robots. However, this does not account for any productivity increases of high-skilled workers nor for improvements in the labor market conditions for those living in regions that undergo strong robotization through increased demand for labor unrelated to robot adopting industries. The only significant coefficient in table 9 is that of high-skilled wages between 2009-2019. An additional robot per 1000 workers is associated with a moderate increase in high-skilled wages of 0.4%.

However, the empirical strategy still face endogeneity problems because of the decision to adopt robots by industry. To overcome this issue, we employ an instrumental variable analysis in Equation 8 as well, using the IV based on replaceability for 2005-2009 and an IV using robot expansion in Singapore between 2009 and 2019. We use Singapore's data for the following reasons. First, during our observation period, Singapore was ahead of South Korea in terms of robotization.

Table 9: Long Differences in a Local Labour Market Approach

2005-2009					
	Life satisfaction	Log employment	log of LS wage	log of MS wage	log of HS wage
$\Delta robot_{t_{2005},d}^{t_{2009}}$	0.014 (0.022)	-0.015 (0.016)	-0.010 (0.020)	0.017 (0.022)	0.015 (1617.732)
Observations	85	85	83	85	85
$R^2$	0.20	0.35	0.16	0.26	0.22
2009-2019					
	Life satisfaction	Log employment	log of LS wage	log of MS wage	log of HS wage
$\Delta robot_{t_{2009},d}^{t_{2019}}$	0.002 (0.002)	0.003 (0.003)	-0.000 (0.004)	0.001 (0.002)	0.004* (0.002)
Observations	85	85	83	85	85
$R^2$	0.27	0.22	0.28	0.27	0.25

Standard errors in parentheses

\*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ 

Table 10: Long Differences in a Local Labour Market Approach

2005-2009 (IV based on replaceability)					
	Life satisfaction	Log employment	log of LS wage	log of MS wage	log of HS wage
$\Delta robot_{t_{2005},d}^{t_{2009}}$	0.064 (0.080)	-0.024 (0.087)	0.047 (0.071)	0.049 (0.110)	0.097 (0.093)
Observations	80	80	79	80	80
F-stat.	8.47	8.47	8.47	8.47	8.47
2009-2019 (IV using Singapore)					
	Life satisfaction	Log employment	log of LS wage	log of MS wage	log of HS wage
$\Delta robot_{t_{2009},d}^{t_{2019}}$	-0.001 (0.721)	-0.002 (0.885)	0.005 (0.012)	-0.001 (0.004)	-0.002 (0.006)
Observations	85	85	83	85	85
F-stat.	22.7	22.7	22.7	22.7	22.7

Standard errors in parentheses

\*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

The results can be seen in Table 10. However, none of the coefficients are significant. The outcomes lead us to two suggestive conclusions. First, the productivity effect observed in a regional aggregated level on life satisfaction is small. This supports our results in section 5.2 and 6.2; the negative effect of automation is largely explained by the displacement effect.<sup>31</sup>

Second, the changes in life satisfaction of workers are not due to the fear of being replaced by robots in the future but rather by the actual labor market outcome changes. The psychological fear of the robotization could be confirmed when diminishing life satisfaction is detected without any negative effect of robotization on labor market outcomes in the long term. As Table 10 demonstrates, the life satisfaction of workers is not significantly affected by robotization as the channels, employment and wage have not been impacted by exposure to robots. This shows that workers' life satisfaction is related to the labor market outcomes rather than other indirect channels.

## 8 Robustness Checks

### 8.1 The 2008 Financial Crisis

Table 11: Robustness checks for the 2008 Financial Crisis

Overall Life Satisfaction	(1)	(2)
Exposure $\times$ 2005-2007	-0.027*** (0.006)	-0.028*** (0.006)
Exposure $\times$ 2007-2009	-0.019*** (0.007)	-0.019*** (0.007)
Observations	173150	172161
Mean DV	0.28	0.28
R <sup>2</sup>	0.087	0.393
Controls	Yes	Yes
Year FE	No	Yes
Individual FE	No	Yes

Note: \*\*\* p<0.01, \*\* p<0.05, \* p<0.10. Standard errors are clustered at the district and individual level.

The main results of the impact of robotization on life satisfaction at the individual level are robust to the financial crisis shock in 2008. Table 11 illustrates the results of equation 3 with a minor change in the interaction terms to take into consideration the years 2005 to 2007 as well as 2007 to 2009. In other words, the early years of robotization 2005 to 2009 were subject to the 2008 shock. Therefore, two dummies were created: One for the years of robotization before the 2008 financial crisis and one for right after it from 2007 to 2009. The results in table 11 show that our main results are robust to the 2008 financial crisis. The interaction terms of exposure to robotization with the years 2005 to 2007 as well as with after the 2008 crisis (from 2007 to 2009) show a negative and significant impact on individuals' life satisfaction. This is in

<sup>31</sup>Our previous exposure measure exhibits the replaceability of each occupation by robots

line with our main results which show a decline in the life satisfaction of individuals throughout the early robotization period from 2005 to 2009.

## 8.2 Adding More Fixed Effects

To enhance the robustness of our empirical strategy, we undertake a robustness check that incorporates an additional fixed effect into our analysis. Our previous investigation reveals that the impact of robot exposures exhibits considerable variation across different levels of education. In light of these findings, we investigate the application of a two-way fixed effects model, enriched with interaction terms, into our initial Equation 2. This refined approach allows for more control over the unique impacts attributable to each year and education level category, as well as the synergy effects arising at the confluence of these dimensions. By embedding this two-way fixed effects framework within our analysis, we attempt to capture not only the isolated influences of temporal and demographic factors but also the multifaceted effects emerging from their interplay. Echoing this methodology, we incorporate a two-way fixed effects models that employ the interaction term between the replaceability of each occupation (to robot exposure) and year as well as occupation and year. Our construct of replaceability draws on the foundational work of [Graetz and Michaels \(2018\)](#).<sup>32</sup>

Figure 13 presents our results. Employing a two-way fixed effects model that integrates both education and year, we observe no significant impact from robot exposure following the implementation of two automation policies. This lack of significant effect persists even beyond the adaptation period post the second policy wave, starting from 2013. This outcome suggests that the annual variation in the education level of the workforce is a primary factor influencing our results, a finding corroborated by our heterogeneity analysis. Furthermore, our investigation employing a two-way fixed model that examines the interaction between occupation and time also fails to reveal any significant effects on our outcome variable. This indicates that the impact of robot exposure is subject to variation across different occupations. Given that our robot exposure measure is predicted on occupational data, we anticipated that our main outcome would reflect variations attributable to occupational characteristics. The absence of significant findings underscores the importance of our approach in capturing the occupation-dependent effects of robotization.

Our analysis, employing a two-way fixed effects model of job replaceability and year, reveals an intriguing trend: an increase in life satisfaction level post-2013. This finding suggests a key insight. Initially, it indicates that across occupations with uniform levels of replaceability, a unit increase in robot exposure correlates with enhanced life satisfaction following the second robotization wave. This observation suggests that the compatibility between a robot’s capabilities and the job description does not solely determine worker satisfaction. Instead, the presence of robots appears to positively influence worker sentiments, irrespective of the direct applicability of robotics to their specific job tasks. This phenomenon hints at an indirect positive effect of robotization on workforce. Furthermore, this pattern holds true regardless of whether the job tasks are directly substitutable with robots; individuals in environments with higher robot exposure report greater satisfaction compared to those in less automated settings. This underscores an indirect beneficial

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<sup>32</sup>Building on the methodology from [Graetz and Michaels \(2018\)](#), we align the IFR applications with occupational titles from the initial year of our study, 1998. This alignment strategy posits that matching occupational titles to robot functions could yield a valuable source of plausible exogenous variation, as suggested by ([Caselli et al., 2021](#)). This approach enhances our analysis by leveraging potential discrepancies between the intended functions of robots and the roles traditionally fulfilled by human labor, thereby offering a novel perspective on the impact of automation.

impact of robotization, a conclusion that aligns with our previous findings from household-level analyses. In essence, our research illuminates the relationship between automation and worker well-being, highlighting the broader, positive ramifications of robotization beyond mere task substitution.

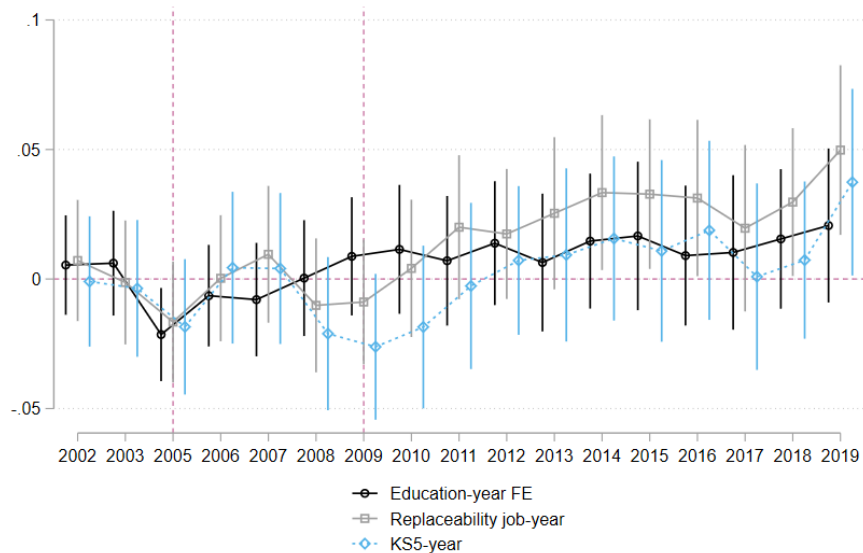


Figure 13: Robustness Check with Two-Way Fixed Effects

## 9 Conclusion

In South Korea, adopting robots was a two-step procedure that started in 2005 in the manufacturing sector followed by a sharp increase in robot adoption in all the sectors as of 2009. Our results at the individual level show that robotization before 2009 led to a decrease in the life satisfaction of individuals followed by an increase in life satisfaction due to a rise in employment levels. To disentangle our findings, we explore the labor market channels that could possibly drive the results. We find that these results are driven by young males aged 20 to 29 who happen to be highly educated. The results are displayed at the low, vocational and high education levels as robotization is expected to have a different effect depending on these levels. The early wave of robot adoption from 2005 to 2009 witnessed a displacement effect of the low educated workers at the individual level. This indicates that the low educated individuals were the ones with the lowest life satisfaction as a result of being exposed to robots at work. The vocationally and highly educated individuals were not impacted.

The mechanisms leading to these results can be explained in light of the displacement of robots at workplace. From 2005 to 2009, the low and the vocationally educated individuals have been displaced of their work in the form of the rise in part-time employment and the switching of their workplace. From 2009, we confirm that the vocational and high educated individuals benefitted from the robotization in the form of wage increases. This was not the case for the low educated individuals. The gap between the low and the other two educational groups in wages can be translated into differences in their ability to adjust to the increased

volume of robots at their workplace. Additionally, the enhanced wage of the higher educated workers signals the productivity effect in certain occupations and sectors employing vocational and high educated workers.

In addition to the individual case, we also explored the life satisfaction change of spouses owing to the increase in their husbands' exposure to robots. Aligning with the outcome from the individual case, we confirm that the negative effect of robot exposure is mainly driven from the spouses whose husbands are low educated or vocational educated workers due to the decrease in the total household wage. Our result signifies that the negative effect of robotization is not just limited to the individuals but it is amplified within the household. This is especially true when we pay attention to their quality of lives.

Last but not least, we employed a local labor market approach instrumented with Singapore and a replaceability IV to exhibit the productivity effect of robotization as well as possible channels to proxy for psychological effects that were not explained by our exposure measure. Despite the confined sample size, our results show evidence of neither a productivity effect nor a psychological effect of robotization on workers.

The life satisfaction of workers matters not only because it indicates their quality of life, but also because it is highly correlated with the productivity of workers. As our study proves a general positive effect of robotization at the aggregate level and a specific negative effect for the low educated groups in the short term, it suggests that the government should design appropriate labor protection policies to promote low educated workers' ability to adjust to new working environments with newly-added robots instead of having them frequently switch their workplace.

## 10 Appendix

### 10.1 Figures

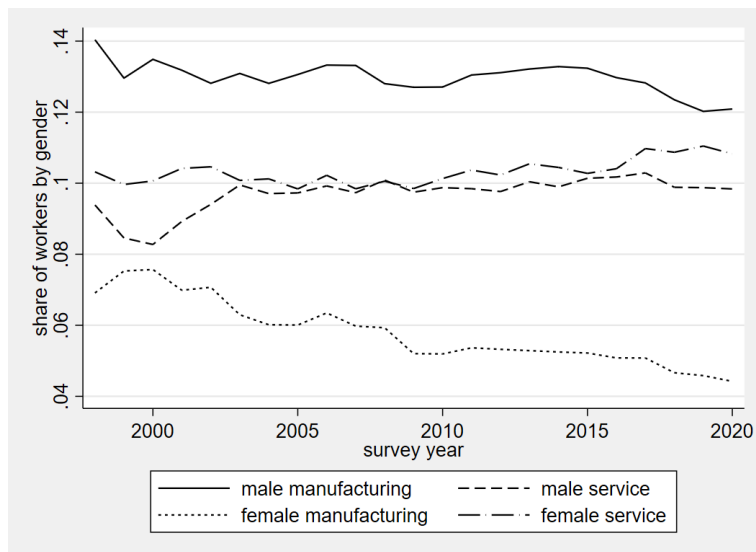


Figure A1: Labor participation rate by gender (KLIPS)

Note: The graph shows the labor participation rates of manufacturing and service sector by gender. As we mention in the main text, males' participation rate in manufacturing sector is dominant to the females.

### 10.2 Tables

Table A1: The impact of wages on individual life satisfaction

Overall Life Satisfaction	(1)	(2)
Log Wage	0.035*** (0.001)	0.023*** (0.001)
Observations	162995	161955
R <sup>2</sup>	0.099	0.402
Controls	Yes	Yes
Year FE	No	Yes
Ind.ID FE	No	Yes

Note: \*\*\* p<0.01, \*\* p<0.05, \* p<0.10. Standard errors are clustered at the district and individual ID level.

Table A2: Results by Subsample: Males over 40

Life Satisfaction	(1)	(2)
Exposure X 2005-2009	-0.024** (0.011)	-0.006 (0.011)
Exposure X Post 2009	-0.012 (0.012)	0.027** (0.013)
Observations	56413	56001
Mean DV	0.10	0.53
R <sup>2</sup>	0.115	0.434
Controls	Yes	Yes
Year FE	No	Yes
Ind.ID FE	No	Yes

Note: \*\*\* p<0.01, \*\* p<0.05, \* p<0.10. Standard errors are clustered at the district level

Table A3: Results by Subsample: Males over 40

Life Satisfaction	(1)	(2)
Exposure X 2005-2009	-0.024** (0.011)	-0.006 (0.011)
Exposure X Post 2009	-0.012 (0.012)	0.027** (0.013)
Observations	56413	56001
Mean DV	0.10	0.53
R <sup>2</sup>	0.115	0.434
Controls	Yes	Yes
Year FE	No	Yes
Ind.ID FE	No	Yes

Note: \*\*\* p<0.01, \*\* p<0.05, \* p<0.10. Standard errors are clustered at the district level

Table A4: The Impact of Exposure to Robotization on Life Satisfaction by Age Groups

Life Satisfaction	(1)	(2)	(3)	(4)	(5)
	Age 20	Age 30	Age 40	Age 50	Age 60
Exposure X 2005-2009	-0.023 (0.020)	-0.038*** (0.009)	-0.018* (0.010)	-0.004 (0.014)	-0.026 (0.029)
Exposure X Post 2009	0.048 (0.061)	-0.012 (0.012)	0.013 (0.013)	0.020 (0.018)	-0.025 (0.038)
Observations	14017	43022	50989	41027	20226
Mean DV	0.22	0.34	0.29	0.26	0.24
R <sup>2</sup>	0.436	0.475	0.501	0.495	0.560
Controls	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Ind.ID FE	Yes	Yes	Yes	Yes	Yes

Note: \*\*\* p<0.01, \*\* p<0.05, \* p<0.10. Standard errors are clustered at the district and individual level

Table A5: Results by Subsample: Married Males over 40 dummy (age40)

Life Satisfaction	(1)	(2)
Exposure X 2005-2009	-0.015 (0.012)	-0.010 (0.013)
Exposure X Post 2009	-0.026* (0.014)	0.017 (0.017)
Observations	26194	25773
Mean DV	0.10	0.52
R <sup>2</sup>	0.144	0.506
Controls	Yes	Yes
Year FE Yes	No	Yes
Ind.ID FE	No	Yes

Note: \*\*\* p<0.01, \*\* p<0.05, \* p<0.10. Standard errors are clustered at the district and individual level

Table A6: The impact of individual's exposure to robotization on life satisfaction by gender

Overall Life Satisfaction	Male		Female	
	(1)	(2)	(1)	(2)
Exposure $\times$ 2005-2009	-0.037*** (0.008)	-0.021*** (0.008)	-0.025* (0.014)	-0.017 (0.014)
Exposure $\times$ Post 2009	-0.017* (0.009)	0.011 (0.008)	-0.014 (0.014)	0.006 (0.015)
Observations	84759	84240	88391	87921
Mean DV	0.27	0.28	0.28	0.28
R <sup>2</sup>	0.117	0.395	0.121	0.392
Controls	Yes	Yes	Yes	Yes
Year FE	No	Yes	No	Yes
Ind. FE	No	Yes	No	Yes

Note: \*\*\* p<0.01, \*\* p<0.05, \* p<0.10. Standard errors are clustered at the district and individual level.

Table A7: The impact of householders' exposure to robotization on spouses' life satisfaction by satisfaction level

	Discontent	Neutral	Content
Exposure $\times$ 2005-2009	-0.072 (0.055)	0.369*** (0.096)	-0.297*** (0.090)
Exposure $\times$ Post 2009	-0.201*** (0.059)	0.293** (0.120)	-0.092 (0.106)
Observations	47734.000	47734.000	47734.000
Mean DV	0.10	0.54	0.36
sd DV	0.31	0.50	0.48
R <sup>2</sup>	0.312	0.218	0.325
Controls	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
HH.ID FE	Yes	Yes	Yes
Age FE	Yes	Yes	Yes

Note: \*\*\* p<0.01, \*\* p<0.05, \* p<0.10. Standard errors are clustered at the district level.

Table A8: Household descriptive statistics

	Mean	SD	Min	Max	N
Average household size	2.365	0.189	2	2.6810625	245662
Householder age	53.172	13.975	15	100	319230
Spouse age	49.165	12.378	19	94	258750
Householder, average wage	295.582	246.837	1	18971.732	185654
Spouse, average wage	186.301	148.665	3	5099.1792	81851
%Householder, low education	0.234	0.000	0	.23437615	245662
%Householder, mid education	0.389	0.000	0	.38920099	245662
%Householder, high education	0.376	0.000	0	.37638614	245662
%Spouse, low education	0.287	0.000	0	.2874727	245662
%Spouse, mid education	0.414	0.000	0	.4144274	245662
%Spouse, high education	0.298	0.000	0	.29777962	245662
%Male householder	0.830	0.027	1	.88132823	108936
%Male spouse	0.028	0.009	0	.03810504	108936

Note: \*\*\* p<0.01, \*\* p<0.05, \* p<0.10. Standard errors are clustered at the district level.

Table A9: Effect of spouse exposure on the household dynamics

	Log Total Wage	Log Wage Gap	Log Hours Gap
Exposure × 2005-2009	-0.023** (0.010)	-0.070*** (0.026)	0.033 (0.036)
Exposure × Post 2009	-0.016 (0.013)	-0.056* (0.032)	-0.024 (0.035)
Observations	13585	10357	8585
Mean DV	8.17	6.97	2.66
sd DV	0.51	0.93	0.83
R <sup>2</sup>	0.769	0.579	0.399
Controls	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
HH.ID FE	Yes	Yes	Yes

Note: \*\*\* p<0.01, \*\* p<0.05, \* p<0.10. Standard errors are clustered at the district level. We confirm that the increase in spouses' robot exposure also negatively relates to the total household income; however, the declines in wage gap implies that it is spouses who receive relatively higher benefit from the robotization in regard to the wage raise. Interestingly, it is not detected from the table 8.

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