Automation and Employment

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Abstract: Using panel data from 63 countries and the generalised method of moments, this paper examines the impact of industrial robot utilisation on employment. Results show a 1% increase in new industrial robot installations per 10,000 workers reduces the unemployment rate by 0.037%-0.039%. The impact is more pronounced for male workers (0.045%) than female workers (0.033%), and youth unemployment is more significantly affected. Lastly, automation is found to reduce the unemployment rate by 0.052% for people with intermediate education, yet with little effect on those with basic or advanced educational attainment.

Key words: Automation; Employment; Generalised method of moments; Panel data

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1. **Introduction**

Every new surge in technological advancement reignites discussions on the relationship between automation and employment. While there has been concerns about automation displacing human workers, job losses attributed to technological advancements have not always occurred (Acemoglu et al., 2023). This can be attributed to new technologies automating only specific tasks within jobs, rather than replacing entire positions. Such augmentation innovations increase productivity, which in turn generates new demands for human labor (Autor, et al., 2023).

The recent advancements in automation, robotics, and artificial intelligence (AI), characterized by the development of autonomous systems, enhanced computing power, and sophisticated machine learning algorithms, have the potential to transform the nature of work and reshape the future of jobs. Machines have become increasingly capable of performing non-routine and cognitive tasks that were previously thought to require human intelligence and dexterity. The swift pace of technological advancements has led to a renewed examination of a longstanding question by scholars, industry experts, and policymakers alike, though with a nuanced concern: will this time be different? This concern is well-founded, as studies do find that the 19th-century manufacturing technologies largely substituted for skilled labor, while the Computer Revolution of the 20th century caused a hollowing-out of middle-income jobs. Furthermore, researchers predicted that computerisation of the 21st century will mainly impact low-skill and low-wage occupations (Frey and Osborne, 2017). As a result, adapting to the rapidly evolving job market demands through workforce upskilling and reskilling has become increasingly challenging.

The literature on technological advancement and employment is extensive, especially now with the emergence of generative AI which has garnered unparalleled attention. Research has been done to assess the impact of generative AI on jobs in the United Statues, and it is estimated to automate as much as 10% of work tasks for up to 80% of the workforce in the United States (Eloundou et al., 2023). Another study investigated the global impact and concluded that the potential employment effects vary significantly across country income groups, where a larger share of total employment in high-income countries is potentially exposed to automation effects than low-income countries (5.5% vs 0.4%) (Gmyrek et al., 2023).

Studies have also focused on the analysis of potential exposure of occupations to computerisation or automation, and in general the technological advancement in the 21st century is found to affect the broad occupation of clerical work the most (Frey and Osborne, 2017; Gmyrek et al., 2023). Although there is a substantial amount of research on the topic, there remains a gap in detailed investigations that dissect the effects of automation through various lenses such as gender, age, and levels of educational attainment. Such nuanced analyses are crucial for several reasons.

First, understanding the differentiated impact by gender could provide insights into how policies could be made to ensure equitable access to the benefits of technological advancements. Second, analyzing the effects by age could shed light on which segments of the workforce are more vulnerable to automation, particularly important for crafting targeted support and re-skilling programs for workers at different stages of their careers. Third, detailed investigation for people of different educational background can help identify the types of skills that will be most in demand in future, and therefore guide lifelong learning, and vocational training programs to better align with future job market needs.

This study aims to fill the gap by using data from the International Federation of Robots and World Bank, and General Methods of Moments methodology to study the overall impact of industrial robotics on employment. In particular, we would like to investigate (i) the overall effect of technological advancement on unemployment rates; specifically, whether it leads to an increase or decrease in unemployment; (ii) the variation in the impact of technological advancement on the labor force when examined by gender, age and different levels of education, to determine if there are varying effects for males and females, if certain age groups are more affected than others, and if the effects are distinct for individuals with basic, intermediate, or advanced education backgrounds.

Our results show that if the new installations of industrial robots per 10,000 labour force increase by 1%, unemployment rate will reduce by 0.037%~0.039%. The impact varies by gender, which has a larger impact on male, with a 1% increase of installations reducing the unemployment rate of males by 0.045%, versus 0.033% reduction of female's unemployment rate. However, the new installations of industrial robots per 10,000 labour force do not affect the unemployment rate of youth labour force differently from that of the overall labour force. As for its impact on people with different educational attainment, the new installations of industrial robots per 10,000 labour force have a significantly negative effect (-0.052) on the unemployment rate of the labour force with intermediate education, but not on that of the basic or advanced education.

The rest of the paper is organised as follows. Section 2 provides a comprehensive review of the literature examining the employment effect of technological advancement. Section 3 introduces data used in this paper, as well as econometric methodologies. Section 4 analyses data and discusses results. Section 5 concludes, and provides future research directions.

2. Literature review

Recent and emerging breakthroughs in highly developed robots and artificial intelligence are profoundly shifting the ever-changing dynamics of human-machine partnerships. Whether this partnership is mutually complementary or competitive, depends on the factors and characteristics of the labour market that are being put under investigation. While some studies have advocated for robots, stating the opportunities they bring for economic development and productivity, most have documented a negative effect of robot adoption on workers. This nuanced effect of automation and robots on employment has spurred the development of countless scholarly articles delving into this subject matter through various lenses. This literature review examines the gradation and subtlety in how various groups of workers are differentially affected by automation depending on both skill-level and tasks or occupations.

In bolstering the argument for robot adoption, Graetz and Michaels (2018) find that robots increased labour productivity and lowered output prices without a significant reduction in total employment. Similarly, a study by Koch et al. (2021) reported that robot adoption generates significant output gains while cutting down on the labour cost share and even resulting in the creation of new jobs, thereby increasing employment opportunities. In Japan, Adachi et al. (2022) supports this by reporting a rise in employment by boosting the productivity and production scale of robot-adopting industries. Employing a long-term industry-level panel data from Japan between 1979-2012, Dekle (2020) posits that industries that implement robots raise productivity thereby increasing demand in all industries. This in turn enhances the product and labour demand for the industry incorporating robots. These studies emphasise the complementarity between robots and promoting productivity without devastating effects on employment outcomes.

Nevertheless, a prolific number of studies share a concerned outlook on unemployment when the effects of automation are examined in the context of skill-level. Workers in the low-skilled category experienced a drop in employment share when there was an increase in the adoption of industrial robots (Graetz & Michaels, 2018). Moll et al. (2021) further expands on this by contextualising the benefits of automation to a specific group of workers, particularly for high-skilled workers and the owners of capital, consequently leading to an increase in inequality. This skill-biased effect is also supported by a study conducted by Balsmeier and Woerter (2019). They present complementary evidence derived from representative survey data in Switzerland that is consistent with this view. The survey found that increased investment in firms that employ robots or implement digitalisation was associated with increased employment of high-skilled workers while reducing the employment of low-skilled workers within the firm, with a slightly positive net effect. In Germany, Deng et al. (2021) use plant-level data to establish that the proportion of high-skilled labour (employees with a university degree) lowers the likelihood of robot adoption. This again is congruous with the aforementioned studies, further demonstrating that high-skilled workers carry an advantage in performing more complex and less automatable tasks which are also less prone to be replaced by robots. Another study by Brambilla et al. (2023) reported a higher unemployment rate in districts exposed to more robot adoption when comparing its effects on labour market outcomes of Latin America, more specifically in Argentina, Brazil and Mexico. It corroborated with other reports supporting the view that highly skilled workers were the least affected by robotisation. Using firm level data analyses in China, Qin et al. (2022) also concluded that automation inflates the proportion of high-skilled workers while having the opposite effect on that of low-skilled workers. However, they acknowledge that the benefit of this effect is that it leads to skill upgrading. Therefore, the concept of skill-biasness reinforces the possibility that automation and technological evolution accumulate benefits only for a sub-group of workers, particularly high-skilled labour. While the debate on how automation ultimately affects unemployment persists through time, there is undoubtedly a growing consensus that at least in terms of workers in differing skill groups, those in the low-skilled category are at a higher risk of substitution by robots whereas their high-skilled counterparts are believed to procure benefits through the increasing use of automation.

Apart from investigating how the escalated use of robots, technological software, and artificial intelligence affect unemployment from a skill dimension, recent research in this field has shifted the focus onto the types of tasks and their related endangered jobs that are vulnerable to automation. Autor et al. (2003) sorted job tasks into four categories, i) routine manual tasks, ii) routine cognitive tasks, iii) non-routine manual tasks, and iv) non-routine cognitive tasks. Individuals working in routine (repetitive) tasks were deemed to be more substitutable by automation than those carrying out non routine (non-repetitive) tasks. With the rampant progress in technological dexterity and exceptional cutting-edge software engineering, robots are becoming increasingly proficient at managing a wide variety of tasks. They now have an excellent capacity to perform manual activities such as vacuuming, mopping, and lawn mowing (Frey and Osborne, 2017). Abel and Deitz (2012) believe that such routine manual tasks (e.g. Administrative workers, machine operators) have a higher probability of being replaced by technology. Owing that these tasks require a systematic and methodical repetition of operation, they can be coded and programmed into machines or robots to undertake these functions and assignments. Chuang (2021) conducted a survey to identify 30 displaceable skills from endangered jobs among a total sample of 423 adult employees in Indiana USA. The survey results showed that the top 10 displaceable skills performed by the respondents were "self-control (n = 372; 88%), getting information (n = 360; 85%), independence (n = 355; 84%), deductive reasoning (n = 341; 81%), monitoring (n = 337; 80%), organising/planning/prioritising work (n = 335; 79%), documenting/recording information (n = 333; 79%), being exact or accurate (n = 331; 78%), interacting with computers (n = 310; 73%) and near vision (n = 306; 72%)." What this demonstrates is that these skills share a common characteristic, mainly utilising repetitive movements while lacking social interaction (Chuang, 2021). However, it is pertinent to state that there are roles that continue to be resistant to automation. These jobs require high cognitive skills, decision-making and coordination, (e.g.

doctors, lawyers and software engineers) as well as jobs that emphasise on personal and physical human interactions (e.g. childcare workers) (Abel and Deitz, 2012).

So far, we have discussed a litany of research that target the effects of automation and robots and on labour demand and displaceable skills, with most literature demonstrating the pros and cons of machines substituting human capital. A vast number of reports have put the spotlight on automation and its effect on unemployment of workers in certain professions, industries or in the context of skills redundancy. For low-skilled workers who are aware of their susceptibility to automation, they could be more motivated to engage in upskilling programmes as a strategy to retain employment by acquiring skills that are complementary or supplementary to machine-operated procedures. As a result, employment loss could be mitigated through education. Cords and Prettner (2022) extended their research model to predict if endogenous skill acquisition would affect employment of low-skilled workers when displaced by automation in Germany, Austria, USA and Australia. It is noteworthy that when endogenous skill acquisition was incorporated as a long-term adjustment measure, the employment outcome of automation becomes positive in all four countries. The authors concluded that unemployment in low-skilled employees could therefore be addressed by enhancing education investments and incentives for individuals to enrol in higher education. While there is acknowledgement that this would act as a long-term solution, retraining programmes for low-skilled displaced workers could be effective over a shorter time period (Cords & Prettner, 2022). Similarly, using two decades of administrative data from Austria, Schmidpeter & Winter-Ebmer (2021) demonstrate that active labour market policies such as unemployment training can be one successful measure to overcome the implications imposed by automation and digitalisation. Interestingly, they highlight that individuals who are equipped with the skills to adapt to new technology face better employment outcomes with higher wages and job stability than those who lack the capacity to cope with technological change.

3. Data and methodology

This paper uses data from the International Federation of Robotics (IFR), and the World Bank's World Development Indicators. The IFR, founded in 1987, provides comprehensive data, market analysis and forecast on the production, use, and economic impact of industrial robots and service robots across different sectors in the world. From IFR, we retrieve data on the number of installations, and operational stock of industrial robots in 75 countries for the period of 1993-2021. Given the concentration of industrial robots in the manufacturing sector and the fact that only a select number of countries have accessible industry-level data dating back to 1993, our analysis will focus on the aggregate annual figures for robots within the country, rather than the sector-specific data.

The number of industrial robots in the United States and Western Europe has increased four-fold between 1993 and 2007. Similarly in Korea, the adoption of industrial robots has been by far the highest since 2010, according to the International Federation of Robotics' World Robot Statistics (Park et al., 2021). In 2016, Korea recorded 631 robots per 10,000 employees in the manufacturing industry, followed by Singapore, Germany, and Japan. By 2016, there were on average 74 industrial robots installed per 10,000 employees globally. This number is remarkably higher in Singapore, where 488 robots per 10,000 employees are deployed (IMDA, 2018). The total number of industrial robots deployed globally is estimated to grow from around 1.5 million in 2014 to about 5 million by 2025 (Boston Consulting Group, 2015) and this trend has important implications on labour markets. In the US context, Acemoglu and Restrepo (2020) demonstrated that “one more robot per thousand workers reduces the employment to population ratio by about 0.18-0.34 percentage points”.

Furthermore, due to a significant methodological shift in how the IFR reported the operational stock of robots between 2004 and 2005 (Bordot, 2022), we choose the starting point 2005, so as to ensure the consistency in the measurement of installation/stock of robots across the entire period studied. This leads to a sample of 63 countries, spanning the years 2005 to 2021.

The dataset sourced from the World Development Indicators encompasses a diverse array of economic and demographic statistics. This includes different measures of the unemployment rate, detailed population figures, labor force metrics, and the GDP growth rate.

We employ a dynamic panel data approach, and the difference Generalised Method of Moments (GMM) estimation technique. The model is specified as follows:

$$lnU_{i,t} = \beta_0 + \beta_1 lnU_{i,t-1} + \beta_2 lnRobots_{i,t} + +\beta_3 lnGDP_{i,t} + \varepsilon_t$$

where the superscript “i” and “t” represent country and year, respectively. The variables lnU, lnRobots, and lnGDP stand for the logarithms of unemployment rate, number of robots per 10,000 labor force, and GDP growth rate. lnRobots is used to measure the technological advancement in our analysis.

Table 1 lists the variables and the descriptive statistics. It is observed that on average, female workers have a higher unemployment rate than male workers, across all age groups; and the unemployment rate tends to decrease as the education level of the labor force increases.

[Table 1 about here]

4. Results and discussion

Table 2 shows results from the difference GMM estimation. In Model (1), we use lnInstall to measure the technological advancement, i.e., the logarithm of the number of installations of industrial robots per 10,000 labor force. Results from both the one-step first difference GMM and the two-step first difference GMM estimations are reported. In Model (2), the technological advancement is measured by lnStock, which is the logarithm of the number of operational stock of industrial robots per 10,000 labor force. Similarly, both the one-step and the two-step first difference GMM results are shown. It is found that the coefficient of lnU, t-1 is statistically significant and positive at the 1% significance level; suggesting that the unemployment rate is persistent and autocorrelated. The coefficient of lnGDP is statistically significant and negative at the 1% significance level, indicating that a 1% increase in the GDP growth rate is associated with a reduction in the unemployment rate ranging from 0.040% to 0.046%.

[Table 2 about here]

The variables of particular interest are lnInstall and lnStock. We find that the coefficient of lnInstall is statistically significant and negative, at least at the 10% significance level; suggesting that the introduction of new industrial robots is linked to lower unemployment rates or an enhancement in employment levels within the labor force. Specially, if the robot installations per 10,000 labor force increase by 1%, the unemployment rate will drop by approximately 0.037% to 0.039%. Furthermore, the coefficient of InStock is significant and negative, at the 5% significance level. This finding reinforces the earlier results regarding the impact of lnInstall, suggesting that increased utilisation of industrial robots correlates with improved employment outcomes for the workforce. Specifically, a 1% increase in robot stock per 10,000 labor force is associated with a reduction in the unemployment rate by 0.024% to 0.025%. The diagnostic checks show that the errors do not exhibit serial correlation, as confirmed by the AR(2) test, and the instrument variables used in the model are valid, as evidenced by the Hansen test statistic.

Table 3 repeats the analysis by measuring lnInstall and lnStock using per 10,000 population rather than 10,000 labor force. The main findings remain qualitatively consistent, with variations observed only in the magnitude of the effects. In subsequent analysis, we use only the variable lnInstall measured as the logarithm of the number of industrial robots installations per 10,000 labor force, and the one-step difference GMM approach for further detailed breakdown analysis. This choice is underpinned by the robustness of results for lnRobots measured by both lnInstall and lnStock, either per 10,000 labor force or per 10,000 population, across both one-step and two-step difference GMM approaches, as evidenced in Table 2 and Table 3.

[Table 3 about here]

Table 4 delves into the analysis by examining the effects on unemployment rates differentiated by gender, as well as the impact on youth unemployment rates. Interestingly, the utilisation of robots has a more pronounced effect on male employment, resulting in a 0.045% decrease in their unemployment rate, compared to a 0.033% decrease in the female unemployment rate. Furthermore, the impact on youth unemployment rate seems to be more profound than its impact on the overall unemployment rate. Within the youth segment of the labor force, the effect is also observed to be stronger for males than for females. However, it should be noted that the model of the youth unemployment rate is suffering from the 2^{nd} order autocorrelation, and it should be further refined in order to get a better estimate of the impact.

[Table 4 about here]

Lastly, Table 5 presents estimation results segmented by the education levels of the labor force. Results show that the coefficient of lnInstall is not statistically significant for labor forces with either basic or advanced education levels. However, for those with intermediate education, the coefficient is significantly negative, indicating the adoption of industrial robots tends to boost employment opportunities for workers with medium level of skill, while having no discernible impact on job prospects for both low and high-skilled workers.

[Table 5 about here]

5. Conclusion

Using panel data covering 63 countries for a period of 2005-2021, and the generalised method of moments econometric methodology, this paper examines how the industrial robot utilisation affects labour force employment. In general, we find a positive effect of automation on employment, that a 1% increase in new industrial robot installations per 10,000 labour force correlates with a decrease in the unemployment rate by approximately 0.037% to 0.039%. The impact is more pronounced among male workers than female workers (0.045% vs 0.033% reduction of unemployment rate). Youth unemployment rates, compared to the overall unemployment rate, are more profoundly affected by robot installations. Lastly, it is also found that automation decreases the unemployment rate by 0.052% for people with intermediate education levels, yet it has little impact on those with either basic or advanced educational attainment. Therefore, the gap of unemployment rates between genders is likely to be reduced by automation, and it will also reduce the gap of unemployment between workers with intermediate and advanced education.

It is noteworthy that our analysis was based on international data on the industrial robots for a period of 2005-2021. It does not take into consideration the service robots and other technologies such as artificial intelligence or the recent development of generative AI. However, as Agrawal et al. (2019) claimed, “the net effect (of artificial intelligence on labour) is an empirical question and will vary across applications and industries”. In the same vein, the accurate estimation of the net effect of automation or technological advancement on unemployment also requires an in-depth examination of the industry-specific technologies and relevant data within each particular country. For example, for the generative AI, which has drawn a lot of discussion in 2023, scholars found that a majority of workers in the US (80%) will be somewhat affected (at least 10% of their work tasks) (Eloundou et al., 2023).

Concerns centre on the potential displacement of workers in traditionally labour-intensive sectors, the emergence of new types of employment opportunities, and the need for workforce re-skilling to adapt to the changing demands of the job market. Consequently, this discourse has led to a diverse range of policy discussions aimed at mitigating the adverse effects of automation while maximizing its benefits, such as the implementation of universal basic income, education and training programs tailored to future job markets, and strategies to foster the development of sectors likely to benefit from automation.

Hence, it is strongly recommended that organisations, together with the help of government institutions, collaborate on enabling workers, particularly those in sectors vulnerable to high automation, to transition to new industries. If these workers are in sectors where industrial robots create more job opportunities, then it would be highly beneficial if employees were provided with upskilling and upgrading avenues so that their skills can complement the nature of their roles in a more technologically reliant workplace. Therefore, it is imperative that policy makers put in place appropriate policy changes that will aid in facilitating these transitions, reduce the social cost of automation and empower employees with the right skill sets to maximise their capabilities and contributions to the labour force.

Table 1: Definition of variables and descriptive statistics

Variable	Definition	Mean	SD	Min	Max	N
lnU(total)	Rate of unemployment (%), log	1.831	0.674	-1.386	3.359	1800
lnU(female)	Rate of unemployed female labor force (%), log	1.908	0.696	-1.431	3.454	1800
lnU(male)	Rate of unemployed male labor force (%), log	1.783	0.702	-1.351	3.357	1800
lnU(youth)	Rate of unemployed labor force ages 15-24 (%), log	2.648	0.690	-0.865	4.151	2102
lnU(youth female)	Rate of unemployed female labor force ages 15-24 (%), log	2.686	0.682	-0.685	4.161	1800
lnU(youth male)	Rate of unemployed male labor force ages 15-24 (%), log	2.626	0.641	-0.104	4.029	1800
lnU(basic education)	Rate of unemployment with basic education (%), log	2.169	0.808	-1.715	3.673	1,192
lnU(intermediate education)	Rate of unemployment with intermediate education (%), log	1.956	0.631	-0.916	4.561	1,186
lnU(advanced education)	Rate of unemployment with advanced education (%), log	1.481	0.592	-0.416	3.410	1,197
lnInstall (per 10000 labor force)	Installations of industrial robots per 10,000 labor force, log	0.321	0.505	0	2.778	2,102
lnStock (per 10000 labor force)	Operational stock of industrial robots per 10,000 labor force, log	1.006	1.191	0	4.855	2,102
lnInstall (per 10000 population)	Installations of industrial robots per 10,000 population, log	0.203	0.350	0	2.333	2,102
lnStock (per 10000 population)	Operational stock of industrial robots per 10,000 population, log	0.738	0.950	0	4.274	2,102
lnGDP	GDP growth rate, log	1.226	0.844	-4.539	4.488	1,789

Note: The table gives descriptive statistics from 1993-2021.

Table 2: Results from difference GMM estimation (per 10,000 labor force)

	Model 1				Model 2			
Variables	One-step difference		Two-step difference		One-step difference		Two-step difference	
lnU, t-1	0.948***	(0.029)	0.943***	(0.028)	0.942***	(0.032)	0.936***	(0.032)
lnInstall	-0.039**	(0.020)	-0.037*	(0.023)				
lnStock					-0.025**	(0.011)	-0.024**	(0.010)
lnGDP	-0.046***	(0.009)	-0.040***	(0.010)	-0.046***	(0.009)	-0.040***	(0.010)
Year dummies	Yes		Yes		Yes		Yes	
No. of Obs.	823		823		823		823	
Groups/Instruments	63/45		63/45		63/45		63/45	
AR(1)	-3.16	[0.002]	-3.19	[0.001]	-3.10	[0.002]	-3.19	[0.001]
AR(2)	0.58	[0.565]	0.57	[0.566]	0.55	[0.581]	0.55	[0.582]
Hansen Statistic	47.19	[0.269]	47.19	[0.269]	47.38	[0.263]	47.38	[0.263]

Note: Robust standard errors in paratheses. P-values in square brackets. *** p<0.01, ** p<0.05, * p<0.1.
lnInstall and lnStock are logrithms of installations/operational stocks per 10000 labor force.

Table 3: Results from difference GMM estimation (per 10,000 population)

	Model 1				Model 2			
Variables	One-step difference		Two-step difference		One-step difference		Two-step difference	
lnU, t-1	0.948***	(0.029)	0.942***	(0.028)	0.944***	(0.032)	0.937***	(0.031)
lnInstall	-0.052**	(0.026)	-0.050	(0.031)				
lnStock					-0.032**	(0.014)	-0.030**	(0.013)
	-				-		-	
lnGDP	0.046***	(0.009)	-0.040***	(0.010)	0.046***	(0.009)	0.041***	(0.010)
Year dummies	Yes		Yes		Yes		Yes	
No. of Obs.	823		823		823		823	
Gropus/Instruments	63/45		63/45		63/45		63/45	
AR(1)	-3.16	[0.002]	-3.19	[0.001]	-3.10	[0.002]	-3.19	[0.001]
AR(2)	0.57	[0.566]	0.57	[0.567]	0.55	[0.582]	0.55	[0.583]
Hansen Statistic	47.15	[0.270]	47.15	[0.270]	47.30	[0.265]	47.30	[0.265]

Note: Robust standard errors in paratheses. P-values in square brackets. *** p<0.01, ** p<0.05, * p<0.1. lnInstall and lnStock are logrithms of installations/operational stocks per 10000 population.

Table 4: Results from first-step difference GMM estimation: by gender and youth (installations of industrial robots per 10,000 labor force)

Variables	Total		Female		Male		Youth_Total		Youth_female		Youth_male	
lnU, t-1	0.948***	(0.029)	0.959***	(0.026)	0.922***	(0.034)	0.918***	(0.039)	0.929***	(0.037)	0.876***	(0.049)
lnInstall	-0.039**	(0.020)	-0.033*	(0.019)	-0.045**	(0.022)	-0.042**	(0.018)	-0.038**	(0.018)	-0.049**	(0.020)
lnGDP	-0.046***	(0.009)	-0.046***	(0.009)	-0.047***	(0.009)	-0.044***	(0.008)	-0.047***	(0.010)	-0.044***	(0.009)
Year dummies	Yes		Yes		Yes		Yes		Yes		Yes	
No. of Obs.	823		823		823		823		823		823	
Gropus/Instruments	63/45		63/45		63/45		63/45		63/45		63/45	
AR(1)	-3.16	[0.002]	-2.61	[0.009]	-3.53	[0.000]	-4.12	[0.000]	-3.66	[0.000]	-4.48	[0.000]
AR(2)	0.58	[0.565]	1.46	[0.144]	0.62	[0.534]	2.36	[0.018]	2.09	[0.037]	1.89	[0.058]
Hansen Statistic	47.19	[0.269]	47.19	[0.269]	47.29	[0.265]	43.49	[0.408]	42.95	[0.430]	41.76	0.481

Note: Robust standard errors in paratheses. P-values in square brackets. *** p<0.01, ** p<0.05, * p<0.1. lnInstall is the logrithm of installations of industrial robots per 10000 labor force.

Table 5: Results from first-step difference GMM estimation: by education (installations of industrial robots per 10,000 labor force)

Variables	Basic		Intermediate		Advanced	
lnU, t-1	0.899***	(0.077)	0.943***	(0.022)	0.907***	(0.038)
lnInstall	-0.033	(0.030)	-0.052**	(0.024)	-0.045	(0.030)
lnGDP	-0.038***	(0.011)	-0.059***	(0.009)	-0.060***	(0.009)
Year dummies	Yes		Yes		Yes	
No. of Obs.	609		611		612	
Gropus/Instruments	55/44		56/44		56/44	
AR(1)	-2.22	[0.026]	-3.07	[0.002]	-4.53	[0.000]
AR(2)	1.35	[0.176]	0.63	[0.532]	-0.80	[0.427]
Hansen Statistic	48.05	[0.209]	45.30	[0.297]	46.36	[0.261]

Note: Robust standard errors in paratheses. P-values in square brackets. *** p<0.01, ** p<0.05, * p<0.1. lnInstall is the logrithm of installations of industrial robots per 10000 labor force.

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