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Impact of technological change on employment of low-skilled workers and income

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ABSTRACT
As technology advances, the impact of automation and new tasks on the labor market and the national economy are debated topics in America. The American labor market is concerned that technological changes will lead to redundant labor (Acemoglu & Restrepo 2018) because automation will replace low-skilled workers and increase unemployment. Nevertheless, creating new tasks where a human has an irreplaceable advantage over robots could benefit low-skilled workers in the long run, reducing unemployment (Acemoglu & Restrepo 2018). Thus, this led this research to consider maintaining employment and productivity in a labor market that automation is gradually replacing. And this research will combine the relevant previous research to further explore the impact of technological change, especially new tasks, on low-skilled workers.

KEYWORDS
technology advances; automation; labor market

1 Introduction

Technological change, including the creation of new tasks and automation, reduces the employment of low-level employees in the American labor market in the short run (Acemoglu & Restrepo 2018). This is because technological changes can bring to labor redundant. Creating new tasks in a stagnant economy where capital is unchanged will lead to more employment opportunities and increased wages and income (Acemoglu & Restrepo 2018). However, automated technology can have the opposite result. According to Acemoglu and Restrepo (2018), when automation technologies replace low-skilled labor and labor-intensive tasks are created, new jobs and automation affect income inequality differently in the short term and long term. In the short run, automation will replace low-skilled workers while new tasks will benefit the high-skilled workers, which might increase income inequality.

Furthermore, in the long run, new tasks will benefit low-skilled workers, which might limit the increase in income inequality. In addition, technological change, including automation, increases the scale of production, thereby increasing the demand for labor to maintain employment (Irmen 2020). It can be proved that human has significant comparative advantages in complicated and new tasks compared with automation (Acemoglu & Restrepo 2018). Therefore, creating new jobs will help low-skilled workers and reduce income inequality. As mentioned before, how to maintain the employment of low-experienced employees and narrow the income gap between low-skilled and high-level workers in the face of changing technology has become a topic of research by economists. This study explores the relationship between technological change and the employment of low-experienced workers and factor prices.

Based on the research question, this study further explores the endogenous relationships among various factors. Firstly, this study presents a framework aimed at examining the impact of technological change on the employment and income of low-skilled workers. The study primarily employs empirical models and enterprise-level data to endogenize factors such as capital, automation, and new tasks. To test the effects of this type of technological growth, a combination of natural experiments and empirical strategies will be utilized, with a specific focus on new labor-intensive tasks that help employ low-skilled workers to counteract the adverse effects of automation. The data for this project is based on census and US community survey data, which can be easily accessed online. Finally, instrumental variable models and econometric methods will be employed to study the endogenous relationship between the labor market and technological growth. Through this study, there is a conclusion that new tasks in the US labor market benefit low-skilled workers in terms of employment, alleviate income inequality, and impact factor prices associated with work.

2 Data

The data for the original paper and this study are from the 1980, 1990, and 2000 U.S. Census data. The study's group was low-experienced workers aged 16-64 in the U. S. labor market, while the original paper looked at all labor groups. In addition, the study will include observable and experimental data. Furthermore, the study combines panel data and uses the OLS method to analyze trends over time and in different industries through linear regression. Finally, the study calculated the employment data of 304 occupational categories and demographic characteristics such as age, gender, and education through census data.

The study classifies workers with less than a college degree as low-experienced employees. Therefore, the dependent variable is low-skilled workers. Jongwanich et al. (2022) show that automation technology will affect the employment of low-experienced employees. According to Dauth et al. (2021), automation technology puts low-experienced workers at a higher risk of unemployment than other factors. This study focuses on the impact of technological progress on the employment of low-experienced employees, so the corresponding job share of low-level workers is the key explanatory variable in this study. The explanatory variable explains changes in the dependent variables, such as average years of education among workers and the share of workers with a college degree. And then, this study will apply regression analysis to estimate the effects of technological change. The control variables used in the regression models include occupation size, demographics, and sectoral content. Precisely, occupation size consists of the variable named the log of employment. Demographics contain the variables called male, foreigner, black, Hispanic, and age, which are demographic characteristics. In addition, sectoral content includes manufacturing, primary, and service variables. These variables investigate the relationship between the share of new job titles and the low-skilled workers with less than a college education while controlling for occupation size, demographics, and sectoral content. The study used 1980, 1990, and 2000 Census data and 2010 and 2015 American Community Survey data to calculate the total number of jobs and the number of new jobs for each of the 304 occupational categories. According to Lin (as cited in Acemoglu & Restrepo 2018), a job is defined as a new job if it performs different tasks than the previous job. At the same time, the research also calculated employment shares for various sectors, including manufacturing, services, and primary industries.

From the table above, the mean employment value is approximately 473, 236, indicating a relatively high average level of employment. And the standard deviation of 916, 893.53 indicates substantial variability in employment levels across the observations. In addition, the mean value of job paid with 430, 944.23 suggests a slightly lower average level of paid employment than total employment. The minimum and maximum values indicate that paid employment levels range from 2,596 to 8,773,827. Furthermore, the mean value of 0.687 in low-skilled suggests that, on average, around 68.7% of jobs within the dataset are classified as low-skilled. Finally, the table also provides descriptive statistics for several other variables, including the proportion of employment in manufacturing, services, and primary sector. It also includes statistics for variables related to age, ethnicity, gender, and education.

Table 1 Descriptive Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
occ1990dd acs	304	406.967	253.879	4	889
employment	304	473236.42	916893.53	2773	10124664
employment paid	304	430944.23	835745.39	2596	8773827
emp hours	304	9.376e+08	1.901e+09	3206812	2.315e+10
emp last	304	516495.02	990342.18	3079	10590885
manufacturing	304	0.186	0.284	0	0.977
services	304	0.564	0.375	0	1
primary	304	0.051	0.169	0	0.988
lowskilled	304	0.687	0.305	0	0.991
age	304	41.184	3.671	28.279	49.503
. age16 25	304	0.153	0.107	0	0.597
age26 35	304	0.234	0.053	0.088	0.417
age36 45	304	0.21	0.045	0.045	0.335
age46 55	304	0.216	0.051	0.033	0.367
age56 65	304	0.188	0.062	0.03	0.389
foreigner	304	0.173	0.097	0.031	0.653
hispanic	304	0.161	0.101	0.009	0.738
black	304	0	0	0	0
edyears	304	13.474	1.834	9.807	18
year	304	2015	0	2015	2015

3 Empirical Strategy

The theoretical framework of the original paper, named the race between Man and Machine, concludes the benefits of technological changes and explores the relationship between automation, new tasks, and employment in the American labor market. This main paper emphasizes that a policy is significant to reducing the adverse influence of automation and new tasks, such as improving the education level of workers. For example, according to Dauth et al. (2021), new tasks are of higher quality than previous jobs, requiring higher professional skills. This means new tasks will benefit low-skilled workers who accept vocational training in college or other educational institutions. The main paper uses the analytical framework and empirical analysis to explore the impact of automation on job shares and wages. In addition, this main paper analyzes the relationship between employment and factor prices and automation by manipulating, merging, and collapsing data and using least squares (OLS) for linear regression.

The original paper performed linear regression on panels A and B.

In panel A: Average years of education for employees

Main model : $edyears = \beta_0 + \beta_1 novelvar + \beta_2 Year\_1980 + \beta_3 Year\_1990 + \beta_4 Year\_2000 + \varepsilon$

In the main model, the original paper estimates workers' average years of education. β1, β2, β3 and β4 are the parameters to estimate. These coefficients represent the connection between the variables in this model and the average years of education. Novelvar represents new job shares in a specific year. In addition, Year_1980, Year_1990, and Year_2000 are indicator variables representing different years. These variables capture the impacts of different periods on average years of education. And then, ε is the residual. Models 2, 3, and 4 follow a similar structure in the main model but contain additional variables and interactions to show other factors affecting the average years of education, including occupation size, demographics, and sectoral contents. Model 5 is a random effects model containing a random effect (u) and the fixed effect. The random effect is used to capture unobserved heterogeneity in different groups, which might influence the average years of education. Panel B represents the shares of workers with a college degree with a similar formula to plan A. Still, the shares of workers replace the dependent variable with a college degree. The original paper applies a panel data regression model and uses fixed effects and random effects to control the fixed characteristics of individuals and time. The original paper uses these models to examine the relationship between employment change and independent variables, including new job titles, occupation size, demographics, education, and sectoral content.

This study draws on the main models in panel A and panel B of the original paper and changes the dependent variable in panel B to low-skilled workers. Meanwhile, workers with less than a college degree are classified as low-skilled workers.

Main model in panel B: $lowskilled = \beta_0 + \beta_1 novelvar + \beta_2 Year\_1980 + \beta_3 Year\_1990 + \beta_4 Year\_2000 + \varepsilon$

The original paper mentioned there is a clear linear relationship between the mean years of education and new job shares. Therefore, this study also adopt the OLS method. Models 2, 3, and 4 also have a structure similar to Model 1 and include additional variables such as occupational size, demographics, and sector content.

Model 5 (Random effects model): $lowskilled = \beta_0 + \beta_1 novelvar + \beta_2(occupation\_size) + \beta_3(demographics) + \beta_4(sectoral\_content) + \beta_5(occupation\_size \times Year\_1980) + \beta_6(occupation\_size \times Year\_1990) + \beta_7(occupation\_size \times Year\_2000) + \beta_8(demographics \times Year\_1980) + \beta_9(demographics \times Year\_1990) + \beta_{10}(demographics \times Year\_2000) + \beta_{11}(sectoral\_content \times Year\_1980) + \beta_{12}(sectoral\_content \times Year\_1990) + \beta_{13}(sectoral\_content \times Year\_2000) + \beta_{14} Year\_1980 + \beta_{15} Year\_1990 + \beta_{16} Year\_2000 + u + \varepsilon$

Model 5 is also a random effects model. This research also uses random effects and fixed effects to address endogeneity. For example, this study captures the impact of time on the proportion of low-skilled workers by using dummy variables like Year_1980, Year_1990, and Year_2000. Next, model 5 captures the effect of unobserved heterogeneity in individuals or groups on the proportion of low-skilled workers by introducing u. Finally, this study explores the relationship between technological changes and the shares of low-skilled workers through these models.

4 Results

Table 2 The relationship between average years of schooling and shares of new jobs in 1980, 1990 and 2000

	(1)	(2)	(3)	(4)	(5)
VARIABLES	edyears	edyears	edyears	edyears	edyears
new job shares	3.144***	3.082***	1.685***	1.324***	1.221***
	(0.522)	(0.543)	(0.363)	(0.335)	(0.304)
1980.yearlog(employment)		0.085	-0.003	-0.043	-0.070
		(0.084)	(0.056)	(0.056)	(0.047)
1990.year log(employment)		0.122*	0.017	-0.059	-0.080*
		(0.069)	(0.046)	(0.048)	(0.047)
2000.year log(employment)		0.259***	0.086*	-0.004	-0.034
		(0.067)	(0.046)	(0.051)	(0.051)
1980.year log_titles		-0.495***	-0.295***	-0.159**	-0.130**

Table 2 The relationship between average years of schooling and shares of new jobs in 1980, 1990 and 2000(Continued).

	(1)	(2)	(3)	(4)	(5)
		(0.073)	(0.055)	(0.063)	(0.052)
1990.year log_titles		-0.389***	-0.202***	-0.067	-0.025
		(0.058)	(0.041)	(0.052)	(0.052)
2000. year log_titles		-0.806***	-0.291***	-0.141*	-0.088
		(0.083)	(0.062)	(0.072)	(0.072)
1980.year male			-0.971***	-0.168	0.007
			(0.310)	(0.316)	(0.239)
1990.year male			-0.924***	-0.322	-0.291
			(0.246)	(0.281)	(0.252)
2000.year male			-1.039***	-0.472	-0.524*
			(0.258)	(0.297)	(0.272)
1980.year foreigner			20.273***	18.544***	26.050***
			(3.425)	(3.604)	(2.078)
1990.year foreigner			13.816***	13.364***	17.713***
			(2.471)	(2.731)	(1.629)
2000.year foreigner			8.566***	8.429***	10.326***
			(1.436)	(1.505)	(1.098)
1980.year black			-7.909***	-7.059***	-4.976***
			(2.092)	(1.842)	(1.181)
1990.year black			-6.720***	-6.111***	-4.217***
			(1.517)	(1.468)	(1.244)
2000.year black			-6.146***	-5.695***	-5.556***
			(1.210)	(1.173)	(1.174)
1980.year hispanic			-38.443***	-34.945***	-46.190***
			(6.224)	(5.704)	(2.564)
1990.year hispanic			-27.684***	-26.206***	-31.649***
			(3.134)	(3.355)	(1.983)
2000.year hispanic			-19.478***	-18.619***	-19.553***
			(1.416)	(1.544)	(1.356)
1980.year age			0.012	0.028	0.001
			(0.023)	(0.024)	(0.016)
1990.year age			0.039*	0.057**	0.047***
			(0.022)	(0.023)	(0.018)
2000.year age			0.056***	0.077***	0.079***
			(0.020)	(0.021)	(0.019)
1980.year manufacturing				-0.098	-0.244
				(0.360)	(0.303)
1990.year manufacturing				-0.659**	-0.853***
				(0.328)	(0.309)
2000.year manufacturing				-0.468*	-0.622**
				(0.243)	(0.280)
1980.year primary				0.847	0.111
				(0.682)	(0.395)
1990.year primary				0.222	0.336
				(0.608)	(0.398)
2000.year primary				0.172	0.066
				(0.611)	(0.414)
1980.year services				1.580***	1.034***
				(0.324)	(0.255)
1990.year services				0.965***	0.676***
				(0.277)	(0.262)

Table 2 The relationship between average years of schooling and shares of new jobs in 1980, 1990 and 2000(Continued).

	(1)	(2)	(3)	(4)	(5)
2000.year services				0.945***	0.838***
				(0.240)	(0.254)
1990.year	0.353***	-0.374	-1.113**	-0.125	-0.967
	(0.040)	(0.394)	(0.543)	(0.639)	(1.251)
2000.year	0.616***	0.423	-1.658**	-0.915	-2.193*
	(0.045)	(0.619)	(0.782)	(0.875)	(1.292)
Constant	12.381***	12.717***	14.935***	12.956***	14.264***
	(0.126)	(0.938)	(0.959)	(1.077)	(0.836)
Observations	910	910	910	910	910
R-squared	0.045	0.173	0.667	0.709	0.749

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

The linear results of combining the five models with mean years of education as the dependent variable are shown in Table 2. The sample size is 910. It can be seen from Table 2 that the linear results of the five models all show that there is a positive relationship between the new job share and the average years of education. The independent variables in these models are represented by "new job shares," "1980. year", "1990. year", and "2000. year". In these five models, the coefficients for new job shares are 3.144, 3.082, 1.685, 1.324, and 1.221, respectively. In model 1, a 1% increase in the new job shares increases the average years of schooling by 3.144%. In model 5, holding other factors constant, a 1% increase in the percentage of new jobs increases the average number of years of education by 1.221%. The coefficients in models 1, 2, 3, 4, and 5 are all statistically significant at the 0.001 level. Table 2 shows that new job shares can encourage workers to accept more comprehensive education to adapt to new challenges in new tasks.

Table 3 The relationship low-skilled workers and shares of new jobs in 1980, 1990 and 2000

	(1)	(2)	(3)	(4)	(5)
VARIABLES	lowskilled	lowskilled	lowskilled	lowskilled	lowskilled
new job shares	-0.420***	-0.414***	-0.215***	-0.160**	-0.131**
	(0.085)	(0.088)	(0.068)	(0.065)	(0.053)
1980.year log(employment)		0.004	0.012	0.014	0.017**
		(0.011)	(0.008)	(0.009)	(0.008)
1990.year log(employment)		-0.006	0.007	0.014	0.017**
		(0.011)	(0.008)	(0.009)	(0.008)
2000.year log(employment)		-0.030***	-0.006	0.005	0.011
		(0.011)	(0.009)	(0.010)	(0.009)
1980.year log_titles		0.048***	0.030***	0.017	0.014
		(0.010)	(0.008)	(0.010)	(0.009)
1990.year log_titles		0.046***	0.024***	0.009	0.005
		(0.009)	(0.007)	(0.010)	(0.009)
2000.year log_titles		0.104***	0.037***	0.019	0.009
		(0.014)	(0.011)	(0.014)	(0.013)
1980.year male			0.061	-0.045	-0.077*
			(0.047)	(0.048)	(0.042)
1990. Year male			0.108**	0.012	-0.025
			(0.046)	(0.052)	(0.044)
2000.year male			0.178***	0.076	0.068
			(0.050)	(0.056)	(0.047)
1980.year foreigner			-3.260***	-3.076***	-4.215***
			(0.507)	(0.530)	(0.363)
1990.year foreigner			-2.737***	-2.713***	-3.731***

Table 3 The relationship low-skilled workers and shares of new jobs in 1980, 1990 and 2000(Continued).

	(1)	(2)	(3)	(4)	(5)
			(0.434)	(0.475)	(0.284)
2000.year foreigner			-1.759***	-1.744***	-2.293***
			(0.268)	(0.285)	(0.192)
1980.year black			0.789**	0.547**	0.244
			(0.309)	(0.264)	(0.206)
1990.year black			1.131***	0.913***	0.484**
			(0.268)	(0.268)	(0.217)
2000.year black			1.335***	1.180***	1.075***
			(0.225)	(0.226)	(0.205)
1980.year hispanic			4.727***	4.547***	5.719***
			(0.947)	(0.807)	(0.447)
1990.year hispanic			3.924***	3.861***	4.995***
			(0.567)	(0.590)	(0.346)
2000.year hispanic			2.667***	2.558***	2.881***
			(0.272)	(0.294)	(0.237)
1980.year age			-0.006*	-0.008**	-0.005*
			(0.003)	(0.003)	(0.003)
1990.year age			-0.010***	-0.012***	-0.009***
			(0.004)	(0.004)	(0.003)
2000.year age			-0.011***	-0.014***	-0.014***
			(0.004)	(0.004)	(0.003)
1980.year manufacturing				-0.044	-0.018
				(0.050)	(0.053)
1990.year manufacturing				0.042	0.058
				(0.057)	(0.054)
2000.year manufacturing				0.031	0.060
				(0.047)	(0.049)
1980.year primary				-0.271***	-0.197***
				(0.096)	(0.069)
1990.year primary				-0.172*	-0.203***
				(0.097)	(0.070)
2000.year primary				-0.122	-0.113
				(0.099)	(0.072)
1980.year services				-0.234***	-0.144***
				(0.046)	(0.044)
1990.year services				-0.169***	-0.114**
				(0.046)	(0.046)
2000.year services				-0.175***	-0.144***
				(0.043)	(0.044)
1990.year	-0.020***	0.112**	0.136	0.011	0.038
	(0.005)	(0.055)	(0.090)	(0.101)	(0.218)
2000.year	-0.063***	0.059	0.167	0.082	0.147
	(0.006)	(0.081)	(0.129)	(0.145)	(0.225)
Constant	0.813***	0.633***	0.640***	0.967***	0.871***
	(0.016)	(0.127)	(0.153)	(0.172)	(0.146)
Observations	910	910	910	910	910
R-squared	0.032	0.117	0.553	0.595	0.642

Table 3 shows the effects of dummy variables on low-skilled workers, including occupation size, population, and sector content. For example, in Model 2, employment significantly impacted low-skilled workers in 2000. A one-unit increase in the employment rate decreased the low-level employees by 0.0003% in 2000. And then, demographic also has a significant impact on low-experienced workers. In Model 5, a 1% increase in foreigners reduced the job shares with low-skilled workers by approximately 4.22% in 1980. Finally, the primary sector has the most significant effect on low-level workers relative to other industries. In model 4, one unit rise in the primary will lead to a 27% decrease in low-skilled employees in 1980.

5 Discussion

Table 2 shows a positive linear connection between the average years of education and shares of new job titles. In other words, creating new tasks will encourage low-level employees to adopt more training and education to be qualified for demanding positions. The results from Table 2 also prove that high-skilled workers have absolute advantages in creating new jobs compared with low-level employees. In the original paper, according to Acemoglu and Restrepo (2018), creating new tasks will benefit the high-skilled labor force, while automation will replace large numbers of low-experienced employees in the short run, leading to income inequality. However, in the long run, new tasks will reduce income inequality by favoring the employment of low-skilled workers due to its standardization. In addition, technological change increases factor prices to keep jobs stable.

Summarizing the data in Table 3, it becomes evident that new job titles will adversely affect low-skilled employees. This means new tasks reduce the employment of low-skilled workers and hence income. In the original paper, Acemoglu and Restrepo (2018) argue that in the face of high-quality and complex jobs, low-skilled workers are at a disadvantage in being replaced relative to high-functioning workers. Workers with ICT skills can only retain their jobs or be promoted if they move from manufacturing to service industries (Jongwanich et al., 2022).

Jongwanich et al. (2022) also suggest automation and new tasks lead to upskilling and a widening wage gap between low-skilled and high-skilled workers. In addition, Dauth et al. (as cited in Jongwanich et al. 2022) show that automation positively affects worker wages but does not impact total employment.

6 Conclusion

The main question studied in this study is the impact of technological change, including automation and the creation of new tasks, on low-skilled workers and their incomes. Based on the model in the original paper, this study changed the explanatory variable to low-skilled workers, thereby using the OLS method to study the impact of new job shares on the average years of education and low-skilled workers. From the experimental results, high-skilled workers have more advantages in the automation field. In contrast, low-skilled workers are easily replaced in the short term, thus increasing the income inequality between low-level and high-experienced workers. However, according to Acemoglu and Restrepo (2019), new tasks will give the workforce an edge and offset the negative impact of automation on the workforce. For example, automation can expand productivity and production channels while flexibly assigning new tasks to various production factors, benefiting labor demand in the non-automation field due to lower factor prices (Acemoglu & Restrepo 2019). In other words, a lower factor price will improve the total employment.

Future research could explore the relationship between technological advancement and job polarization. Polarized work means that low-skilled and high-skilled jobs grow at the expense of middle-skilled jobs. There is value in studying the impact of job polarization on income inequality. In addition, technological progress will affect many industries, many new fields will emerge, and the development potential of some enterprises will be improved. Future research could explore job opportunities created by technological advances and their impact on industry.

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