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Strengthening Social Protection to Pave the Way for Technological Innovation

Evidence from the U.S.

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Strengthening Social Protection to Pave the Way for Technological Innovation: Evidence from the U.S.

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ABSTRACT: This paper investigates the impact of automation on the U.S. labor market from 2000 to 2007, specifically examining whether more generous social protection programs can mitigate negative effects. Following Acemoglu and Restrepo (2020), the study finds that areas with higher robot adoption reduced employment and wages, in particular for workers without college degrees. Notably, the paper exploits differences in social protection generosity across states and finds that areas with more generous unemployment insurance (UI) alleviated the negative effects on wages, especially for less-skilled workers. The results suggest that UI allowed displaced workers to find better matches The findings emphasize the importance of robust social protection policies in addressing the challenges posed by automation, contributing valuable insights for policymakers.

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WORKING PAPERS

Strengthening Social Protection to Pave the Way for Technological Innovation

Evidence from the U.S.

Prepared by Fernanda Brollo[1]

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Contents

Glossary

AI	Artificial Intelligence
ALMPs	Active Labor Market Policies
EMDEs	Emerging Market and Developing Economies
EU	European Union
IFR	International Federation of Robotics
LMPs	Labor Market Programs
SI	Social Insurance
SSN	Social Safety Net
TANF	Temporary Assistance for Needy Families
UBI	Universal Basic Income

I. Executive Summary

This paper provides novel evidence on whether enhanced social protection programs can lessen the long-term detrimental effects of automation on labor markets. Building on Acemoglu and Restrepo (2020), it analyzes U.S. commuting zones' exposure to automation during the period 2000-2007 and explores how social protection mitigates the impact of robot adoption. Findings show that more generous unemployment insurance (UI) reduces the negative effect of automation on wages, particularly for workers without a college degree. Additionally, areas with high robot adoption see slight increases in poverty, alleviated by relatively more generous social assistance measures.

Technological innovation is a crucial catalyst for long-term economic growth and improved living standards, with labor productivity growth being a key determinant. However, the benefits of technological progress may not be uniformly distributed, potentially worsening income inequality. The rapid advancement of automation raises concerns about their impact on labor markets, as recent automation has displaced workers in routine tasks, contributing to lower average wages, and increasing polarization in wages and employment, particularly affecting middle-wage workers. Social protection programs can mitigate these adverse effects, but empirical evidence on their effectiveness in addressing the challenges from innovation remains limited.

The analysis in this paper indicates that unemployment insurance alleviates two-thirds of the negative effects of robots' adoption on wages, suggesting that more generous UI allows displaced workers time to find a job that better matches their skill set, contributing to more efficient labor allocation, particularly for workers without a college degree. Additional results indicate that exposure to robots has some long-term effect on poverty rates and these effects are eliminated in areas with higher social assistance generosity.

II. Introduction

This paper provides novel empirical evidence on the role of social protection schemes in mitigating the adverse effects of automation on labor market outcomes. Social protection systems can play an instrumental role in protecting households and helping retrain workers at risk from disruption. By offering financial support during unemployment, promoting new skills acquisition, and creating a safety net, social protection systems can help individuals adapt to job market changes.[1] Building on the work of Acemoglu and Restrepo (2020), this paper exploits variations in robot adoption across U.S. commuting zones to evaluate the effectiveness of social protection in softening the impact of robots on local labor markets. The results indicate that unemployment insurance (UI) reduces the adverse effects of robotization on wages in states with more generous UI, suggesting that UI can help displaced workers to find better job matches. The study also reveals that areas with high robot adoption experience slight increases in poverty, and social assistance helps alleviate these effects.

Technological innovation is a major driver of long-term economic growth and improving living standards. Long-term economic growth, which can be broadly defined as an increase in the quantity and quality of the economic goods and services that a society produces, is key in driving prosperity and reducing poverty (Dollar and Kraay 2002; Banerjee and Duflo 2019). The primary determinant of long-term economic growth is the growth rate of labor productivity, defined as the amount of output created per hour worked. As described by Krugman (1997) "[p]roductivity isn't everything, but in the long run, it is almost everything. A country's ability to improve its standard of living over time depends almost entirely on its ability to raise output per worker." Consistent with this evidence, modern economic theories emphasize the key role of innovation in driving economic growth.[2]

While technological progress has historically driven economic growth, its benefits may not be equally distributed, potentially exacerbating income inequality. Technological innovation may not only increase overall output but can also change how this output is distributed among the members of a society, and thus not everyone may benefit from innovation (Korinek, Schindler and Stiglitz, 2022). There are at least two channels through which innovation can affect income inequality. First, innovation may affect workers with different skills differently and may reduce the share of wage income accruing to lower-skilled workers (so called "skill-biased technological change"). Second, innovation may also reduce the overall share of income accruing to labor relative to capital. These two effects may increase income inequality as wages are typically the main source of market income for most households and capital ownership is concentrated among the top of the income distribution (Wolff 2010).

The rapid progress in automation has raised concerns about their impact on labor markets. The concerns have recurred at least since the Luddites destroyed cloth-making machinery in the 19th century. Recent surveys find growing concerns in advanced economies about the effects of automation and other technological trends (Pew Research Center, 2017). Regions and countries heavily dependent on industries affected by these technological changes are particularly vulnerable, as automation could potentially displace a significant portion

[1] Unemployment insurance (UI) can enhance individual and social welfare by smoothing consumption in the presence of credit and insurance market failures. It enables the unemployed to look for better jobs that match their skills, thereby improving the quality of job matches (Marimon and Zilibotti 1999; Chetty 2008). Active labor market policies (ALMP) complement UI and can shorten unemployment spells by improving workers' skills (through retraining programs) and reducing information gaps between job seekers and job providers. Cash transfers and other forms of noncontributory social assistance (SA) programs provide financial support to more low-income households during long unemployment spells.

[2] Romer 1990; Aghion and Howitt 1992; Kremer 1993; Barro and Sala-i-Martin 1995; Aghion, Akcigit, and Howitt 2015; Akcigit, Celik, and Greenwood 2016; Akcigit and Kerr 2018; Acemoglu, et al. 2018.

of their workforce and negatively impacting their economies. Moreover, there is a growing concern that AI may even affect skilled workers, as it can automate a wide range of tasks (Pizzinell et al 2023; Cazzaniga et.al. 2024).

Innovation can affect employment and wages through several channels. On the one hand, new or improved technologies may lead to a decline in the demand for labor, reducing wages and employment by replacing workers in tasks they previously performed (Autor and Dorn 2013; Goos et al. 2009; Acemoglu and Restrepo 2020). For instance, information and communications technology accelerates the automation of routine tasks and induces firms to substitute capital for workers engaged in these tasks (Autor et al. 2003; Dao et al. 2017), and AI can potentially replace workers in non-routine tasks (OECD 2021).[3] On the other hand, innovation may increase the demand for labor through a variety of mechanisms. First, new technologies may be complementary to labor rather than substituting for it, helping workers be more productive in their jobs by taking over or improving certain tasks. Second, even if technological progress is labor-saving in the short run, it may also trigger additional capital accumulation that increases labor productivity and the demand for labor. Third, technological innovation may lead to the creation of new tasks, functions, and activities.[4] As industrial robots, computers, and digital technologies increasingly automate certain tasks, new jobs and tasks are created.[5] Last, innovation can boost labor demand through a productivity effect: as production costs decrease, the economy expands, increasing overall demand for labor. Even if innovation increases labor demand through one or several of these channels, this increased demand may not be in those sectors directly affected by innovation, and the reallocation of workers to new sectors and jobs is a slow process, especially when these new jobs require skills that workers displaced by innovation do not possess. As a result, innovation can adversely affect some workers, even when it leads to an increase in overall labor demand.

Mounting evidence indicates that automation in recent decades has displaced workers in routine tasks, resulting in lower average wages, intensifying wages and employment polarization by diminishing opportunities for middle-wage workers. In the United States, the increased use of robots during the last decades had negative impacts on local labor markets, reducing employment and wages, especially in manual and routine cognitive tasks (Acemoglu and Restrepo 2020). Displaced workers moved into lower-paying occupations (Braxton and Taska 2023). In Europe, the impact of industrial robots varies. While some studies indicate increased labor productivity, most point to displacement effects for lower-skilled workers in high-income countries (e.g., Graetz and Guy 2018; Acemoglu et al. 2020). In Germany, areas with more exposure to robots saw job displacement in the manufacturing sector, particularly impacting young workers. However, the lost manufacturing jobs were balanced by new positions in the service sector. Young workers adjusted their education choices, favoring colleges and universities over vocational training, with positive effects on workers in roles with complementary tasks (Dauth and others 2021). In both Europe and the U.S., the rise of information technologies has increased the demand for high-skilled and low-skilled workers but reduced opportunities for middle-skilled jobs. This phenomenon has led to job polarization, characterized by a decline in middle-wage positions. Routine cognitive work, such as sales and administrative tasks, has been particularly affected, while demand has increased for nonroutine labor at both the high and low ends of the occupational skill distribution.

[3] Most of the studies focus on the AI's potential labor market effects rather than actual outcomes, and their conclusions are heavily influenced by assumptions about which job tasks can be automated (e.g., Arntz, Gregory, and Zierahn 2016).

[4] Indeed, during the Second Industrial Revolution, as tasks in textiles, metals, agriculture, and other industries were being automated a new range of tasks in factory work, engineering, repair, back-office, management, and finance generated demand for workers (e.g.,; Chandler 1977; and Landes 2003).

[5] Acemoglu and Restrepo (2018) estimate that about 60% of jobs created in the U.S. between 1980 and 2015 were in occupations with new job titles.

This encompasses nonroutine cognitive jobs requiring advanced skills and nonroutine manual jobs involving limited formal education and in-person interactions, like food service, home health assistance, and janitorial roles (Autor and Dorn 2013; Goos et al. 2009).

Social protection programs can be instrumental in helping individuals adapt to changes in the job market, offering financial support during unemployment, promoting skill development, and creating a safety net (IMF 2022). While they contribute to a resilient workforce amid technological advances, credible empirical evidence on their effectiveness in mitigating the effects of these new technological advances is scarce.[6]

This paper fills this gap in the literature and provides new empirical evidence on whether social protection programs can reduce the negative impact of automation on labor market outcomes across U.S. commuting zones over the period 2000-2007. The paper follows Acemoglu and Restrepo (2020) to estimate the long-term effects of robots on employment and wages and exploits differences in social protection generosity (maximum legal benefit amount and duration) across U.S. states (Agrawal and Matsa 2013; Hsu et al. 2023). The results indicate that the impact of robotization on employment does not depend on UI generosity. This is not surprising as UI benefits are temporary, and thus unlikely to generate long-term effects (neither positive income effects that boost local labor demand nor negative effects on labor supply from discouraging workers to search for jobs). In contrast, states with more generous UI benefits saw a smaller decline in wages due to robotization—about two thirds smaller than other states. This finding suggests that more generous UI allows displaced workers to find jobs that better match their skills, contributing to more efficient labor allocation. This effect is particularly pronounced for workers without a college degree, possibly because these workers rely relatively more on unemployment insurance benefits when unemployed. These findings suggest that UI programs can be effective in lessening the adverse effects of industrial robots on wages because they facilitate intensive job searches, and allow more time for new skills acquisition, potentially leading to better job matching and increased worker productivity. Furthermore, in areas with high adoption of robots experience small increases in poverty, and social assistance helped to reduce these effects.

In addition to this introduction, the paper is organized as follows. Section 2 briefly describes the data and empirical methodology. Section 3 discusses the empirical findings. Section 4 discusses policy recommendations.

III. Methodology and Data

To estimate the effects of advances in the robotics technology on long-term employment and wages at the local level, the study relies on Acemoglu and Restrepo (2020), which used a Bartik-style measure of exposure of robots.[7] Exposure to robots is an adjusted measure which combines industry-level variation in the usage of robots and baseline employment shares at the commuting zone level, adjusting for overall expansion of each industry's output. Simple ordinary least squares (OLS) estimate with the variable for US exposure to robots computed from US data on the adjusted penetration of robots would lead to biased estimates, as some industries may be adopting robots in response to other changes that they are undergoing, which could directly

[6] Empirical evidence shows that social protection serves as an automatic stabilizer to mitigate the economy's sensitivity to shocks (Di Maggio and Kermani 2016; Brollo and other 2024), but there is no empirical evidence on how social protection can attenuate the effects of structural transformations as advancements in new technologies.

[7] The International Federation of Robotics (IFR) defines an industrial robot as "an automatically controlled, reprogrammable, and multipurpose [machine]" (IFR 2014)

impact their labor demand. Also, any shock to labor demand in a commuting zone affects the decisions of local businesses, including robot adoption. To address the concern that industry level adoption of robots in the U.S. will be related to other industry trends or economic conditions in local areas specializing in an industry, US exposure to robots is instrumented using an analogous measure constructed from the penetration of robots in European countries that are ahead of the United States in robotics technology.

This strategy has the advantage of focusing on the variation that results solely from industries in which the use of robots has been concurrent in most advanced economies. The identifying assumption is that industries in local labor markets (proxy by commuting zones level) with greater advances in robotics technology are not differentially affected by other labor market shocks or trends. Note that the main objective of this paper is to analyze the role of social protection policies in mitigating negative effects of automation. The average penetration rate of robots in the U.S in the previous period (1990-1999) was around fifty percent lower than the subsequent decade, making it harder to find heterogeneous effects for differences in social protection policies. For the period after 2007, social protection policies in the U.S. were highly affected by the financial crisis. Therefore, the analysis in this paper focuses on the period 2000-2007.

The effects of changes in exposure to robots on changes in employment and wages during the period 2000-2007 can be estimated by regressing the change in these variables on exposure to robots:

$$\Delta Y_{c,(t_1-t_0),s} = \beta \ \Delta Exposure\ to\ robots_{c,(t_1-t_0),s} + \delta X_{c,t_0,s} + \varepsilon_{c,(t_1-t_0),s} \tag{1}$$

$\Delta Y_{c,(t_1-t_0),s}$ represents change in employment to population ratio or log average wage in commuting zone *c* in state *s* between 2000-2007 – one observation per commuting zone.

$\Delta Exposure\ to\ robots_{c,(t_1-t_0),s}$ represents change in ratio of robots to workers in commuting zone *c* in state *s* between 2000-2007. Note that changes in robot adoption may respond to shocks to labor demand or other factors that are also correlated with labor demand. To take this into account the study uses an analogous measure constructed from the penetration of robots in European countries (industry-level changes in robot penetration in the EU and local industry employment in each commuting zone) as instrument for exposure to robots in the U.S. commuting zones.

$X_{c,t_0,s}$ represents covariates, including census division dummies, demographic characteristics of commuting zones in 2000 (log population, share of females, share of the population over 65 years old, share of the population with no college, some college, college or professional degree, and masters or doctoral degree, and the share of Whites, Blacks, Hispanics, and Asians), manufacturing employment in 2000, exposure to Chinese imports and the share of employment in routine jobs.

$\varepsilon_{c,(t_1-t_0),s}$ represents the error term.

A credible empirical analysis on how social protection policies can mitigate the adverse effects of innovation would require variation in social protection policies within countries, but usually the rules that govern these policies are defined at the national level. Even if there is micro-level evidence on how social protection affects individuals affected by innovation, it may be unclear how these findings translate to broader, aggregate outcomes at the societal or macroeconomic level. Understanding the macroeconomic implications is crucial for policymakers to design effective, large-scale interventions. This paper exploits variation in the caps for social protection generosity across U.S. states to provide novel evidence on how social protection benefits can mitigate the adverse effects of exposure to robots on workers. To analyze whether the effects of exposure to robots differs depending on the generosity of social protection programs, equation 2 is estimated as follows:

$$\Delta Y_{c,(t_1-t_0),s} = \beta\ \Delta Exposure\ to\ robots_{c,(t_1-t_0),s} + \delta Social\ protection\ generosity_{c,(t_0),s} + \alpha\ (\Delta Exposure\ to\ robots_{c,(t_1-t_0),s} * Social\ protection\ generosity_{c,(t_0),s}) + \delta X_{c,t_0,s} + \varepsilon_{c,(t_1-t_0),s} \quad (2)$$

$Social\ protection\ generosity_{c,(t_0),s}$ is a dummy variable that equals 1 if generosity of unemployment insurance (UI) or social safety net (SSN) in 2000 is high, and zero otherwise. Note that α is the coefficient of interest and captures whether the (adverse) effect of robot penetration on labor market outcomes was different in areas with more generous social protection policies. Note that this interaction term is also instrumented by the analogous measured discussed above interacted with the dummy that denotes social protection generosity. It is worth to clarify that this study focuses on the analysis of how social protection can mitigate the negative effects of robotization on wages, and not on the interpretation of δ, which denote the correlation between wages and social insurance generosity. The validity assumption for β and α are similar. Assuming the instruments are exogenous, one could still cast doubts on the interpretation of the interaction term, as the generosity of social protection could be correlated with other factors. However, note that if this is the case, these "factors" should not only reduce the negative effects of the shocks and commuting zone levels on wages but, at the same time, not affect employment.

A. Exposure to robots: data and variables definition[8]

Following Acemoglu and Restrepo (2020), data on counts of the stock of robots by industry, country, and year comes from IFR for Denmark, Finland, France, Italy, Sweden, and the United States. Data for the use of Robots are classified in six broad industries (agriculture, forestry and fishing, mining, utilities, construction, education, research, and development, and services) plus manufacturing, which is disaggregated from more 13 industries. The data is combined with employment counts and output by country and industry from the European Union–level analysis of capital, labor energy, materials, and service inputs (EU KLEMS) Growth and Productivity Accounts to measure penetration of robots.

B. Unemployment insurance in the U.S.

The United States unemployment insurance system offers temporary income to eligible workers who lose their jobs. While the federal-state system has a uniform structure, each state has the authority to set its own rules, including benefit amounts and duration. States typically provide benefits that replace about 50 percent of an individual's prior wages, up to a maximum weekly benefit amount. States also limit the number of weeks for which benefits are paid, with state caps ranging from 26 to 30 weeks. Information on these benefit schedules is sourced from the U.S. Department of Labor's publication "Significant Provisions of State UI Laws." The generosity of UI benefits in each state is measured by the product of the maximum weekly benefit amount and the maximum benefit duration (in weeks) in 2000, the year before the period of analysis. This measure provides a proxy for the total benefits that a UI claimant can receive during an unemployment spell, which strongly

[8] For more details on commuting zone data, industry data, and exposure to robots measure see Acemoglu and Restrepo (2020).

correlates with actual compensation payments (Agrawal and Matsa 2013; Hsu et. al. 2023).[9] The variable of interested "High UI generosity" is a dummy variable that equals 1 when generosity is greater than the median across U.S. states, and zero otherwise.

C. Social assistance in the U.S.

The generosity of social assistance at the state level is based on the generosity of the Temporary Assistance for Needy Families (TANF), the largest cash assistance program in the U.S. The generosity of TANF benefits in each state is measured by the maximum monthly benefit for a family of three with no income in 1999, the year before the period covered in the analysis. This measure provides a proxy for the total benefits a family receives. The variable of interested "High SA generosity" is a dummy variable that equals 1 when generosity is greater than the median across U.S. states, and zero otherwise.

IV. Results of Empirical Analysis

Table 1 presents IV estimates of the effects of exposure to robots on employment and wages at the commuting zone level, for the period 2000-2007 (Acemoglu and Restrepo 2020) and the role of unemployment insurance in mitigating its adverse effects on employment and wages, where changes in employment and wage measures are regressed on the variable for exposure to robots for the same period. All regressions include controls for census divisions, baseline covariates, demographics and industry shares of commuting zones (log population; the share of females; the share of the population over 65 years old; the shares of the population with no college, some college, college or professional degree, and masters or doctoral degree; and the shares of whites, blacks, Hispanics, and Asians), exposure to imports from China, and the share of employment in routine jobs. First-stage coefficients and their F-statistics and p-value are reported. Standard errors that are robust against heteroskedasticity and correlation within states are given in parentheses. Results are robust to the inclusion of state fixed effects and different specifications at commuting level zone and demographic groups.

According to the results, one additional robot per thousand workers in a commuting zone reduces its employment to population ratio by approximately 0.6 percentage points (column 1), roughly 1.7 percent decline, and average hourly wages by approximately 0.8 percent (column 3) relative to other commuting zones.[10] These magnitudes include both the direct effects of robots on employment and wages and the spillover effects on non-tradables resulting from the decline in local demand.

Columns 1, 4, 5 and 6 (Table 1) and Figure 1 report the results of regressions that include the dummy that denotes states with relatively high UI generosity at the beginning of the period, and its interaction term with changes in exposure to robots that captures whether the (adverse) effect of robot penetration on labor market outcomes was different in areas with more generous social protection policies. The results indicate that there are no differential effects in employment (column 2) – unemployment insurance does not attenuate the long-term effects of exposure to robots on employment. This non-result is expected as unemployment insurance is

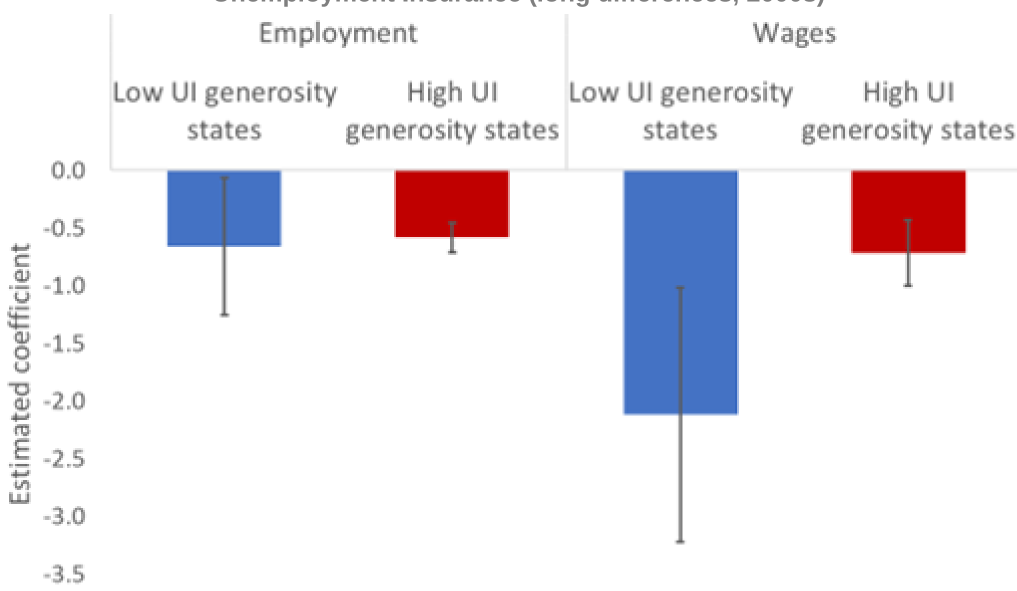
[9] Most of the variance in the caps for generosity of UI in the U.S. during the period of the analysis relies on maximum benefit amounts as most of the states the maximum length of UI benefits allowed is around 26 weeks.

[10] The increase in robots during the period we are analyzing is around 1 robot per thousand workers.

likely to affect long-term employment only if the short-term effects of UI on consumption are large enough to permanently increase demand for labor. In contrast, two thirds of the negative effects of robotization on wages in areas highly exposure to robots are attenuated in states where UI are relatively more generous (column 4). This suggests that more generous UI allows displaced workers to take the time to find a job that better matches their skill set, thus contributing to more efficient labor allocation. This seems to be concentrated on workers without college degree (Table 1, column 6, and Figure 2), as they might rely relatively more on unemployment insurance benefits while unemployed.

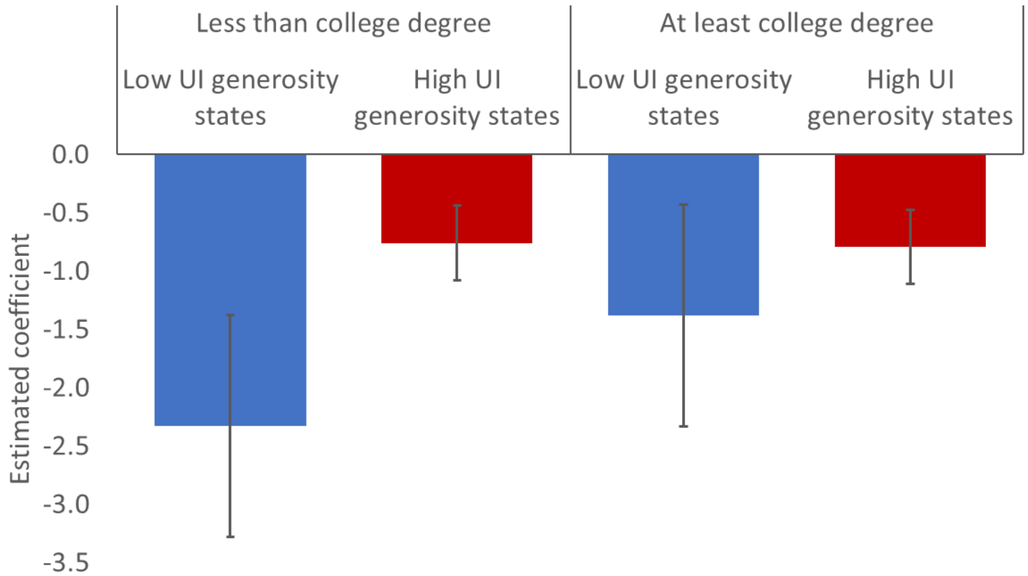
There might be concerns that α, the coefficient of interest that captures whether the (adverse) effect of robot penetration on labor market outcomes was different in areas with more generous social protection policies, is capturing a selection effect. This would happen in case that generous UI triggers a relatively stronger discouragement effect for lower productivity workers, implying in changes in the composition of workers. Dropout rates would be relatively higher for workers with lower productivity in areas espoused to robots, and the share of higher productivity workers will go up, which is consistent with my finding. However, this would also imply that employment would go down, which is not consistent with findings reported in Table 1. If unemployment insurance had large long-lasting discouragement effects (over at least seven years – the period of the analysis), labor supply would fall more in places with more generous unemployment insurance and, in equilibrium, employment would also fall more in these places. According to the findings, total employment decreases by a similar amount in places with high and low unemployment insurance following a negative shock (column 2). It is worth mentioning that the results are robust to the inclusion of state dummies and alternative specifications for the social protection generosity dummy.

Figure 1. Effect of Robots on Employment and Wages in the U.S. Local Labor Market: The Role of Unemployment Insurance (long differences, 2000s)



Note: This figure illustrates IV coefficient estimates of the effects of exposure to robots on employment and wages for the period 2000-2007 in states with different degree of unemployment insurance generosity as described in equation 2 and displayed in Table 1 (columns 2 and 4). Confidence intervals are illustrated by the vertical lines.

Figure 2. Effect of Robots on Wages in the U.S. Local Labor Market: The Role of Unemployment Insurance by Levels of Education (long differences, 2000s)



Note: This figure illustrates IV coefficient estimates of the effects of exposure to robots on wages for the period 2000-2007 in states with different degree of unemployment insurance generosity and by level of education as described in equation 2 and displayed in Table 1 (columns 5 and 6). Confidence intervals are illustrated by the vertical lines.

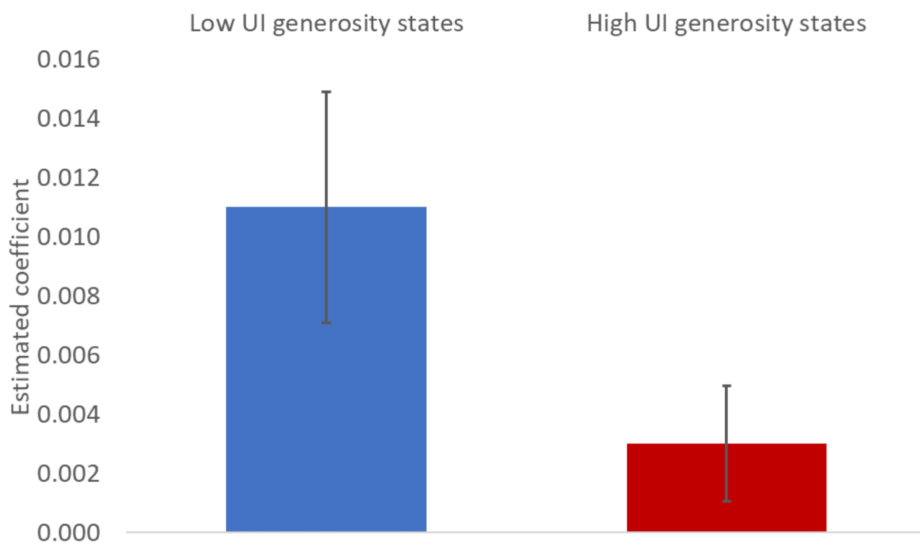
Table 1. Effect of Robots on Employment and Wages in the U.S. Local Labor Market:
The Role of Unemployment Insurance (long differences, 2000s)

Effects of Robots on Employment and Wages in the U.S. Local Labor Market (2000-2007)						
Dependent Variable	Change in Employment-to-Population Ratio		Change in Log Hourly Wages			
	All workers		All workers		At least college degree	Less than college degree
	(1)	(2)	(3)	(4)	(5)	(6)
Exposure to robots (a)	-0.585***	-0.663**	-0.783***	-2.124***	-1.380***	-2.332***
	(0.067)	(0.303)	(0.165)	(0.561)	(0.485)	(0.575)
Exposure to robots * High UI generosity (b)		0.079		1.409***	0.587	1.563***
		(0.298)		(0.531)	(0.431)	(0.549)
High UI generosity		-0.087		-2.726***	-1.256*	-3.241***
		(0.281)		(0.651)	(0.689)	(0.711)
Observations	722	722	722	722	722	722
First-stage coefficient	0.75	0.53	0.75	0.53	0.53	0.53
First-stage F-statistic	124	16	124	16	16	16
(a)+(b)		-0.584		-0.715	-0.793	-0.769
(a)+(b)=0 - p-value		0.000		0.000	0.000	0.000
(a)+(b)=0 - se		0.065		0.146	0.161	0.165

Note: This table presents IV estimates of the effects of exposure to robots on employment and wages for the period 2000-2007, one observation per commuting zone Exposure to robots is defined as in Acemoglu and Restrepo (2020). The generosity of UI benefits in each state is obtained from U.S. Department of Labor's publication "Significant Provisions of State UI Laws", and it is measured by the product of the maximum weekly benefit amount and the maximum benefit duration (in weeks) in 2000. The variable of interested "High UI generosity" is a dummy variable that equals 1 when generosity is greater than the median across U.S. states, and zero otherwise. All regression control for census divisions, baseline covariates, demographics and industry shares of commuting zones (log population; the share of females; the share of the population over 65 years old; the shares of the population with no college, some college, college or professional degree, and masters or doctoral degree; and the shares of whites, blacks, Hispanics, and Asians), exposure to imports from China, and the share of employment in routine jobs in 2000. Results are robust to the inclusion of state fixed effects and different specifications at commuting level zone and demographic groups. First-stage coefficients and their F-statistics and p-value are reported. Standard errors that are robust against heteroskedasticity and correlation within states are given in parentheses.

The paper also provides new evidence of the effects of exposure to robots on poverty.[11] In addition to its effects on labor markets, robotization could also contribute to increasing poverty, especially if the negative impact of robotization is more pronounced for workers at the bottom of the wage distribution. These workers are at higher risk of falling into poverty because it is harder for them to find new jobs with similar pay. Social assistance programs can play a key attenuating role in this regard. Results reported on Table 2 (column 1) show that robotization resulted in a small long-term increase in poverty: one additional robot per thousand workers increased the poverty rate by 0.3 percentage points (3 percent increase).[12] The analysis also suggests that temporary unemployment insurance benefits do not eliminate poverty effects (column 2). In contrast, this negative effect is offset in areas where social assistance generosity is relatively higher (columns 3 and 4 and Figure 3) Overall, these findings suggest that the design of social protection systems played a role in ameliorating adverse labor market and poverty impacts in the past.

Figure 3. Effect of Robots on Poverty: The Role of Social Assistance
(long differences, 2000s)



Note: This figure illustrates IV coefficient estimates of the effects of exposure to robots on poverty for the period 2000-2007 in states with different degree of social assistance generosity in equation 2 and displayed in Table 2 (columns 5 and 6). Confidence intervals are illustrated by the vertical lines.

[11] Following the Office of Management and Budget's (OMB) Statistical Policy Directive 14, the Census Bureau uses a set of money income thresholds that vary by family size and composition to determine who is in poverty. If a family's total income is less than the family's threshold, then that family and every individual in it is considered in poverty.

[12] According to the U.S. census, the poverty rate in the U.S. was 11.3 percent in 2000.

Table 2. Effect of Robots on Poverty:
The Role of Social Assistance (long differences, 2000s)

The Effects of Robots on Poverty (2000-2007)

	Change in Poverty Rate			
	(1)	(2)	(3)	(4)
Exposure to robots	0.003***	0.005**	0.011***	0.011***
	(0.001)	(0.002)	(0.002)	(0.002)
Exposure to robots * High UI generosity		-0.002		0.003
		(0.002)		(0.004)
High UI generosity		0.003		-0.001
		(0.003)		(0.003)
Exposure to robots * High SA generosity			-0.008***	-0.011***
			(0.002)	(0.004)
High SA generosity			0.013***	0.015***
			(0.004)	(0.005)
Observations	722	722	722	722
First-stage coefficient	0.75	0.53	0.86	0.82
First-stage F-statistic	124	16	246	11
(a)+(b)		0.003	0.003	0.000
(a)+(b)=0 - p-value		0.000	0.000	0.975
(a)+(b)=0 - se		0.001	0.001	0.004

Note: This table presents IV estimates of the effects of exposure to robots on employment and wages for the period 2000-2007. Exposure to robots is defined as in Acemoglu and Restrepo (2020). The generosity of SA benefits in each state is obtained from the Welfare Rules Database provided by the Urban Institute, and it refers to the maximum benefit amount in each U.S. state in 2000. The variable of interested "High SA generosity" is a dummy variable that equals 1 when generosity is greater than the median across U.S. states, and zero otherwise. All regression control for census divisions, baseline covariates, demographics and industry shares of commuting zones (log population; the share of females; the share of the population over 65 years old; the shares of the population with no college, some college, college or professional degree, and masters or doctoral degree; and the shares of whites, blacks, Hispanics, and Asians), exposure to imports from China, and the share of employment in routine jobs. Results are robust to the inclusion of state fixed effects and different specifications at commuting level zone and demographic groups. First-stage coefficients and their F-statistics and p-value are reported. Standard errors that are robust against heteroskedasticity and correlation within states are given in parentheses.

V. Policy Discussion: Social Protection to Make Innovation Work for All

New technologies advancements can lead to significant labor market disruptions. These include the displacement of middle-wage workers, particularly in cognitive and routine jobs, and the potential displacement of employees in more complex roles. This trend is coupled with modest economic growth and a decreasing share of income allocated to labor versus capital, raising concerns about escalating poverty and inequality.

Social protection is crucial to help individuals navigate through the impacts of new technologies advances on labor markets, but the effectiveness of the policy instrument will depend on several factors. This includes the degree of exposure to automation, and the coverage, design, and generosity of these systems. Although many advanced economies have comprehensive unemployment benefits, access is inconsistent and often excludes temporary workers and those re-entering the labor market. Social protection systems anchored in insurance-based instruments combined with strong labor market institutions can be effective to provide crucial financial support to unemployed workers actively seeking new jobs. Well-designed UI enables individuals to dedicate sufficient time to securing employment that better aligns with their skills, allowing skills development and better job matches, thereby improving efficiency in job allocation and smoothing transitions in a rapidly changing job market. Many advanced economies have established generous unemployment benefit schemes, but the extent to which workers are eligible to such programs varies. Access to basic social protection is not universal but largely fragmented along occupational lines, and social benefits are not portable. As these technological changes are transforming the dynamics of work and the employer-employee relationship, employment insurance eligibility rules should be more flexible with adequate coverage and benefit generosity, also including workers in self-employment and non-standard employment (NSE) contracts.[13] Additionally, integrating UI with proactive labor market policies that support skill development and job searching is crucial. To achieve this, ALMPs should be refined by shifting the focus from mere job search assistance to the development of human capital (Card et al. 2017; Levy Yeyati et al. 2019). Collaboration with the private sector can be relevant, leveraging their understanding of required skills to contribute to program success (Kluve et al, 2019).

Nevertheless, the effectiveness of labor market policies can be constrained by the pace and geographical distribution of technological advances, the complexity of new skills required, and the ability of displaced workers to adapt. Comprehensive Social Safety Net (SSN) programs are crucial for supporting workers directly or indirectly affected by technological shifts, such as those facing long-term unemployment or reduced local labor demand due to industry closures or automation.

[13] Even in advanced economies, non-standard employment (NSE), including numerous forms of self-employment and part-time work often found through the online platforms and the “gig economy”, is posing similar challenges to those faced by the world’s informal workers (World Bank, 2019). This shift primarily reduces jobs in standard forms of employment in middle-skilled positions and increases those in low-skilled occupations with NSE contracts. Social protection coverage among NSE workers is much lower as many of them does not meet the minimum requirements, or in case they are eligible, benefit levels are insufficient, exacerbating income inequality (OECD 2017; Gassmann and Martorano 2019). Workers engaged in platform work (‘gig-workers’) are often classified as independent contractors and are as such not covered by existing labor and social protection laws. This shift in labor demand, away from conventional job structures, poses risks for individuals and society at large. Workers under NSE contracts, including the self-employed, face higher poverty rates. In Europe, the risk to fall into poverty for the self-employed is three times higher compared to those with more traditional employment contracts (Spasova et. al., 2017). Without appropriate regulation, there is a risk of a "race to the bottom" in terms of job quality and conditions (OECD 2017).

References

Acemoglu D., and P. Restrepo (2020). "Robots and Jobs: Evidence from US Labor Markets". Journal of Political Economy. Volume 128, Number 6.

Acemoglu D., and P. Restrepo (2018). "The Race between Man and Machine: Implications of Technology for Growth, Factor Shares, and Employment". American Economic Review 2018, 108(6): 1488–1542.

Aghion P., Howitt P. (1992) "A Model of Growth Through Creative Destruction". Econometrica, Vol. 60, No. 2, pp. 323-351.

Aghion P., Akcigit U., Howitt P. (2015) "Lessons from Schumpeterian Growth Theory" American Economic Review. Volume 105, No. 5. pp. 94-99.

Agrawal A. K., Matsa, D. (2013) "Labor unemployment risk and corporate financing decisions". Journal of Financial Economics. Volume 108, Issue 2, pp 449-470.

Akcigit U., and Kerr W. R. (2018) "Growth through Heterogeneous Innovations." Journal of Political Economy." Volume 126, Number 4.

Akcigit U., and Celik, M. L. and Greenwood J., (2016). "Buy, Keep, or Sell: Economic Growth and the Market for Ideas," Econometrica, vol. 84, pages 943-984.

Arntz M., Gregoryi T., and Zierahn U. (2016) "The Risk of Automation for Jobs in OECD Countries". OECD Social. Employment and Migration Working Papers.

Autor, David H., and David Dorn. 2013. "The Growth of Low-Skill Service Jobs and the Polarization of the US Labor Market." American Economic Review, 103 (5): 1553-97.

Autor D., Levy F., & Murnane R. J. (2003) "The Skill Content of Recent Technological Change: An Empirical Exploration" Quarterly Journal of Economics 118.

Banerjee A. V., Duflo E. (2019) "Good Economics for Hard Times: Better Answers to Our Biggest Problems". Penguin Books Limited.

Barro R. J., Sala-I-Martin X. (1995) "Technological Diffusion, Convergence, and Growth". Journal of Economic Growth, Vol. 2, No. 1, pp. 1-26.

Braxton, J. Carter, and Bledi Taska. 2023. "Technological Change and the Consequences of Job Loss." American Economic Review, 113 (2): 279-316.

Brollo F., Ibarra G. L., and Vale R. C. (2024) "Strengthening Income Stabilization through Social Protection in Emerging and Developing Economies: The Brazilian Experience" IMF Working Paper.

Card D., Kluve J., Weber A. (2017) "What Works? A Meta Analysis of Recent Active Labor Market Program Evaluations". Journal of the European Economic Association, Volume 16, Issue 3, June 2018, Pages 894–931.

Cazzaniga, Mauro, Florence Jaumotte, Longji Li, Giovanni Melina, Augustus J. Panton, Carlo Pizzinelli, Emma J. Rockall, and Marina Mendes Tavares (2024). "Gen-AI: Artificial Intelligence and the Future of Work." Staff Discussion Notes, no. 001.

Chandler A. D. (1977) "The Visible Hand: The Managerial Revolution in American Business". Harvard University Press, Belknap Press.

Chetty Raj (2008) "Moral Hazard versus Liquidity and Optimal Unemployment Insurance". Journal of Political Economy. Volume 116, Number 2.

Dao M., Das M., Koczan Z., Lian W. (2017) "Why Is Labor Receiving a Smaller Share of Global Income? Theory and Empirical Evidence" IMF Working Paper.

Dauth W., Findeisen S., Suedekum J., Woessner N., (2021) "The Adjustment of Labor Markets to Robots". Journal of the European Economic Association, Volume 19, Issue 6, December 2021, Pages 3104–3153.

Di Maggio M., and Kermani A. (2016) "The Importance of Unemployment Insurance as an Automatic Stabilizer". NBER Working Paper 22625.

Dollar, David, and Aart Kraay (2002). "Growth Is Good for the Poor." Journal of Economic Growth 7, no. 3.

Gassmann F., and Martorano B.,(2019). "The future of work and its implications for social protection and the welfare state," MERIT Working Papers 2019-039, United Nations University - Maastricht Economic and Social Research Institute on Innovation and Technology.

Goos, Maarten, Alan Manning, and Anna Salomons. (2009). "Job Polarization in Europe." American Economic Review, 99 (2): 58-63.

Graetz G., Guy M. (2018) "Robots at Work" The Review of Economics and Statistics.100 (5): 753–768.

Hsu, Joanne W., David A. Matsa, and Brian T. Melzer. 2018. "Unemployment Insurance as a Housing Market Stabilizer." American Economic Review, 108 (1): 49-81.

IMF 2022 "IMF Engagement on Social Safety Net Issues in Surveillance and Program Work". IMF Technical Note.

IFR (International Federation of Robotics). 2014. "World Robotics: Industrial Robots." Tech. report, Internat. Fed. Robotics, Frankfurt.

Kluve J., Puerto S., Robalino D., Romero J. Rother F., Stöterau J., Weidenkaff F. Witte M., (2019) "Do youth employment programs improve labor market outcomes? A quantitative review". World Development 114 (548): 237-253.

Korinek A., Schindler M., Stiglit J. E. (2022). "Technological Progress and Artificial Intelligence" in "How to Achieve Inclusive Growth" Oxford University Press.

Kremer M. (1993) "Population Growth and Technological Change: One Million B.C. to 1990". The Quarterly Journal of Economics, Vol. 108, No. 3, pp. 681-716.

Marimon R., Zilibotti F. (1999) "Unemployment vs. Mismatch of Talents: Reconsidering Unemployment Benefits" Economic Journal. Volume109, Issue 455.

Krugman P. (1997) "How Fast Can the U.S. Economy Grow?" Harvard Magazine Review.

Landes David. (2003) "The Unbound Prometheus: Technological Change and Industrial Development in Western Europe from 1750 to the Present" Cambridge Press.

Levy-Yeyati, E., Montané, M. & Sartorio, L.. (2019). "What Works for Active Labor Market Policies?".

OECD 2017 "Future of Work and Skills".

OECD 2021 "Artificial Intelligence and Employment" Policy Brief.

Pew Research Center (2017) "Americans and Automation in Everyday Life" Pew Research Center.

Pizzinelli, Carlo, Augustus J. Panton, Ms Marina Mendes Tavares, Mauro Cazzaniga, and Longji Li. "Labor market exposure to AI: Cross-country differences and distributional implications". International Monetary Fund Working Paper No. 2023/216, 2023.

Romer P. (1990) "Endogenous Technological Change". Journal of Political Economy, Vol. 98, No. 5, Part 2: The Problem of Development: A Conference of the Institute for the Study of Free Enterprise Systems (Oct., 1990), pp. S71-S102.

Spasova, S., Ghailani, D., Bouget, D. (2017) "Access to social protection for people working on non-standard contracts and as self-employed in Europe – A study of national policies 2017", European Commission, Directorate-General for Employment, Social Affairs and Inclusion.

Wolff E., (2010) "Household Wealth Trends in the United States, 1962 to 2016: Has Middle Class Wealth Recovered?" NBER Working Paper.

World Bank (2019) "Changing the nature of Work" World Development Report.

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