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New Technologies: End of Work or Structural Change?

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Abstract: This paper examines the impact of new technologies, particularly automation and artificial intelligence (AI), on labor markets. The existing literature documents ambiguous and only limited overall employment effects, while new technologies induce significant shifts in workforce composition. The implied firm-level productivity gains primarily benefit larger, skilled-labor-intensive firms. AI adoption remains limited but continues to reshape skill demands. The implied worker reallocation is costly, exacerbating inequality. This calls for policies such as targeted support for displaced workers, investment in education and skill development, promoting technology diffusion, and encouraging complementary human capital investments.

Keywords: inequality; unemployment; digitalization; artificial intelligence; technology

JEL Classification: J31; J21; J24

1 Technology and Jobs: Automation Versus Reinstatement

The recent decades have been characterized by an astonishing increase in the capabilities of new technologies to perform tasks that previously seemed genuinely human, such as for example the abilities of *ChatGPT* to conduct conversations with humans. Such advancements are accompanied by fears that new technologies may

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make human labor obsolete. These fears in the public debate are fueled by reports which claim that about half of jobs were "at risk of computerization".[1]

While studies have shown such predictions to be massively exaggerated due to methodological problems,[2] there still exists a large discrepancy between public alarmists who claim the end of work on the one side, and some economists on the other side who argue that past technological revolutions have not persistently reduced labor demand, and that there is no reason to believe that this time is different. This is what Acemoglu and Restrepo (2018a) call the false dichotomy.

In their seminal new theoretical framework, Acemoglu and Restrepo (2018b, 2018c) show that the effect of new technologies on the demand for labor is ambiguous and depends on two opposing forces, automation and reinstatement. Automation, i.e. technological capital learning to take over human tasks, reduces demand for labor. Via reinstatement, however, humans develop new tasks that machines cannot yet do. The net effect of employment then depends on the relative speed of these two processes and is ultimately an empirical question.

There now exists a large empirical debate on the effects of new technologies on labor demand. In the US, evidence indicates that automation has been exceeding reinstatement, recently (Acemoglu and Restrepo 2019). For Europe, the existing evidence suggests actually positive effects. In particular, Gregory, Salomons, and Zierahn (2022) show that computerization has had positive employment effects because job-creating effects of new technologies outweigh the job-destructive effects. Also Autor and Salomons (2018) find that employment losses due to automation technologies in adopting industries are compensated for by employment gains in customer industries and rising aggregate demand in a cross-country study. They rely on a very broad definition of automation technologies.

While the evidence thus suggest no large employment losses due to automation technologies more broadly, the experience might differ for specific technologies. For example, Acemoglu, Lelarge, and Restrepo (2020) find that robot adoption in France has positive effects within the robot adopters, but negative effects at the market level because robot adopters grow in employment but crowd out more workers in competing firms. Dauth et al. (2021), in contrast, find no destructive effects of robot adoption in German local labor markets, because displacement effects in manufacturing are offset by new service jobs. In the US, again, robots do reduce demand for labor (Acemoglu and Restrepo 2020). In a cross-country study, Graetz and Michaels (2018) find no negative employment effects of robots. These differences in

1 See for example Frey and Osborne (2017), whose claims have received widespread attention in the public debate.

2 See for example Arntz, Gregory, and Zierahn (2017), Nedelkoska and Quintini (2018), Dengler and Matthes (2018), Pouliakas (2018).

the experiences between countries indicate that country-specific institutions (such as labor protection legislation or training measures) might play a role for the macroeconomic effects of automation.

2 Technology-Driven Job Polarization

While there is no broad evidence in favor of large negative employment effects of new technologies at the macro-level – except for specific technologies and specific countries – this does not mean that the labor market does not respond to technological change. To the contrary, these technologies do substitute for specific types of jobs, inducing a restructuring of the workforce. Automation technologies – and in particular computerization – are efficient at performing tasks that follow clear, repetitive tasks that can be codified to be executed automatically via computer-controlled machines. These tasks are called routine tasks. The idea was developed by Autor, Levy, and Murnane (2003), who show that computerization indeed induces a decline in routine jobs. Goos, Manning, Salomons (2009, 2014) show that routine jobs are middle-wage jobs, and that computerization therefore leads to declining shares of middle-wage jobs in European countries. This is known as job polarization, and is also found for example in the US (Acemoglu and Autor 2011). The effects are not limited to changes in employment, but are analogously reflected in wage changes: workers who perform routine tasks suffer from a significant and growing wage penalty in contrast to workers who perform abstract tasks, who enjoy positive and growing wage returns (Ross 2017).

This restructuring of jobs due to new technology has an unequal effect on workers. While there are deteriorating opportunities for workers exposed to automation, other workers may not experience any direct effects or become more productive as they are aided in their tasks. The net total positive effect for the labor market as a whole is the combination of concentrated negative effects for some and more than compensating positive effects for other. These negative effects materialize in lower earnings for those affected. Research has studied both how the opportunity to work as well as the wage have contributed to these earnings effects.

The declining demand for automation exposed work explains a large share of the restructuring of the wage structure over the long run. In particular, Acemoglu and Restrepo (2022) show that between 50 % and 70 % of changes in the U.S. wage structure over the last four decades can be attributed to relative wage declines of worker groups specialized in routine tasks in rapid automating industries.

3 Firm-Level Consequences

As the scientific literature has found limited macroeconomic employment effects of new technologies, but strong reallocation effects, it has zoomed in to the micro level. In recent years, a growing literature studies the consequences of adoption automation technologies at the firm level. These studies either study new technologies more broadly, automation technologies more particularly, or – more recently – zoom in on robots. A common finding across most studies is that firms which adopt new (automation) technologies are generally larger, have a more skilled workforce, and pay higher wages. Older literature, which focuses on broader technologies, does not find large shifts in workforce structure after the adoption of the technologies (Doms, Dunne, and Troske 1997; Dunne and Troske 2005). This differs for the more recent literature which zooms in on robot adoption and large automation events, identified at the firm level. These studies find that the adoption of robots and other automation technologies is associated with faster growth of employment, revenues, and productivity and either stable or declining labor shares as well as a restructuring of the workforce towards more skilled workers (Acemoglu, Lelarge, and Restrepo 2020; Aghion et al. 2020; Bessen et al. 2023; Bonfiglioli et al. 2021; Dinlersoz and Wolf 2018; Dixon, Hong, and Wu 2019; Koch, Manuylov, and Smolka 2021).

The difference between positive employment effects at the firm- and zero or negative effects at the macro-level suggest that there exist competition effects between robot adopters and non-adopters. Indeed, Koch, Manuylov, and Smolka (2021) report substantial job-losses among non-adopters and reallocation of employment towards robot-adopters. Acemoglu, Lelarge, and Restrepo (2020) similarly find that robot adoption in France has positive effects within the robot adopters, but negative effects at the market level because robot adopters grow in employment but crowd out more workers in competing firms. Hence, firms that adopt new technologies grow in employment, but at the expense of firms that do not adopt. This is potentially efficient, as the adopting forms are more productive and pay higher wages. However, the restructuring of employment likely comes at a cost for workers who have to adapt.

4 Worker-Level Adjustments

The absence of substantial technology-induced job losses in the aggregate does not imply the absence of negative consequences for workers. To the contrary, the sizable restructuring of the workforce induces costs for workers. One important dimension of worker-level adjustment during this restructuring is labor market participation. The declining demand for routine manual jobs leads to declining employment particularly among prime-age low educated man, while declining demand for routine cognitive jobs reduces employment primarily among prime-age women with intermediate education. These groups face rising non-employment as well as rising unemployment in low-wage non-routine manual (service) jobs (Cortes, Nir Jaimovich, and Henry 2017). This indicates that adjustment to technological shocks is sluggish and costly for exposed workers. In a complementary study by Bessen et al. (2023) researchers find that incumbent workers at a firm that engaged in an automation capital investment increases the probability that they will spend time out of employment after the investment has been made. This is mostly driven by older and middle-educated workers losing out.

Similarly, workers who are exposed to automation also have a lower chance of finding work after job displacement from a restructuring firm (Blien, Dauth, and Roth 2021). This suggests that mass lay-offs may act as a catalyzer for automation exposed workers to spend time in unemployment (Goos, Rademakers, and Röttger 2021). This is particularly worrisome given the documented scarring effects of job displacement (Davis and von Wachter 2011; Jacobson, LaLonde, and Sullivan 1993).

These results highlight that reallocation to other occupations with better prospects either is costly or sometimes simply unavailable. As a consequence, technological change not only creates winners, whose occupations are complementary to the technology, but also losers whose occupations are substitutes and who are not sufficiently mobile to move to expanding segments of the labor market with better job prospects. Mobility of people who lost their job is typically limited to only the most similar jobs outside of job seekers' previous labor markets, as highlighted by Dabed et al. (2023). They show that existing mobility patterns are insufficient to substantially move newly unemployed job-seekers from automation-exposed jobs to expanding labor market segments. As a consequence, existing occupational mobility is insufficient to significantly alleviate the costs for automation-exposed workers, creating a wedge between them, and those who benefit from new technologies due to complementary skills. Governments could try to reduce the rising gap by supporting the transition of workers into growing segments of the labor market via information on which jobs are on the rise and how they can be made available, as well as by reducing the transition costs via suitable (re-)training measures.

5 Artificial Intelligence and Complementary Skill Investments

Today, we are faced with the onset of a new general purpose technology: artificial intelligence (AI). Given that AI has the capacity to impact a new set of tasks, this has reignited the question: Is this time different? Several studies hypothesize that new AI technologies might reduce non-routine cognitive work (Brynjolfsson, Mitchell, and Rock 2018; Webb 2020). To date, only few data on AI adoption exist. AI technologies in particular, and frontier technologies more broadly, are used by a relatively small but growing share of firms in the US (Acemoglu et al. 2024; McElheran et al. 2024) and Germany (Arntz et al. 2024). Those are typically larger firms, which make more use of skilled workers (Acemoglu et al. 2024; Arntz et al. 2024; Zolas et al. 2020). Furthermore, AI adoption is more widespread in few "superstar" cities. Among young dynamic firms, AI is most widespread alongside firms whose owners are more educated, more experienced, and younger (McElheran et al. 2024). US firms report to adopt the technologies to, among others, automate tasks that previously were performed by humans. They also report higher productivity and lower labor shares (Acemoglu et al. 2024). Acemoglu et al. (2022) show that firms increasingly require workers to possess AI skills, and that AI adoption shifts skill demands, but does not (yet) have measurable effects on employment and wage growth. Hence, to date, AI adoption continues to affect the content of work, but less so the amount of work. From a policy perspective, AI to date thus has little effects, but may well be associated with rising between-firm inequality as only a subset of large, fast growing firms adopts AI technologies.

Arntz et al. (2024) document that the adoption of frontier technologies – which among others constitutes AI technologies – continues to contribute to de-routinization. They uncover a remarkable heterogeneity among adopters, finding that only a subset of frontier technology adopters contribute to aggregate de-routinization: While the average adopter does not contribute to de-routinization, those adopters that had a less routine workforce grow faster during frontier technology adoption, and larger adopters reduce their routine workforce shares faster during frontier technology adoption. Their results indicate that successful technology adoption either requires having established complementary workforce skills prior to adoption, or establishing this complementary during adoption. These results align with previous literature highlighting that the successful adoption of technologies more broadly requires complementary conditions such as a skilled workforce, innovations and organizational change (Brynjolfsson, Jin, and McElheran 2021; Brynjolfsson, Rock, and Syverson 2019; Ciarli et al. 2021; Harrigan and Reshef 2024; Ransbotham et al. 2017). From a policy perspective, this highlights the importance of the availability of a skilled workforce, and suitable (re-)training measures to ensure wide adoption of new technologies.

6 Conclusions and Policy Implications

This paper has reviewed the current state of research on the impact of new technologies, particularly automation and artificial intelligence (AI), on labor markets.

Several key findings emerge from this analysis: The overall impact of new technologies on employment is ambiguous, small, and depends on the balance between automation (which reduces labor demand) and reinstatement (which creates new tasks for humans). While some studies suggest negative employment effects in the US, evidence from Europe indicates positive overall employment impacts. Nevertheless, technological change has led to job polarization, with declining demand for routine tasks predominantly affecting middle-wage jobs. This has resulted in a restructuring of the workforce, with varying impacts across different demographic groups. At the firm level, adopters of new technologies tend to be larger, more productive, and employ a more skilled workforce. While these firms often experience employment growth, there may be negative spillover effects on non-adopting competitors. So far, a relatively small share of large and skill-intensive firms adopts AI technologies. However, this share is increasing. The impact of AI on employment and wages is still emerging, but it is already shifting skill demands within firms. Worker reallocation in response to technological change is often costly and imperfect, potentially exacerbating inequality. The ability of workers to transition to less exposed occupations is crucial but often limited.

These findings have several important policy implications: Given the uneven impact of technological change, policymakers should focus on providing targeted assistance to workers in routine-intensive occupations. This could include target retraining programs and job search assistance that allow them to access growing segments of the labor market, and transitional income support. To prepare the workforce for future technological changes, there is a need for continuous investment in education and skill development. This should include both technical skills relevant to new technologies and adaptable, non-routine cognitive skills. While early adopters of new technologies often benefit, policies should aim to promote wider technology diffusion to prevent the concentration of gains in a small number of firms. This could involve incentives for technology adoption or support for smaller firms in implementing new technologies. Given the concentration of AI adoption in "superstar" cities, policies should aim to promote more geographically balanced technological development to prevent exacerbating regional inequalities. Policies that enhance labor market flexibility and support worker mobility across occupations and regions could help mitigate the negative impacts of technological change on specific groups of workers. Successful technology adoption often requires complementary investments in human capital and organizational change. Policies should encourage firms to make these complementary investments alongside technology adoption. Given the rapidly evolving nature of AI and other frontier technologies, continued research and monitoring of their labor market impacts is crucial for informed policymaking.

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