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ROBOTS, AUTOMATION, AND EMPLOYMENT: WHERE WE ARE

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Introduction

“Robots will destroy our jobs – and we’re not ready for it” titled *The Guardian* in early 2017.¹ Headlines like this have become more and more common over the past couple of years, with newspapers and media outlets reporting that “the robots are coming! And they are going to take all our jobs,”² asserting that “sometime in the next 40 years, robots are going to take your job,”³ and that “robots may steal as many as 800 million jobs in the next 13 years,”⁴ and proclaiming gloomy headlines such as “automation threatening 25% of jobs in the US,”⁵ and “robots to replace up to 20 million factory jobs by 2030.”⁶

While idea that technology can render human labor obsolete is not new, and concerns about technological unemployment go back at least to Keynes (1930; p. 3) who in 1930 wrote about potential unemployment “due to our discovery of means of economizing the use of labor outrunning the pace at which we can find new uses for labor,” the recent proliferation of reports warning about the potential effect of new technologies, particularly advances in machine learning and robotics, on employment stands out in terms of the number of jobs allegedly under threat of replacement by machines and obsolescence. Different studies mention anywhere from 10 to 800 million jobs globally as in jeopardy over the next decade or so.

How should we think about automation and potential job loss? Where do the predictions of rising automation and job replacement come from? And what does current research say on the effects of technological change on employment? This memo will address these questions by 1) providing a summary of the economic framework of thinking about job displacement and productivity gains, 2) summarizing and analyzing the most influential studies claiming imminent job loss due to automation, 3) surveying recent research in economics on the historical effect of technological change on employment, and 4) summarizing the results and offering avenues for future research on the effect of automation technology on employment.

*Helpful comments and feedback from Suzanne Berger and members of the Ohio Group of the MIT Work of the Future Task Force.

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¹The Guardian, January 11, 2017: <https://www.theguardian.com/technology/2017/jan/11/robots-jobs-employees-artificial-intelligence>

²The Washington Post, July 7, 2017: https://www.washingtonpost.com/opinions/the-robots-are-coming-heres-what-to-do-about-it/2017/07/07/d82dd5f4-6027-11e7-a4f7-af34fc1d9d39_story.html

³Mother Jones, December 2017: <https://www.motherjones.com/politics/2017/10/you-will-lose-your-job-to-a-robot-and-sooner-than-you-think/>

⁴Fortune Magazine, November 17, 2017: <https://fortune.com/2017/11/29/robots-automation-replace-jobs-mckinsey-report-800-million/>

⁵MSNBC, January 25, 2019: <https://www.cnbc.com/2019/01/25/these-workers-face-the-highest-risk-of-losing-their-jobs-to-automation.html>

⁶BBC, June 26, 2019: <https://www.bbc.com/news/business-48760799>

1 The basic framework: The displacement and productivity effects

The introduction of new technologies, including industrial robots, software, and other computer-controlled machines, capable of executing tasks traditionally performed by human labor, may displace workers and increase technological unemployment (Keynes, 1930; Brynjolfsson and McAfee, 2014). At the same time, however, the introduction of new technologies often also creates new tasks, and might complement labor such that productivity increases, augmenting the scale of production and demand, which in turn increases labor demand (Autor, 2015). This productivity effect has the potential to offset any displacement effect induced by the introduction of new technology.

To understand the effect of automation on employment, we therefore have to understand whose jobs might be displaced and whose productivity might increase in the wake of technological change. Scholars have long argued that computers and machines are most likely to perform tasks that follow explicit rules, and thus displace those occupations that mostly consist in routine tasks, for instance machine operators, cashiers, or bookkeepers. On the other hand, non-routine tasks, particularly those requiring high cognitive skills and involve complex problem solving, are more likely to be complemented rather than replaced by new technology, and occupations consisting of these kinds of tasks, for instance researchers and managers, are likely to see their productivity increase (Autor, Levy and Murnane, 2003; Acemoglu and Autor, 2011).

The effect of automation on *aggregate employment* in the long run then depends on how the displacement and productivity effects play out in general equilibrium. As tasks previously executed by human labor are automated, new and more complex tasks are created, in which humans have a comparative advantage vis-à-vis machines. Recent work by Acemoglu and Restrepo (2018) argues that if the rental rate of capital is not too low relative to labor, we can imagine a stable growth path in which automation replaces some tasks, decreasing the cost of producing with labor, which in turn discourages further automation and encourages the creation of new and more complex tasks, increasing labor demand and productivity.

Given these complex and countervailing effects, answering the question about the effect of automation on employment is a daunting task, and fundamentally an empirical question. Nonetheless, much of the public frenzy about automation originated in studies that attempted to *predict* which tasks and occupations will become automated in the near future. The next section takes a closer look at those studies.

2 Millions of jobs lost to automation: Where do the numbers come from?

2.1 Frey and Osborne (2017)'s influential study predicting 47% of US jobs at high risk of automation

There is an almost innumerable number of publications predicting the effect of automation on employment over the near and far future. Different studies use different prediction methodologies, focus on different industries and different technologies, and come to vastly different results. The first study to attempt to quantify the amount of jobs that might be automated, and among the most influential, was conducted by Frey and Osborne (2017).⁷ Their study, which puts the proportion of US jobs susceptible to automation at 47%, has been cited more than 5,000 times,⁸ and is referenced in numerous media and institutional reports on the future of work, including reports by McKinsey (Manyika et al., 2017) and the World Bank Group (2016). Moreover, their methodology has been applied to produce similar studies, with similar results, in other countries (see, e.g., Brzeski and Burk 2015; Haldane 2015; Pajarinen et al. 2015), and has influenced the methodology employed by important and well cited OECD studies on the same topic (Arntz, Gregory and Zierahn, 2016; Nedelkoska and Quintini, 2018).

⁷(Frey and Osborne, 2017)'s work was first published as a University of Oxford working paper in 2013 before being published in a peer-reviewed journal in 2017.

⁸According to Google Scholar on 16 January 2020.

In their work, Frey and Osborne (2017) argue that recent advances in machine learning and mobile robotics have extended the domain of tasks susceptible to automation beyond routine tasks to include those non-routine tasks that are not subject to what the authors call “engineering bottlenecks.” These bottlenecks, identified by drawing on the literature in machine learning and mobile robotics, define tasks that so far cannot be performed by machines. Specifically, Frey and Osborne (2017) argue that robots are still unable to match the depth and breadth of human perception and have trouble handling irregular objects and working in unstructured environments, thus unable to perform well on (1) *perception and manipulation tasks*. Furthermore, the psychological processes underlying human creativity are difficult to specify in computer code, and machines are thus unable to perform well on (2) *creative intelligence tasks*. Finally, real-time recognition of human emotions and responding intelligently to such inputs remains challenging, and machines are thus unable to perform well on (3) *social intelligence tasks*.

To identify the extent to which occupations can be displaced by machines, Frey and Osborne look at 2010 O*NET data from the US Labor Department that contains information on about the task content of 903 different occupations, which they combine with wage and employment data from the US Bureau of Labor Statistics, resulting in a data set on 702 distinct occupations. They then ask machine learning and robotics researchers in the context of an Oxford University workshop to hand-label those occupations where they are confident that the occupation will certainly be fully automated or will certainly not be fully automated, based on the O*NET task and job description for each occupation. The precise question those experts are asked for each occupation is whether “the tasks of this job can be sufficiently specified, conditional on the availability of big data, to be performed by state-of-the-art computer-controlled equipment.” The authors thus arrive at 70 out of the 702 occupations with a clear yes/no coding of whether machine learning experts think they are fully automatable. Next, Frey and Osborne identify 9 specific “ability” variables in the O*NET data that describe the occupation’s requirements in terms of the “engineering bottlenecks”: finger dexterity, manual dexterity, and cramped work space (for perception and manipulation tasks), originality, and fine arts (for *creative intelligence*), and social perceptiveness, negotiation, persuasion, and assisting and caring for others (for *social intelligence*).

The authors then use the 70 hand-labelled occupations to estimate a logistical model, where the nine ability variables are used to predict automatability. The coefficients of that model are then applied to the remaining 632 occupations, estimating each occupation’s probability of automation as a function of the occupation’s required “bottleneck” abilities. Frey and Osborne thus arrive at an automation score for each of the 702 occupations (see Figure 1), and classify those with an automation probability over 70% as high risk occupations. According to this metric, 47% of all US employment is high risk, i.e., “potentially automatable over some unspecified number of years, perhaps a decade or two” (Frey and Osborne, 2017; p. 265).

A number of studies have used Frey and Osborne (2017)’s results to conduct similar analyses in other countries by simply taking the automatability scores computed by the authors, and applying them to the composition of non-US labor markets. The results are often similarly big, ranging from 59% of jobs at a high risk of automation in Germany (Brzeski and Burk, 2015) to around one third in Finland, Sweden, and the United Kingdom (Haldane, 2015; Pajarinen et al., 2015). Subsequent research by the OECD on automation and employment similarly adopted parts of Frey and Osborne (2017)’s methodology, in particular the automatability scores assigned to the 702 occupations (Arntz, Gregory and Zierahn, 2016; Nedelkoska and Quintini, 2018). However, the OECD researchers criticize that looking at whole occupation automation overestimates automatability as even occupations they qualify as high risk can contain a substantial share of tasks that are hard to automate. Instead of analyzing the potential displacement of whole occupations, the researchers focus their analysis on the potential displacement of individual tasks by machines. In doing so, and treating occupations as bundles of those tasks, they infer that few occupations are fully automatable, and modification rather than replacement is the more likely outcome for many occupations. Indeed, their analysis finds that only 9% of jobs in OECD countries are at a high risk of automation, ranging from 6% in

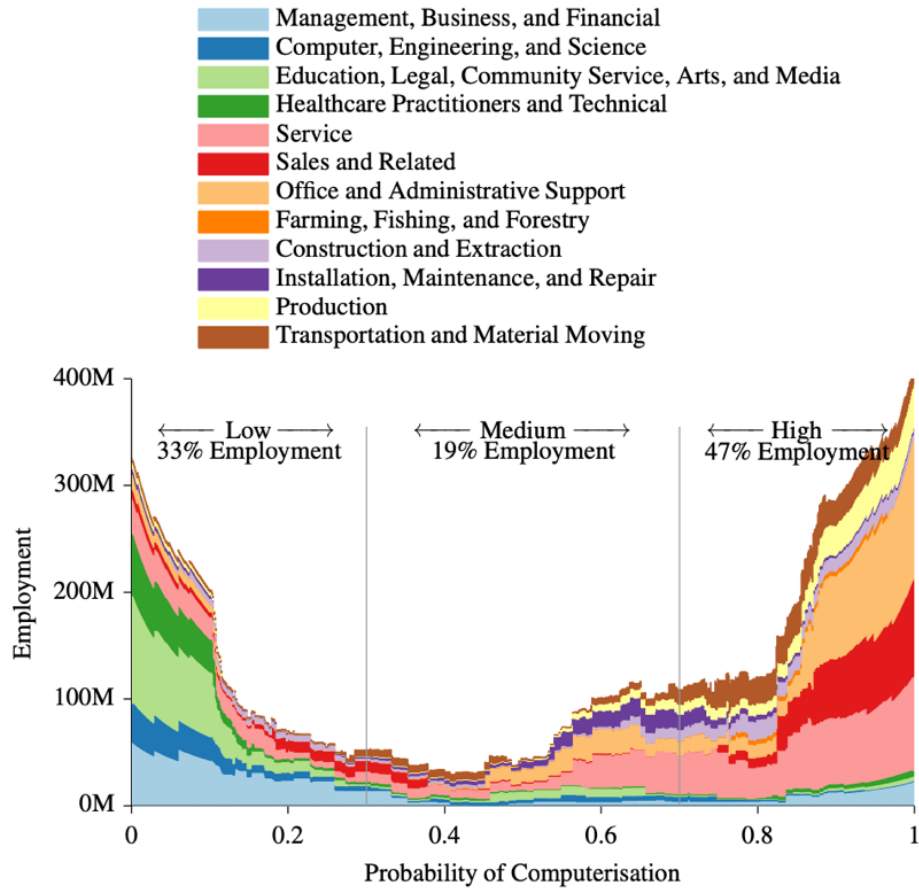


Figure 1: US Employment by Industry and Probability of Automation (Frey and Osborne 2017): This figure, taken from Frey and Osborne (2017), displays the number of jobs by industry and probability of automation, based on the Frey and Osborne (2017)’s model and 2010 employment data from the US Bureau of Labor Statistics. About 47% of all US jobs are assigned an automation probability over 0.7, which the study’s authors take to mean that they are at high risk. These high risk jobs are particularly in the service, sales, and office and administrative support industries.

South Korea to roughly 12% in Austria and Germany.

2.2 A closer look at the methodology of Frey and Osborne’s predictions

Frey and Osborne (2017)’s methodology has had a great impact on numerous subsequent studies on automation and employment. Those studies either take the automatability scores of Frey and Osborne and apply them to the occupational composition of other labor markets or, in the case of the OECD, statistically relate those automatability scores to the tasks performed by different occupations in the US, and then apply this model to the task composition of occupations in other countries. In either case, researchers fundamentally rely on the initial hand coding as automatable or not of 70 occupations by machine learning experts at an Oxford University workshop. All of their results rely on the assumption that the initial hand coding represents the ground truth. Yet, how confident can we be in those expert opinions?

Firstly, we need to remember that those experts, whom Frey and Osborne simply describe as “ML [machine learning] researcher” participating in a “workshop held at the Oxford University Engineering Science Department” at an unspecified date, were asked about the automatability of occupations *conditional on the availability of big data*. Frey and Osborne’s argument is that the increasing availability of large and

complex data sets, i.e., “big data,” has enabled algorithms to detect patterns and similarities between old and new data which, in turn, enables the computerization of non-routine tasks. Thus, the expert coding of 70 occupations does not reflect whether these experts think those occupations are currently automatable but relates to a purely hypothetical world in which vast amounts of data are readily available to all. For instance, the expert coding that “taxi drivers and chauffers” are fully automatable occupations (and therefore at high risk of automation) does not mean that they currently are nor that they soon will be automatable, but rather that *if* there were vast data sets on road mapping, road and weather conditions, and driver behavior, then these occupations could be automated. While Frey and Osborne, as well as the subsequent studies that employ their methodology, emphasize the “engineering bottlenecks” as the last barriers to full automation, they completely neglect the “data bottlenecks”, which are nonetheless inherent in their analytical approach. Indeed, whether the kinds of data necessary to automate driving can be gathered, stored, and rendered accessible is just as important a question as whether robots can handle irregular objects.

Putting aside the question of data availability, we next find a number of issues in both the expert hand coding and the automatability scores computed by the model. There are some occupations where automation has already started but that were nonetheless hand coded as not automatable. For instance, “fashion designers” are categorized as not automatable, yet Amazon first developed software able to recognize particular fashion styles and generate new clothing items in similar styles over two years ago (Knight, 2017). Moreover, some automatability scores contradict the opinion of domain experts. For instance, “airline pilots” are assigned an automation probability of only 18% whereas “industrial truck operators” have a 93% probability of being automated. Yet flying an airplane is much easier to automate as it operates in a much more structured environment than driving a truck. Indeed, much of any typical passenger flight is already today done on autopilot, with the average Airbus pilot only manually flying 3.5 minutes out of every flight (Markoff, 2015). Even takeoff and landing operations can now be executed automatically.⁹

2.3 McKinsey predicting between 10 and 800 million jobs lost to automation

Apart from Frey and Osborne’s work and its descendants, a McKinsey report from December 2017 (Manyika et al., 2017) has importantly guided the public debate around automation and job loss, being both cited directly in media reports and influencing subsequent reports by other think tanks.¹⁰ In contrast to Frey and Osborne, this study takes more than just technical feasibility into account for its prediction of the effect of automation. In addition to automatability of a task, a marketable automation product needs to be developed and adopted before that task will effectively be displaced. The report thus makes a number of predictions about these different stages of automation, and estimates its effect in employment to be anywhere between 2016 and 2030 anywhere from 10 to 800 million jobs globally, with the midpoint of 400 million cited most frequently in the media.

To arrive at their results, Manyika et al. compute a somewhat opaque number of predictions and extrapolations to considers the technical potential for automation and automation adoption timelines for 800 occupations across 46 countries. As in Frey and Osborne, they start with the Labor Department’s O*NET data set on the task composition of occupations. Each task is then further broken down into 18 capabilities, each of which has four levels of requirement. For instance, one capability is “natural language understanding,” and the associated levels range from “does not require natural language understanding” (0) to “high

⁹While automatically landing an aircraft, or autoland, has been used for a number of years, Airbus recently demonstrated the first fully automatic take off: <https://www.airbus.com/newsroom/press-releases/en/2020/01/airbus-demonstrates-first-fully-automatic-visionbased-takeoff.html>

¹⁰See, for instance, a 2019 Brookings Institute report that found that 25% of US employment face high exposure to automation in the coming decades, putting 36 million jobs at risk (Muro, Maxim and Whiton, 2017). To arrive at this number, the authors combine Manyika et al.’s automation potential for each of the 800 occupations defined in the Labor Department’s O*NET data set with localized occupational and employment data obtained from Economic Modeling Systems, a data vendor specializing in labor markets.

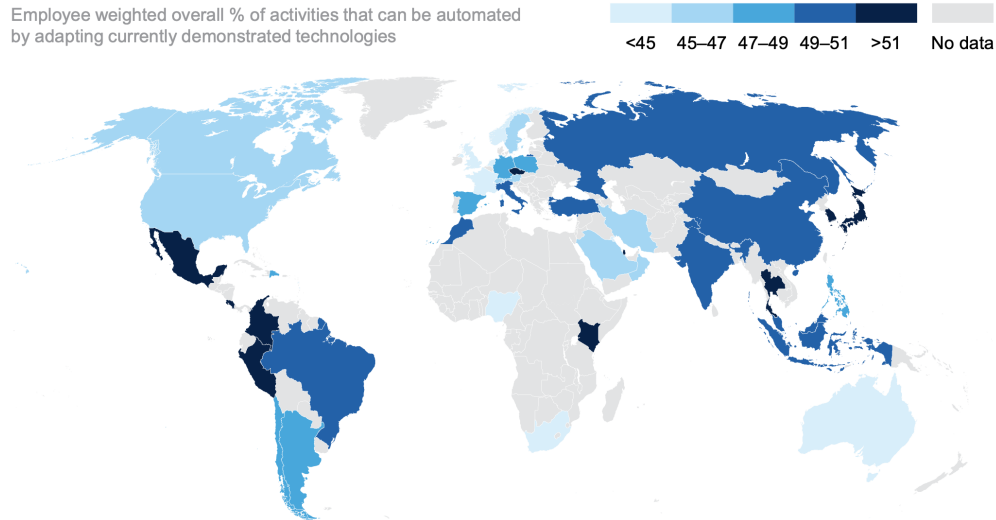


Figure 2: McKinsey Report: Technically Automatable Activities Touch 1.1 Billion Workers (Manyika et al. 2017): This graph, taken from Manyika et al. (2017), shows the employee weighted overall percentage of tasks that can be automated by adapting currently demonstrated technologies. For instance, for the US the researchers estimate that close to 46% of all tasks executed by workers could already be performed by automation technology that already exists.

language comprehension and accuracy, including nuanced human interaction and some quasi language” (4). Other capabilities include social and emotional sensing, logical reasoning, creativity, fine motor skills, and coordination with multiple agents. Next, Manyika et al. use an algorithm to determine which of the 2,000 tasks comprised in the 800 occupations taken from the O*NET data set contain which capabilities and at which level, having trained said algorithm with assessments by experts. The authors remain disappointingly vague about this process even in their technical appendix. Using these results, the authors then estimate the percentage of tasks that workers perform which could already be automated given the current stand of automation technology (see Figure 2).

For work to be automated, every performance capability needed to carry out that particular activity must be automatable at the required level, a marketable automation product needs to be developed and reach economic feasibility, and finally said product needs to be widely adopted. Manyika et al. thus proceed to a number of predictions. First, they develop progression scenarios for the development of those capabilities, trying to predict when which capability could be automated at which level. To do so, they “conducted interviews with industry leaders and academic experts [and] also looked at some recent commercial successes showcasing capabilities, as well as historic trajectory of capabilities” (Manyika et al., 2017; p. 124). Next, they estimate how long it would take to develop a marketable solution once technical feasibility has been established. To do so, they collected the development time of 100 previously automated solutions in both hardware and software, recording the number of years from the initial research to product launch. Once there is a product that could automate a given activity, Manyika et al. assume that the cost of said product needs to be lower than the corresponding wage for the product to reach economic feasibility. The initial cost of the product is assumed to be a proportion, between 0 and 70%, of the highest hourly wage for the corresponding activity across all the countries, with a yearly cost decrease of 16% for hardware products and 5.3% for software, rates determined by triangulating consumer price indices and supplier surveys. Wages are projected using the McKinsey Global Growth Model. Finally, once the product is economically feasible, it needs to be adopted. For this last prediction, the authors use a Bass diffusion model, estimating its parameters by using known historic technology adoptions, including stents, airbags, online air booking, color

TVs, and dishwashers. On average, they predict an economically feasible automation product to reach a 50% adoption rate within 5 to 16 years.

Using this array of predictions, Manyika et al. estimate the number of work hours that could be automated between 2016 and 2030 in 46 countries, assuming that each hour of work that could be automated will result in proportional job loss. In other words, if 10% of work hours based on the task composition of an occupation can be automated, then 10% of jobs in that occupation will be displaced. They further assume that the composition of the labor force in terms of occupations and tasks within occupations remains stable through 2030. Labor force estimates for the future are obtained by combining population projections from the United Nations, labor force participation rates from the International Labor Organization, and natural unemployment rates taken from the OECD. By adjusting some of the inputs in their numerous predictions, such as the time it takes an automation product to become economically feasible or to be widely adopted, Manyika et al. devise a number of potential automation scenarios. In their slowest scenario, only 10 million jobs worldwide will be displaced by automation, whereas 800 million jobs are threatened assuming fast technological development and adaptation.

Both the questionable methodology employed by Frey and Osborne and the opaque prediction techniques used by Manyika et al. highlight the difficulty in determining which tasks and occupations can and will be automated. Automatability depends on a number of difficult to predict factors, including Frey and Osborne's "engineering bottlenecks" but also advances in the availability of data, and the development, production, and adoption of automation products. Instead of attempting to predict future automation, many scholars have therefore analyzed the effect automation has had *so far* on employment.

3 Mixed results from empirical studies on the effect of automation on employment

3.1 Graetz and Michaels (2018): No effect on employment across countries

Graetz and Michaels (2018) were among the first to empirically investigate the effect of automation on employment. The authors use data from the International Federation of Robotics (IFR), covering 17 countries¹¹ from 1993 to 2007, on the number of robots delivered to each country by industry and year. They show that as the price of industrial robots decreased over that time period, robot density, i.e., the number of robots per 1,000,000 hours of human labor, increased across all industries and countries, particularly in transport equipment and in Germany, Denmark, and Italy. Importantly, while Graetz and Michaels find a lower labor share, they find no effect on the aggregate number of hours worked, i.e., no effect on aggregate employment, with some evidence of reduced employment of low-skill workers relative to middle- and high-skill workers. Instead, the researchers find a positive and substantial effect of the introduction of industrial robots on productivity, accounting for 15% of the aggregate economy-wide productivity growth over the time period.

3.2 Acemoglu and Restrepo (2020): Negative effect on US employment

A recent study by Acemoglu and Restrepo (2020) uses the same IFR data; however, instead of relying on cross-country and cross-industry variation, their work is at the level of local US labor markets or commuting zones (i.e., zones in which people can commute to work and which thus constitute one labor market).¹² This allows the authors to investigate the *equilibrium impact* of automation technology where local robot adoption can negatively affect wages and employment (displacement effect) while also resulting in other tasks and other industries increasing their labor demand (productivity effect). As their explanatory variable,

¹¹Fourteen European countries, the United States, South Korea, and Australia.

¹²For a helpful and in-depth review of this paper and its methodology, see Yellen (2020).

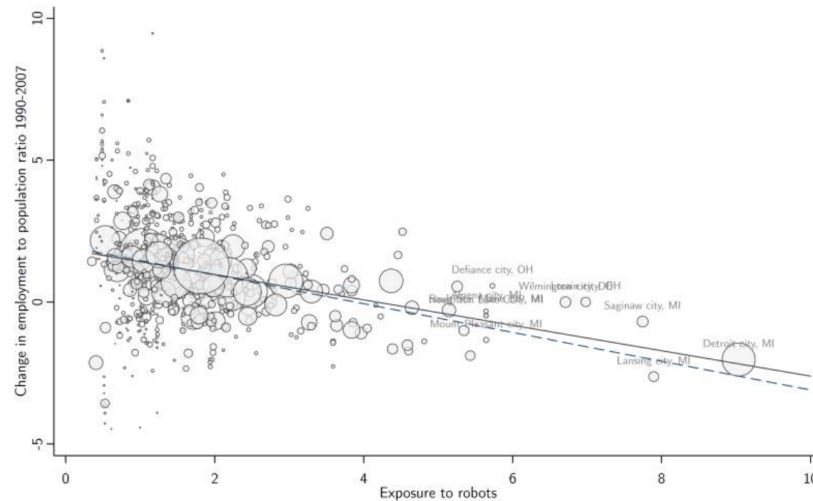


Figure 3: Robot Exposure Decreases Employment in US Labor Markets (Acemoglu and Restrepo 2019): This figure, taken from Acemoglu and Restrepo (2020), presents the long-differences relationship between exposure to robots and changes in the employment to population ratio 1990-2007. The solid line shows the coefficient estimate from a regression with commuting zone population in 1990 as weights. The dashed line is for a regression which in addition excludes the top one percent of commuting zones with the highest exposure to robots. Marker size indicates the 1990 population in the commuting zone.

the authors construct a variable to capture a locality’s *exposure to robots*, using IFR data on changes in robot usage across 19 different industries¹³ between 1993 and 2007, combined with each industry’s baseline employment share in each locality before the onset of recent robotic advances. Across a number of specifications, Acemoglu and Restrepo find a negative association between robot exposure and employment and wage growth (cf. Figure 3). In particular, one additional robot (per 1,000 workers) reduces employment by 6.2 workers and annual wages by approximately \$200 in the affected commuting zone.

These effects are estimated for local labor markets; however, what would be the effect on aggregate employment in the US once we take spillover effects and trade between those local markets into account? If, for instance, the introduction of robots lowers consumer prices in one industry and locality, this might very well stimulate labor demand in downstream industries in other localities. To answer this question, the authors construct a model to extrapolate their findings to the entire country. They find that one additional robot per 1,000 workers reduces employment by 3.3 workers in aggregate, i.e., taking into account both the robot’s direct effect, i.e., displacing human labor, and indirect effect, i.e., reduced wages, cheaper consumer prices, and shared capital gains across local labor markets in the whole economy. Similar to other studies, localities with a high share of employment in manufacturing experience the highest exposure to robots, and the greatest decline in employment.

3.3 Dauth et al. (2017): No aggregate effect on employment in Germany as negative effect in manufacturing, driven by fewer entrants, is offset by gains in the service sector

Moving beyond the level of the locality, researchers in Europe have taken advantage of micro-data on individual workers to estimate the effect of automation on employment. Research in Germany, led by Dauth et al. (2017), uses individual-level data, tracing the employment biographies of 1 million German workers with varying degrees of exposure to robots. This data set is combined with IFR data, covering 53 manufacturing industries and 19 other industries between 1994 and 2014. Local robot exposure is then measured as

¹³Thirteen industries within manufacturing and 6 outside.

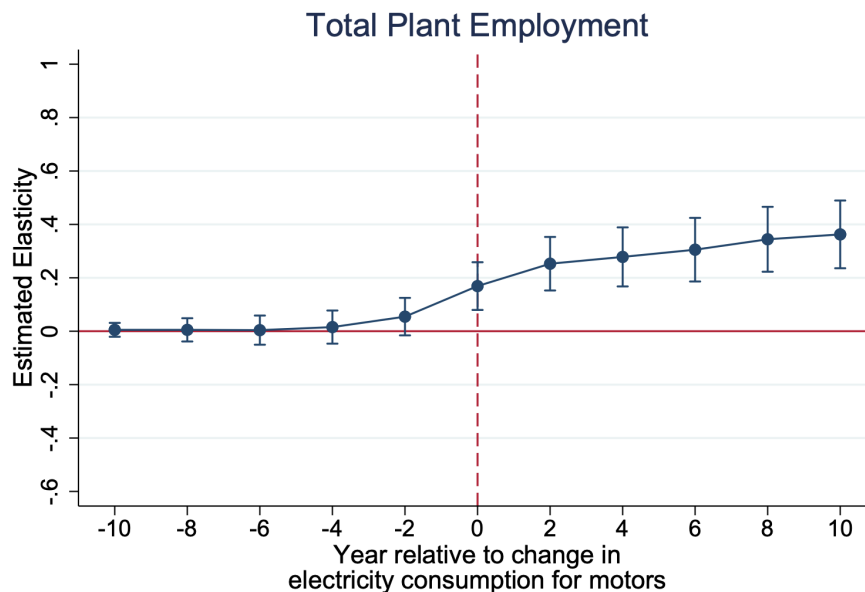


Figure 4: Increased Peak Electricity Consumption for Motors Increases Employment (Aghion et al. 2020): This figure, taken from Aghion et al. (2020), shows the development of plant employment after a change in the plant’s peak electricity consumption for motors, which the authors use as a proxy for increased automation technology. Their model’s specifications include both 4-digit industry and year fixed effects.

the change in the number of installed robots per thousand workers over the period 1994-2014 for each industry, adjusted to the local employment composition in 402 local labor markets. Between 1994 and 2014, robot exposure increased the most in Wolfsburg and Dingolfing, the two biggest production locations for Volkswagen and BMW, respectively. Overall, robot exposure varies from 0 to 7.6 robots per 1,000 workers, a wider range of values than in the United States.

Dauth et al. find a strong positive correlation between robot usage and local employment, driven mainly by the automotive industry. Controlling for local industry structures, the authors find an overall null effect of robots on aggregate employment. They do find negative effects on manufacturing employment, where one additional robot results in two fewer manufacturing jobs. In other words, they estimate robots caused 23% of the overall decline in manufacturing jobs in Germany between 1994 and 2014. Yet, these negative effects are offset by job gains outside of manufacturing, particularly in the service sector.

Even in manufacturing, however, robots do not result in a direct job loss of workers. Indeed, workers from more robot-exposed industries are more likely to remain employed. Instead, the flow of labor market entrants going to robot-exposed industries declined as robot exposure increased. “Put differently, robots do not destroy existing manufacturing jobs in Germany, but they induce manufacturing firms to create fewer new jobs for young people” (Dauth et al., 2017; p. 8). In terms of wages, increases are experienced mostly by high-skilled workers (e.g., managers and scientists), whereas low- and medium-skilled workers with increasing robot exposure experience sizable decreases in wage levels. These decreases are not the result of displacement and interrupted work but mainly arise from existing jobs with lower wage levels.

3.4 Aghion et al. (2020): Positive effect on French manufacturing firms that face international competition

A recent working paper by Aghion et al. (2020) uses micro-data from French firms between 1994 and 2015 to estimate the effect of automation on employment and a number of other variables. Their data encompass the universe of French manufacturing plants, as well as their employees. The authors use two measures to

capture the use of automation technologies: (1) each plant's balance sheet value of industrial equipment and machines and (2) each plant's electricity consumption for motors directly used in the production chain. Using an event study design, in which the authors exploit sudden increases in a plant's equipment expenditure, peak electricity consumption for motors, as well as an instrumental variables design that exploits productivity shocks in foreign suppliers of industrial equipment, Aghion et al. find a positive effect of automation on aggregate employment, even for low-skill workers, in addition to resulting in higher profits, lower consumer prices, and higher sales (see, in part, Figure 4). The authors take this as evidence that increased automation allows the firm to expand its sales and scale, which results in additional hiring of human labor. Interestingly, the authors find that the employment effect is only positive and significant for industries that face international competition, which the authors measure as the export share of final products. In other words, where domestic industries face international competition, automation-induced increased productivity and lower prices can reallocate demand away from foreign imports and toward domestic firms.

3.5 Acemoglu, LeLarge and Restrepo (2020): Firm-level increase but market-level decrease in employment results in overall job losses

Where Aghion et al. (2020) use a very broad measure of automation technologies, Acemoglu, LeLarge and Restrepo (2020) use government and robot supplier data to look more specifically at the effect of the acquisition of industrial robots by French manufacturing firms between 2010 and 2015. Out of 55,390 firms, only around 1% (598 firms) purchased any industrial robots between 2010 and 2015; however, those firms account for 20% of French manufacturing employment. Acemoglu, LeLarge and Restrepo (2020) show that when those firms purchased robots, labor shares generally declined while value added and productivity increased at those firms. With increased productivity and decreased costs, the authors argue, those firms are able to gain a greater market share, resulting in employment increases at the firm-level. However, those gains are offset by employment losses at the industry level as employment decreases at other firms that are losing market share. Overall, Acemoglu, LeLarge and Restrepo (2020) estimate that a 20 percentage point increase in robot adoption in an industry is associated with a 1.6% decline in that industry's employment.

The authors link their results to the "superstar effect", identified by Autor et al. (2020), which explains the declining share of labor in GDP with the reallocation of output to a few "superstar" firms with a lower labor share and higher productivity than average firms. Acemoglu, LeLarge and Restrepo (2020) argue that in France, that reallocation to large "superstar" firms is driven by automation in the form of robot adoption.

3.6 Koch, Manuylov and Smolka (2019): Job creation at firms adopting robots, job losses at those who don't

The question of where the displacement effect takes place, whether within automating firms or within non-automating firms that experience a relative decrease in competitiveness, is one that is starting to attract researchers' attention. A working paper by Koch, Manuylov and Smolka (2019) looks at industrial robot adoption by 1,900 Spanish manufacturing firms between 1990 and 2016. They find that robot adoption was the most likely for firms that were already larger and more productive; conditional on productivity, firms that were more skill-intensive were less likely to adopt robots, arguably because skill-intensive work is more difficult to automate.

Koch, Manuylov and Smolka (2019) find that firms that adopted robots between 1990 and 1998 experienced output gains of 20% - 25% in the four years following adoption, while the labor cost share generally decreased by 7%. Moreover, net employment at those firms increased by an average of 10%. At the same time, the authors find considerable job losses at those firms that did not adopt robots as they face tougher competition from more productive high-technology firms (cf. Figure 5). In particular, Koch, Manuylov

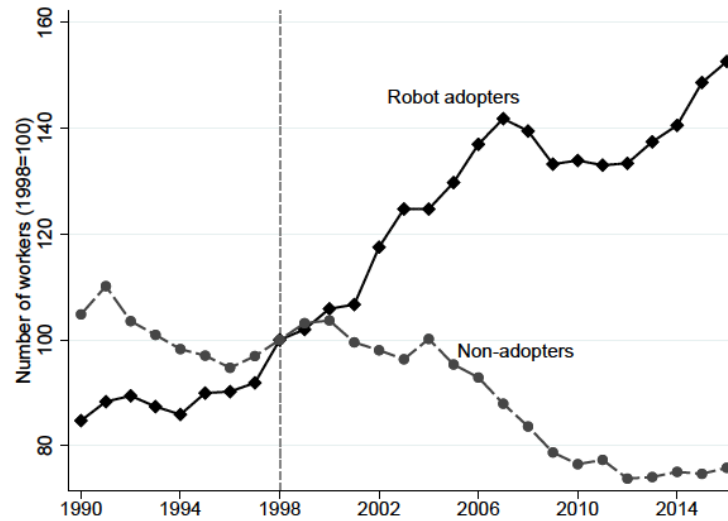


Figure 5: Robot-adopting firms create jobs, non-adopters shed them (Koch et al. 2019): This figure, taken from Koch, Manuylov and Smolka (2019), depicts the evolution of average firm employment in a balanced sample of Spanish manufacturing firms between 1990 and 2016. The solid black line represents robot-adopting firms, i.e., firms that entered the sample in 1990 and had adopted robots by 1998. The dashed line represents non-adopters, that is those who never use robots over the whole sample.

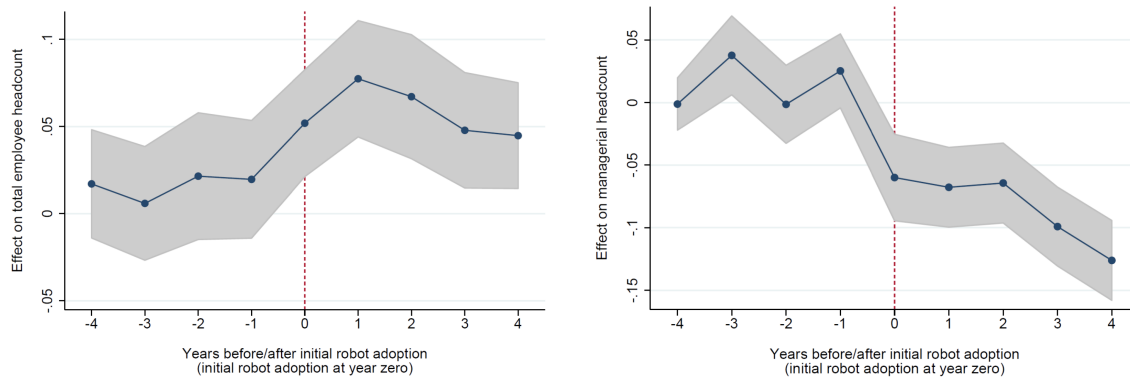


Figure 6: Robot investments are associated with more employees overall but fewer managers (Dixon et al. 2020): These two figures, taken from Dixon, Hong and Wu (2020), depict the coefficients of a multivariate regression of time-indexed dummy variables on the log of employment headcount. The left hand figure shows total employment and the right hand figure managerial employment. Prior to the initial robot adoption, there is no statistically significant difference in employment trends; however, substantial total employment increase happens beginning in the first year of robot adoption while simultaneously managerial employment starts to decrease.

and Smolka (2019) estimate that 10% of jobs in non-adopting firms are destroyed when the share of sales attributable to robot-using firms in their industries increases from zero to one half.

3.7 Dixon, Hong and Wu (2020): Industrial robots lead to fewer mid-level managers and more low- and high-skilled workers in Canada

Beyond the question of whether job displacement happens within automating firms or outside, it is also important to understand where job losses might occur inside firms. Dixon, Hong and Wu (2020) take

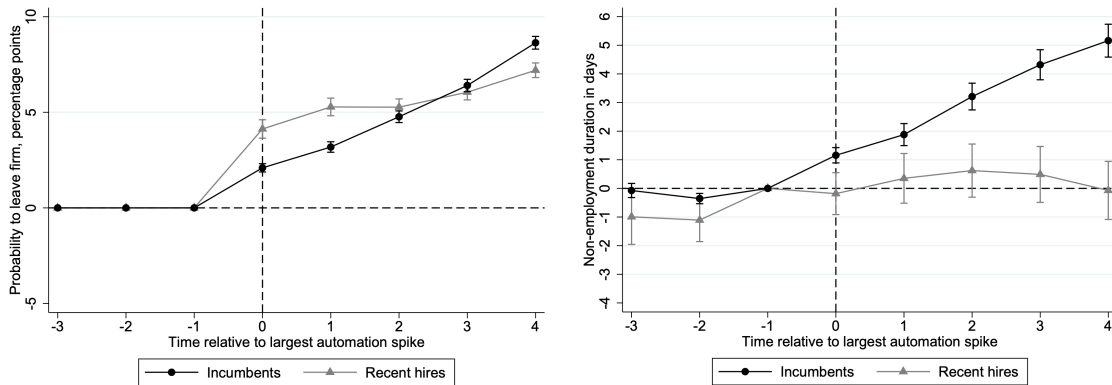


Figure 7: Automation Leads To Layoffs but Unemployment only for Long-term Workers (Bessen et al. 2019): These two figures, taken from Bessen et al. (2019), shows the effect of a spike in a company’s automation expenditure on employment for both incumbents who have been at the company for three years and longer and more recent hires. Automation spikes are defined as sudden increases in automation expenditure that bring the share of automation costs in total operating costs to thrice the previous yearly average. The left hand graph illustrates that the probability that an employee separates from a company after an automation spike is positive and similar for both incumbents and recent hires. The right hand graph shows it is only incumbents who see their number of days in unemployment increase, whereas recent hires are able to find new work elsewhere.

advantage of the fact that Canada relies almost exclusively on foreign robot manufacturers to supply its domestic companies and use data from the Canadian Border Services Agency on imports of industrial robots to study how firms’ investment in automation changes employment structures within those firms. They find that, overall, a one percent increase in robot investments predicts a roughly a 0.015 percent increase in total employment at the firm. However, that increase is not uniform across employees.

In particular, investment in industrial robots predicts a substantial *decline* in managerial employment, combined with a substantial *increase* in non-managerial employment, both low- and high-skilled (cf. Figure 6. Dixon, Hong and Wu (2020) argue that one of the main effects of robots on the production process is a decrease in quality variation, resulting in a decreasing need for mid-level managers to control product quality.

3.8 Bessen et al. (2019): Negative effect on Dutch employment for incumbents only

Moving beyond the effect of just industrial robots, work by Bessen et al. (2019) analyzes the effect of all types of automation technologies on employment. Using Dutch administrative data, covering over 36,000 companies and close to 5 million workers between 2000 and 2016, the researchers are able to directly observe each worker’s employer, gross wage, and number of days worked, as well as each company’s automation expenditure. The latter variable includes the purchasing and operating costs not only of industrial robots but also of software, warehouse storage systems, automated customer service, and other automation technologies. Bessen et al. show that between 2000 and 2016, the share of automation costs in total operating costs has increased across all industries in the Netherlands, though particularly in the information and communication sector as well as the administrative and support activities sector. Moreover, the larger the company, the larger the share of automation costs.

In terms of employment and wages, the authors find that after “automation cost spikes,” sudden increases in a company’s automation expenditure which the authors argue signal changes in work processes related to automation, the probability that the company lays off workers increases. Workers who had been with the company for more than three years (i.e., incumbents) also see their number of days in unemployment

increase and their wages decrease, meaning they're unable to find work elsewhere. However, more recent company hires, i.e., workers employed the year before the automation expenditure spike, are more able to find work elsewhere, and thus experience less of a decrease in their wages and increase in the number of days in unemployment (see Figure 7). Interestingly, Bessen et al. do not find evidence for a skill bias: Workers lower down the wage level for their age, i.e., low-skill workers, are not more likely to be laid off nor see their wage decrease than high-skill workers. Older workers, on the other hand, are less likely to find new employment after an automation induced layoff. The rate of early retirement increases by 24% after an automation spike.

4 Summary: Shaky predictions about job losses that ignore productivity effects, diverging empirical evidence, and future avenues for research

This memo set out to answer a number of questions. First, where are the predictions that automation will lead to unprecedented job losses coming from? Second, how sound are those predictions and what potential weaknesses might be involved in those estimates? Third, what conclusions can be drawn from the major contributions in the literature on how actual adoption of automation technologies has affected employment both in adopting firms and in their industries.

As laid out in Section 2, many of the studies predicting large job automation in the US and Europe have their origin in a study by Frey and Osborne (2017), and incorporate parts of their questionable methodology. In particular, the expert assessment their models rely on assumes a degree of big data availability that is not yet given. While these studies do take “engineering bottlenecks” into account, that is the fact that automation technology still faces technical hurdles in executing certain tasks, they ignore the “data bottlenecks” inherent in their methodology, that is the fact that we still don't have the vast amount of data readily available that their expert assessment on automatability is conditioned upon.

Moreover, just because an occupation or a task can be automated *in theory*, which is what many of these studies estimate, does not mean that they are being automated *in practice*. Purchasing, integrating, and maintaining automation equipment is costly. Once machines are installed and integrated, they cannot easily be returned. Given the limited flexibility of much automation equipment (both in terms of hardware, e.g., grippers, and software),¹⁴ re-programming a robot to perform even a slightly different task is expensive. When labor is relatively cheap and flexible, and product demand is unpredictable, it can thus be cheaper for a company to retain human labor for tasks that it could theoretically automate. It is also worth highlighting that these predictive studies, even those considering not just technical but also economic feasibility (cf. manyika2017future), focus entirely on the potential displacement effect of technology without taking into account possible productivity effects.

Instead of trying to predict what might happen, many academics have look at what has happened to employment after the introduction of new technologies in the past. As laid out in Section 3, this empirical work has come to a number of sometimes contradictory conclusions.

On the one hand, the introduction of new technologies, particularly industrial robots, has been shown to result in large productivity gains which, in turn, can increase employment as automating firms gain a larger market share and new tasks become available (Acemoglu, LeLarge and Restrepo, 2020; Aghion et al., 2020; Dixon, Hong and Wu, 2020; Koch, Manuylov and Smolka, 2019). At the same time, there is also evidence of a direct replacement effect of automation technologies that can lead to a decreasing need for additional (Dauth et al., 2017) and existing (Acemoglu and Restrepo, 2020; Bessen et al., 2019; Dixon, Hong and Wu, 2020) workers at automating firms. That displacement effect is not uniform across workers. In Canada, industrial robots have displaced mainly mid-level managers whose main task of monitoring

¹⁴For an insightful and in-depth discussion, see Fourie and Sanneman (2020).

product quality has been made superfluous by meticulous and exacting production machines (Dixon, Hong and Wu, 2020). In the Netherlands, automation technologies have almost exclusively displaced incumbent workers who have been employed at their firms for more than three years while not affecting the employment of more recent hires (Bessen et al., 2019). Moreover, displacement need not happen purely at the companies that acquire automation technologies. Research has indeed shown that as automating firms become more productive, non-automating firms in the same industry face increasingly tough competition and start to shed jobs (Acemoglu, LeLarge and Restrepo, 2020; Koch, Manuylov and Smolka, 2019).

The overall impact of automation technology on employment then depends on the relative size of the productivity and displacement effects. The empirical results here are mixed. Some studies estimate an aggregate positive effect on jobs (Aghion et al., 2020; Dixon, Hong and Wu, 2020). Others arrive at a neutral effect where the displacement effect is canceled out by the productivity effect within the same (Koch, Manuylov and Smolka, 2019) or other (Dauth et al., 2017) industries (cf. also Graetz and Michaels 2018). A number of studies also conclude that the overall effect is negative (Acemoglu, LeLarge and Restrepo, 2020; Acemoglu and Restrepo, 2020; Bessen et al., 2019).

Several avenues for future research emerge from this literature. First, different automation technologies may have different effects on productivity and jobs. Indeed, the diverse definitions of automation in the aforementioned studies, ranging from industrial equipment and electricity-consuming production motors (Aghion et al., 2020), to industrial robots (Acemoglu and Restrepo, 2020; Dauth et al., 2017; Graetz and Michaels, 2018), to all types of automation technology, including software (Bessen et al., 2019), may partly be responsible for apparently contradictory conclusions. For instance, a clearer understanding of how industrial robots affect manufacturing employment relative to software automation in back offices would be useful.

Second, incorporating labor policy and regulations into our theories would help us to better understand cross-country differences. For instance, an explanation of why industrial robots might reduce aggregate employment in the US but not in Germany needs to take into account the fact that Germany has a dualized political economy in which current core manufacturing workers are highly unionized and protected from layoffs whereas younger workers and employees in other sectors face much more precarious working conditions. Moreover, German works councils, firm-specific shop-floor organizations representing workers, give workers voice in determining firm policies, including automation strategies. Works councils usually elect members of the company's board of directors, and have to be consulted about important management decisions. In a recent study conducted by IG Metall, the dominant metalworkers' union in Germany, about half of all surveyed works councils affirmed being informed about and involved in the development and implementation of automation strategies (IG Metall, 2019). These German particularities could explain why the introduction of industrial robots in Germany did not directly decrease the number of manufacturing workers but rather decreased the number of new hires in that sector (Dauth et al., 2017).

Third, it appears crucial to understand why certain firms within a given industry decide to automate while others do not. Some of the research mentioned in this memo shows that large firms are much more likely to automate than smaller companies, and that by acquiring industrial robots they increase their productivity and subsequently their market share, resulting in increasing product market concentration (Acemoglu, LeLarge and Restrepo, 2020; Koch, Manuylov and Smolka, 2019). Why aren't smaller companies acquiring similar automation technology? And what might the consequences of automation be for market concentration, competition, and small- and medium-sized businesses?

References

- Acemoglu, Daron, Claire LeLarge and Pascual Restrepo. 2020. “Competing with Robots: Firm-Level Evidence from France.”
- Acemoglu, Daron and David Autor. 2011. Skills, tasks and technologies: Implications for employment and earnings. In *Handbook of labor economics*. Vol. 4 Elsevier pp. 1043–1171.
- Acemoglu, Daron and Pascual Restrepo. 2018. “The race between man and machine: Implications of technology for growth, factor shares, and employment.” *American Economic Review* 108(6):1488–1542.
- Acemoglu, Daron and Pascual Restrepo. 2020. “Robots and Jobs: Evidence from US Labor Markets.” *Journal of Political Economy* 128(6).
- Aghion, Philippe, Céline Antonin, Simon Bunel and Xavier Jaravel. 2020. “What Are the Labor and Product Market Effects of Automation? New Evidence from France.” *Working Paper* .
- Arntz, Melanie, Terry Gregory and Ulrich Zierahn. 2016. “The risk of automation for jobs in OECD countries.” *OECD Social, Employment and Migration Working Papers* 189.
- Autor, David. 2015. “Why are there still so many jobs? The history and future of workplace automation.” *Journal of economic perspectives* 29(3):3–30.
- Autor, David, David Dorn, Lawrence F Katz, Christina Patterson and John Van Reenen. 2020. “The fall of the labor share and the rise of superstar firms.” *The Quarterly Journal of Economics* 135(2):645–709.
- Autor, David H, Frank Levy and Richard J Murnane. 2003. “The skill content of recent technological change: An empirical exploration.” *The Quarterly journal of economics* 118(4):1279–1333.
- Bessen, James E, Maarten Goos, Anna Salomons and Wiljan Van den Berge. 2019. “Automatic Reaction-What Happens to Workers at Firms that Automate?” *Boston Univ. School of Law, Law and Economics Research Paper* .
- Brynjolfsson, Erik and Andrew McAfee. 2014. *The second machine age: Work, progress, and prosperity in a time of brilliant technologies*. WW Norton & Company.
- Brzeski, Carsten and Inga Burk. 2015. “Die Roboter kommen.” *Folgen der Automatisierung für den deutschen Arbeitsmarkt. INGDiBa Economic Research* 30.
- Dauth, Wolfgang, Sebastian Findeisen, Jens Südekum and Nicole Wössner. 2017. “German Robots: The Impact of Industrial Robots on Workers.” *Institute for Employment Research Discussion Paper* 30/2017.
- Dixon, Jay, Bryan Hong and Lynn Wu. 2020. “The Employment Consequences of Robots: Firm-Level Evidence.” *Available at SSRN 3422581* .
- Fourie, Christopher and Lindsay Sanneman. 2020. “Lessons from the Robotics Ecosystem: Enablers, Hurdles, and Next Direction.” *MIT Work of the Future Working Paper* .
- Frey, Carl Benedikt and Michael A Osborne. 2017. “The future of employment: How susceptible are jobs to computerisation?” *Technological forecasting and social change* 114:254–280.
- Graetz, Georg and Guy Michaels. 2018. “Robots at work.” *Review of Economics and Statistics* 100(5):753–768.

- Haldane, Andy. 2015. "Labour's Share." *Speech at the Trades Union Congress, 12 November 2015* 12.
- IG Metall. 2019. "Transformationsatlas: Wesentliche Ergebnisse." *Pressekonferenz der IG Metall* . Available at https://www.igmetall.de/download/20190605_20190605_Transformationsatlas_Pressekonferenz_f2c85bcec886a59301dbebab85f136f36061cced.pdf.
- Keynes, John Maynard. 1930. Economic possibilities for our grandchildren. In *Essays in persuasion*. Palgrave Macmillan p. 3.
- Knight, Will. 2017. "Amazon has developed an AI fashion designer." *MIT Technology Review* .
- Koch, Michael, Ilya Manuylov and Marcel Smolka. 2019. "Robots and firms."
- Manyika, James, Michael Chui, Mehdi Miremadi, Jacques Bughin, Katy George, Paul Willmott and Martin Dewhurst. 2017. "A Future That Works: Automation, Employment, and Productivity." *McKinsey Global Institute* .
- Markoff, John. 2015. "Planes Withoutt Pilots." *The New York Times* .
- Muro, Mark, Robert Maxim and Jacob Whiton. 2017. "Automation and Artificial Intelligence: How Machines Are Affecting People and Places." *Metropolitan Policy Program at Brookings, Brookings Institution* .
- Nedelkoska, Ljubica and Glenda Quintini. 2018. "Automation, skills use and training." *OECD Social, Employment and Migration Working Papers* 202.
- Pajarinen, Mika, Petri Rouvinen, Anders Ekeland et al. 2015. "Computerization threatens one-third of Finnish and Norwegian employment." *Etna Brief* 34:1-8.
- World Bank Group. 2016. *World Development Report 2016: Digital Dividends*. World Bank Publications.
- Yellen, Maggie. 2020. "Summary of Acemoglu and Restrepo (2019)." *MIT Work of the Future Working Paper* .