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CENTER *for* RETIREMENT RESEARCH *at* BOSTON COLLEGE

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HOW DID COMPUTERIZATION SINCE THE 1980s AFFECT OLDER WORKERS?

By Anek Belbase and Anqi Chen*

Introduction

Laborsaving machines, from the cotton gin to automotive robots, have dramatically reduced the amount of human effort needed to produce goods and services. And despite anxiety about machine-driven mass unemployment, workers replaced by machines have not remained idle over the long term. Instead, they have found jobs in growing industries by learning to perform new tasks. But these transitions have not always been easy, especially for older workers – who have considerable knowledge tied to their current job and a shorter period over which to benefit from new skills. As machines rapidly take on new tasks, from serving coffee to diagnosing cancer, will older workers continue to find jobs that make use of their skills? For the many people who need to work into their late 60s to afford to retire, the stakes are high.

This *brief* is the second in a three-part series on how increasingly capable machines might affect job prospects for older workers in the near future. The first *brief* reviewed the impact of different types of laborsaving machines over the past two centuries. Since computers are the machines that continue to define our times, this *brief* reviews their impact on older workers starting in the 1980s.

The discussion proceeds as follows. The first section explains how machines can create short-term winners or losers depending on the tasks that the machines take on. The second section describes how computers took on "routine" tasks, which affected workers differently by their education level. The third section analyzes whether these effects extended to workers ages 55-64, and concludes that they did. Across age groups, computers have largely benefited workers with a college degree and computer skills, but made it harder for workers with less education to find good jobs. A shrinking gap between the education level and computer knowledge of young and old workers helps explain their similar outcomes. The final section looks ahead to the next *brief*, which addresses whether the current pattern will continue as computers become more sophisticated.

Background

The steady accumulation and application of technology has powered an unprecedented growth in living standards over the past 200 years.[1] Laborsav-

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ing technologies, from automatic bottling plants to mechanized harvesters, have played a key role in this process. It may seem counterintuitive that less demand for workers would fuel economic growth, but the workers freed up from tasks performed by machines did not remain idle. Instead, they switched to tasks that machines could not perform, which included developing new technologies, products, and services.[2] But it has not always been easy for workers replaced by machines to find new ways to be useful.

In the short term, laborsaving machines have changed the importance of different human abilities, benefiting some workers while hurting others. Historically, the types of workers helped or harmed has been strongly influenced by the type of machine in question.[3] For example, steam and electricity-powered factories reduced demand for workers who relied on their strength to make a living and also hurt craftsmen who created products from start to finish. At the same time, the factories increased the demand for workers with dexterity and stamina, and for those with specialized training in engineering, management, design, and marketing. A question more relevant to workers today is, how did *computers* change demand for human abilities, and how were different types of workers affected?

How Computers Affected Workers

In the 1970s, the United States experienced the start of a revolution in computers. Increasingly capable digital microprocessors and memory devices powered this revolution, which has touched practically every aspect of our lives and continues to this day. Most workers started to feel the effects when businesses ramped up their adoption of a variety of computer-based tools, from industrial robots to mainframes to personal computers.

The earliest application of computers relied on their advantages over humans in repeatedly following simple instructions – for example, tabulating census results. Over time, computer hardware became dramatically more capable and advances in software, such as word processors, spreadsheets, and email, made it easier for workers to access these capabilities.

Economists studying the effect of computerization labeled the tasks that computers took on as “routine tasks,” which leveraged their ability to rapidly, tirelessly, and precisely carry out explicit instructions.[4] Routine tasks included cognitive ones like processing financial transactions and physical tasks like attaching a bumper to a car’s chassis. Since all jobs involve some routine tasks – for example, doctors need to pull up a patient’s medical history and keep a record of their treatment plan – the effect of computers on workers largely depended on the proportion of routine tasks in a job (“routine intensity”).

Until recently, the routine intensity of a job has been strongly correlated with the education level needed to perform the job and the wages it paid. Most routine jobs, such as bank tellers and travel agents, paid mid-level wages to high-school graduates with some additional training – often an associate degree or professional certification. In contrast, non-routine jobs involved two very different types of workers. On one end, workers with a college degree specialized in high-paying jobs that mostly involved mental tasks (“non-routine cognitive”), such as consulting. On the other, workers without education beyond high school specialized in low-paying jobs that involved physical tasks (“non-routine physical”), such as food services (see Table 1).[5]

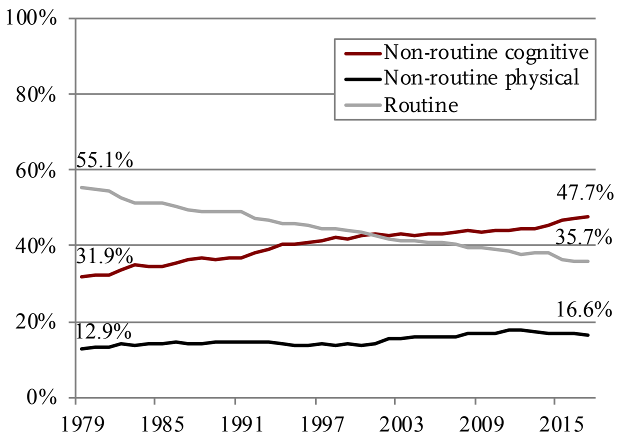
Table 1. Educational Attainment and Median Earnings for Workers Ages 25-64, By Job Type, 2017

	Non-routine physical	Routine	Non-routine cognitive
No college degree	83.3%	79.6%	35.1%
College degree	16.7	20.4	64.9
Median income	$24,000	$35,000	$56,000

Source: Authors’ calculations from U.S. Census Bureau, *Current Population Survey* (CPS) (2018).

Starting in the 1980s, computers steadily reduced employment in routine jobs, but helped create many new non-routine cognitive jobs that required a college degree. Employment in non-routine physical jobs, which did not require any college, was largely unaffected (see Figure 1 on the next page).[6]

FIGURE 1. EMPLOYMENT SHARE FOR WORKERS AGES 25-64, BY JOB GROUP, 1979-2017



Source: Authors' calculations from CPS (1980-2018).

The increase in demand for college-educated workers – like computer programmers, managers, and consultants – is easy to understand: computers made them more useful by magnifying the value of their non-routine cognitive abilities.[7] For example, computer-based tools – like search engines and databases – gave managers and consultants access to data that could be used to improve decisionmaking.

The reason that computers did not replace workers with only a high school degree is less intuitive. It might seem that tasks that do not require much training would be easy to automate. But, in fact, many of the tasks that untrained humans perform – like preparing and serving food, or moving material across a busy worksite – have been near-impossible to program a computer to do.[8] In other words, the rules governing our innate abilities are a mystery. By comparison, many of the jobs performed by workers with some training beyond high school involve tasks related to systems that humans (not evolution) produced, like accounting systems. So the rules were easy to identify, making the tasks "routine."

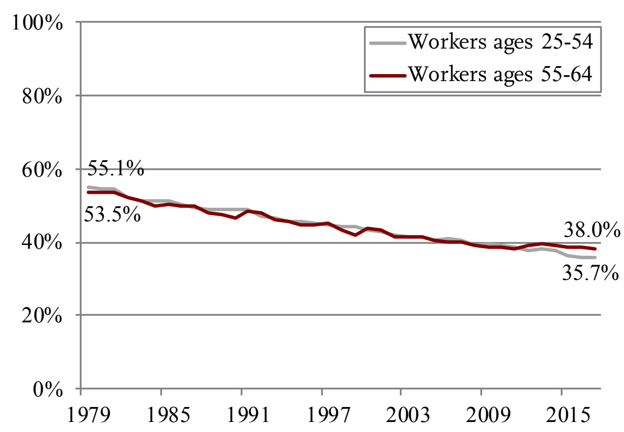
The question is, to what extent did the patterns described above hold true for older workers?

How Did Older Workers Fare?

In the short term, laborsaving machines could especially impact older workers, defined here as those ages 55-64.[9] These workers have already accumulated significant human capital tied to their current job, and they have less time to reap any rewards from learning new skills.[10] Thus, when machines disrupt work, older workers might be less likely to switch occupations or invest in training.[11] Another reason that the effect of machines could depend on age is because certain abilities – like physical power and mental quickness – decline with age. Machines that reduce the need for declining abilities – like power tools for carpenters – could benefit aging workers while machines that make declining abilities more important – like fast-paced assembly lines – could hurt older workers.[12] Given these differences, did computers affect older workers differently?

The answer appears to be that older workers fared just like the rest of the population.[13] First, like other workers, older workers experienced a movement away from routine jobs, despite the incentives they faced to try to hang on to these positions (see Figure 2).

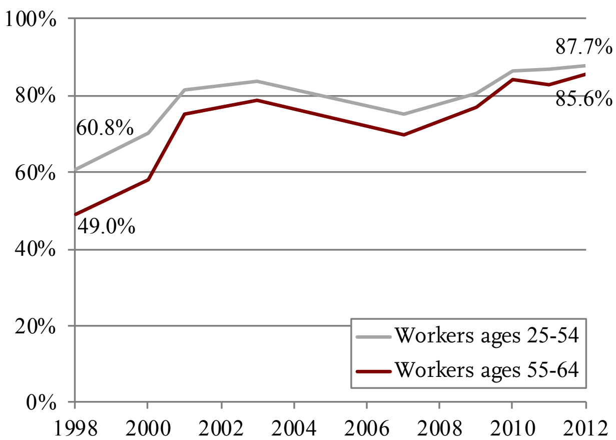
FIGURE 2. EMPLOYMENT-SHARE IN ROUTINE OCCUPATIONS BY AGE GROUP, 1979-2017



Source: Authors' calculations from CPS (1980-2018).

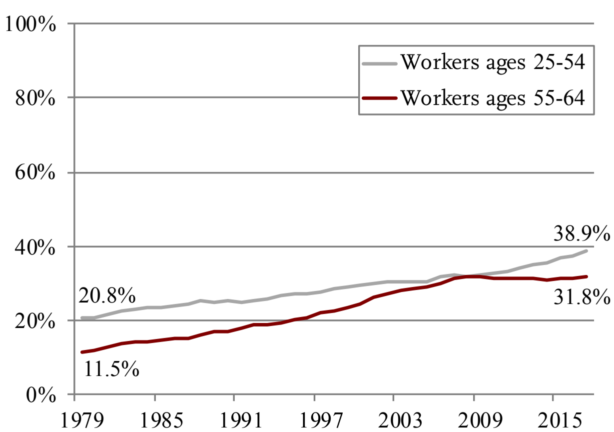
Second, older workers also increased their employment share in non-routine cognitive jobs at approximately the same rate as other workers. One reason might be that – despite their shorter time horizon for investments in new skills to pay off – older workers learned how to take advantage of computers (see Figure 3a). Another reason is that older workers are now more like other workers in terms of education (see Figure 3b).[14]

Figure 3a. Percentage of Workers Who Used Computers, by Age Group, 1998-2012



Source: Authors' calculations from CPS, *Computer Use Supplement* (1997-2012).

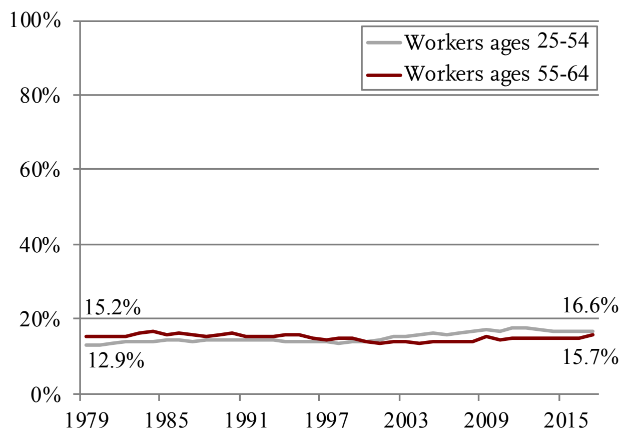
Figure 3b. Percentage of Workers with a College Degree, by Age Group, 1979-2017



Source: Authors' calculations from CPS (1980-2018).

Finally, even though declining physical abilities could potentially have prevented older workers from entering non-routine physical jobs, their employment share in such jobs followed the same trend as younger workers (see Figure 4). One reason computers did not affect older workers in physical jobs might be that non-routine physical jobs tended to be in occupations that relied on workers' ability to communicate – such as retail sales – or in occupations that relied on spatial awareness – such as driving.[15] Unlike physical strength or reaction speed, communication ability and spatial awareness do not decline significantly by the time workers are in their 60s.[16]

Figure 4. Employment-share in Non-Routine Physical Occupations by Age Group, 1979-2017



Source: Authors' calculations from CPS (1980-2018).

Conclusion

Since the dawn of the Industrial Revolution, laborsaving machines have generated enormous economic growth and benefited workers in the long term. But in the short term, machines have improved the job prospects of some workers while making others temporarily redundant. The short-term impact of computers on older workers is especially important to understand because computers continue to automate a wide range of tasks, and older workers represent a growing share of the workforce. The ability of workers in their 60s to remain productive – even if machines change the value of their abilities – will be important not just to their own economic security, but for economic growth overall.

To date, computers appear to have affected older and younger workers in broadly similar ways based on their education level. The effect by education has been driven by computers replacing workers who mainly performed routine tasks. As computers become increasingly capable and automate non-routine physical tasks – such as driving – and non-routine cognitive tasks – such as detecting tumors – will education continue to define who benefits from computerization? Or will other worker qualities, which are less evenly distributed by age, determine workers' fates? These questions will be the subject of the next *brief*.

Endnotes

1 See MIT Task Force on the Work of the Future (2019) and, for a broad historical overview, Belbase and Zulkarnain (2019).

2 Some economists view automation as a race between education and technology, with education allowing humans to take advantage of their flexibility to develop skills that complement machines (Goldin and Katz, 2007).

3 The effect of machines on workers also depends on other factors, such as the social, political, and cultural context in which machines are adopted, which are beyond the scope of this *brief*. See Forslin, Sarapata, and Whitehall (1979) for an example of how the same type of machine can have a different impact on workers depending on how it is adopted.

4 Autor, Levy, and Murnane (2003).

5 Occupation categories are based on Acemoglu and Autor (2011), who classify occupations as either routine or non-routine, and as either cognitive or physical using information collected by the U.S. Department of Labor (specifically, the dictionary of occupational titles and the O*Net databases). For simplicity, in our categorization, routine jobs include both cognitive jobs – such as bookkeeping or clerical work – and physical jobs – such as repetitive production, construction, or transportation.

6 Goos, Manning, and Salomons (2014) and Autor (2019). Computers did affect the types of non-routine physical jobs available, just not the overall employment share in such jobs. Wage growth also followed a similar pattern, with wages stagnating for workers in routine jobs and increasing for workers in both cognitive and physical non-routine jobs.

7 See The National Academies of Science, Engineering, and Medicine (2017) and MIT Task Force on the Work of the Future (2019).

8 This situation is known as "Polyani's paradox;" see Autor (2014). We are learning ways to "train" computers to perform these types of tasks by example (e.g., machine learning), which is the subject of the next *brief*.

9 For example, as typesetting machines were widely adopted, many young typesetters started using them while older typesetters, unable to adjust to the increased pace of work, often relocated to areas where the machines had not yet been adopted (Barnett, 1926).

10 Skilled older workers – like the craftsmen who were displaced by factories in the early 1900s – are particularly exposed to the risk of machine-driven skill-obsolescence. Also, a variety of human-capital accumulation models assume technology-driven skill obsolescence. See Boucekkine, de la Croix, and Licandro (2002); Allen and de Grip (2007); and Kredler (2014) for examples.

11 Macdonald and Weisbach (2004).

12 For example, by emphasizing the need for speed and endurance, early factory jobs put many older workers at a disadvantage (Costa, 1998).

13 For the sake of simplicity, this *brief* addresses broad trends, and the figures used are cross-sectional. Exceptions to these broad trends can be found in a number of studies that examine the fate of specific types of older workers over time – for example, production workers in routine jobs appear to have faced particularly difficult economic circumstances compared to those in white-collar routine jobs (Acemoglu and Restrepo, 2018).

14 Several studies support the idea that workers whose skills are likely to become obsolete respond by learning new skills; for example, see Allen and de Grip (2007) and Friedberg (2003). Friedberg also provides evidence that workers who learned how to use computers delayed retirement as a result.

15 Deming (2017).

16 Belbase, Sanzenbacher, and Gillis (2015).

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