Technological Change and Its Implications for the Labor Market, Productivity and the Nature of Work

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Summary

This report reviews the literature on technological change and its implications for individual workers, firm productivity and the nature of work. The report focuses on academic papers most relevant to the current debate, and particular attention is devoted to the more recent papers from the past ten to fifteen years.

The main results from the list of surveyed papers are:

Chapter 1 – Technological change and the labor market

- For most advanced economies there is strong evidence that technological change increased the relative wage of college-educated workers relative to workers without a college degree in the 1980s and 1990s.
- There is a strong correlation across firms in the use of advanced technology and the level of skill of the workforce, and there is some evidence that upgrading technology leads a given firm to upgrade the level of skill of its workforce.
- For the U.S. labor market there is strong evidence that workers are affected by technology depending on the type of tasks they perform. The tasks affected most negatively are increasingly found in the middle of the income distribution, since such jobs are relatively easy to automate, while jobs in the top and bottom of the income distribution are more difficult to automate. This is because jobs in the top end often consist of abstract cognitive tasks and jobs in the bottom are often physical in nature. Consequently, middle-income jobs have seen employment declines, a trend labeled “job polarization”.
- Most European labor markets, including the Danish, have polarized in ways analogous to the U.S. labor market. These findings are best explained by technological change as opposed to offshoring.
- There is very little evidence that technological change affects overall employment. Many workers in previous middle-skill occupation have not become unemployed. Instead, they have been forced to move down the occupational ladder into services.

- In the U.S. there is some evidence that the majority of the decline in employment in the middle-skill occupations has taken place during downturns. These findings are not mirrored in Europe.
- One study finds that industrial robots have reduced employment in local U.S. labor markets in industries where robots have become increasingly important. Another study shows no impact on overall employment in German local labor markets.

Chapter 2 – Productivity and technological change

- The initial lack of evidence of a link between ICT and productivity referred to as the Solow paradox was mostly related to bad measurement of ICT capital. Once proper measurements are used, there is an unambiguous positive relationship between ICT and productivity, although the direction of causality is more difficult to establish.
- A disproportionally large number of studies are only concerned with the US. In Europe, results generally show evidence of a positive relationship between ICT and productivity, but less strong than in the US. The consensual view is that European firms have been less able to reap the benefits of IT relative to US firms. Differences in managerial quality have been suggested as an explanation.
- There is some new evidence that industrial robots have had strong effects on productivity. However, there is still no trace of a positive contribution of artificial intelligence or machine learning, as it is a more recent trend. AI capital is still under construction, and there are limited measures of AI available to perform proper statistical analysis.

Chapter 3 – Technology adoption and firm (re)organization

- To maximize the benefits of technology adoption, firms need to adopt simultaneously complementary work practices. The practices that appear to be especially relevant are people management practices like selection, incentives, the flexibility of hiring and firing decisions, and the empowerment of workers, indicating that strong human resources practices are crucial to leverage the benefits of technology adoption.

- The introduction of information and communication technologies flattens firms' hierarchies and changes the way firms are organized internally. Information technologies decentralize decisions, while communication technologies move decisions higher up in the firm.
- Due to the lack of appropriate data, there is no evidence about the direct link between IT and wage inequality within firms at this stage.
- To maximize the benefits of IT adoption on firm performance, firms need to simultaneously adopt specific work practices that foster the development of their workers' skills. Firms that benefit the most are the ones that increase their share of skilled workers after adopting a new technology. Following the introduction of new technologies, firms heavily rely on training to upgrade the skills of their workforce, especially in the manufacturing industry (supported by one study only).

Dansk Resume

Denne rapport gennemgår litteraturen om teknologisk udvikling og implikationerne for arbejdstagere, produktivitet og virksomhedernes organisering af arbejdskraft. Rapporten behandler de akademiske artikler, der er mest relevante for debatten om teknologi og arbejdsmarkedet, og den fokuserer på artiklerne fra de seneste ti til femten år.

Hovedresultaterne fra de betragtede artikler er:

Kapitel 1 – Teknologisk udvikling og arbejdsmarkedet

- For de fleste udviklede lande er der stærk evidens for at teknologisk udvikling har øget den relative løn for højtuddannede arbejdstagere i forhold til arbejdstagere uden videregående uddannelse i 1980erne og 1990erne.
- Der er stærk evidens for, at avanceret teknologi og uddannelsesniveauet i arbejdsstyrken på tværs af virksomheder er positivt korreleret. Der er desuden evidens for, at når en virksomhed opgraderer sin teknologi fører det også til opgradering af uddannelsesniveaet i dens arbejdsstyrke.
- For det amerikanske arbejdsmarked er der stærk evidens for, at graden hvormed ny teknologi påvirker arbejdstagerne afhænger af opgaverne, der udføres i det enkelte job. I midten af indkomstfordelingen reducerer ny teknologi beskæftigelsen fordi de opgaver, der udføres her, relativt let kan automatiseres. Jobs i toppen og bunden af indkomstfordelingen er vanskeligere at automatisere. I toppen skyldes det, at disse jobs ofte kræver kognitive evner og i bunden fordi det som oftest er fysiske jobs. Som konsekvens har der været lavest vækst i jobs i midten af indkomstfordelingen, et mønster der betegnes ”job polarisering”.
- De fleste europæiske arbejdsmarkeder, herunder det danske, er blevet polariseret på samme måde som det amerikanske arbejdsmarked. Det kan tilskrives den teknologiske udvikling, hvorimod der er mere begrænset evidens for at udflytning af arbejdspladser spiller en rolle.
- Der er ikke belæg for at den teknologiske udvikling påvirker den samlede beskæftigelse i arbejdsmarkedet. Der er i stedet en tendens til, at arbejdstagerne i midten af indkomstfordelingen finder beskæftigelse i servicesektoren.

- I det amerikanske arbejdsmarked er der evidens for, at størstedelen af beskæftigelsesfaldet for arbejdstagere med mellemlang uddannelse fandt sted under den finansielle krise. I de europæiske arbejdsmarkeder var der ikke et tilsvarende fald i beskæftigelsen for denne gruppe arbejdstagere under recessioner.
- En artikel finder, at industrielle robotter har reduceret beskæftigelsen i de lokale arbejdsmarkeder i USA hvor robotter har haft særlig stor betydning, og en anden artikel finder, at industrielle robotter ikke har påvirket den samlede beskæftigelse i det lokale arbejdsmarkeder i Tyskland.

Kapitel 2 – Produktivitet og teknologisk udvikling

- Oprindeligt kunne man ikke finde evidens for sammenhæng mellem IT produktivitet (Solow paradokset), men dette kunne tilskrives dårlige mål for IT kapital. Med bedre mål for IT kapital findes en klar sammenhæng mellem IT og produktivitet, men årsagssammenhængen er sværere at fastlægge.
- De fleste studier analyserer ny teknologi og produktivitet i USA. I Europa viser resultaterne en positiv sammenhæng mellem IT og produktivitet men sammenhængen er ikke så stærk som i USA. Konsensus er at europæiske virksomheder ikke har været i stand til at udnytte fordele forbundet med IT i samme udstrækning som i USA. Forskelle i ledelseskvalitet er fremført som en mulig forklaring.
- Der er ny evidens, der viser, at industrirobotter har stærk positiv effekt på produktiviteten. Der er imidlertid stadig ingen tegn på at kunstig intelligens eller ”machine learning” har påvirket produktiviteten, idet det er et mere nyligt fænomen og brugbare data mangler stadig.

Kapitel 3 – Teknologi og virksomhedernes organisering

- For at maksimere fordelene ved ny teknologi bør virksomhederne samtidig tilrettelægge arbejdsgangene så de passer til den nye teknologi. Særligt relevant i den forbindelse er virksomhedernes human ressource politik.
- Introduktion af nye informationsteknologier gør virksomhedernes hierarkier fladere og ændrer den interne organisation i virksomhederne. IT decentraliserer beslutnings beslutninger, mens kommunikationsteknologier rykker beslutninger op i hierarkiet.
- På grund af manglende data er der ikke fundet evidens for et direkte link mellem IT og lønulighed inden for virksomhederne.
- Med henblik på at maksimere fordelene ved ny teknologi for virksomhedernes performance, bør de samtidig fremme udviklingen af de ansattes kompetencer. Virksomheder, der har størst fordel af ny teknologi er de der øger anden af ansatte med høj uddannelse. Efter indførelse af ny teknologi er der tendens til, at virksomheder gør brug af efteruddannelse til at opgradere de ansattes kompetencer. Dette gælder særligt i fremstillingssektoren.

Introduction

In this survey, we evaluate empirical economic research regarding the impact of new technologies/technological development on individual workers, firm productivity and the nature of work. The survey is divided into three complementary chapters. Each chapter is followed by a set of tables summarizing the main results of the most important papers in the field and providing background information about the datasets used, the methods employed and the definitions of technological developments used by the authors.

The first chapter analyzes the effects of technological development on the labor market. It brings several key lessons from thirty years of research in macroeconomics and labor economics. First, most advanced economies have experienced an increase in income inequality and a phenomenon called job polarization, i.e. the fact that many jobs in the middle of the income distribution have been lost and much employment has moved to the extremes as a consequence of automation of many routine tasks that was previously performed by humans. Many culprits have been identified for this evolution, but the preferred explanation for a majority of economists has been skilled biased technical change, that stresses the fact that technical change has been relatively more beneficial to skilled workers than to unskilled workers, and this has dramatically changed the relative demand of labor by firms. This phenomenon has had much stronger consequences in the US and Anglo-Saxon countries with lower social protection. Second, while the effect on technological change on inequality is beyond doubt, there is no strong evidence that it has had a significant effect on the level of employment. In other words, individuals have been transferred from old jobs and occupations to new ones in a largely smooth reallocation process.

The second chapter looks at how new technologies have effected firm performance, with an emphasis on labor productivity and total factor productivity. First, hardly visible in aggregate statistics, the contribution of the so-called information and communication technology (ICT) capital, composed of computers, software and telecommunications equipment, quickly became irrefutable and a key component in the rise of productivity growth in the US. Dozens of firm-level studies have confirmed the fact that firms quickly, although not immediately, captured returns from their investment and had higher productivity growth. The effect was measured much later and appeared less strong in Europe, leading to the so-called productivity gap between the US and Europe, that attracted a lot of attention from academics and policy makers alike. It was indeed puzzling that European companies were not able to enjoy such strong benefits from their investments as their US counterparts. Differences in managerial quality and in the adoption of complementary innovations were among the most common explanations. Lately, the focus has switched to a new puzzle, yet to be solved: the new productivity slowdown. While investment in new technologies like AI has never been so large, productivity growth has declined in all Western economies. Many authors argue that we should learn from the past and that it will take a few years before the new developments of AI translate into tangible gains for the firms that invested in it.

The third chapter is concerned with the changing nature of work and the internal organization of firms when they decide to adopt new technologies. ICT's facilitate coordination of activities and communication between workers within the firm and between firms, and therefore facilitates the flow of information, what should in theory have positive implications for firm performance. One important element in this literature was the need to adopt complementary organizational change in order to properly benefit from these new technologies. Evidence suggests that firms that both invested in new technologies and adapted their organization saw large gains in productivity. In particular, ICT's allowed firms to better deploy and take advantage of their human capital. It also facilitated workers' supervision, making managers better able to diffuse their ability, leading to more agile, decentralized organizations with larger spans of control and less hierarchical layers, more responsive to changes in their competitive environment.

Several cautions should be noted before moving on to the main text. First, this is by no means an exhaustive survey; yet we have tried to cover the widest spectrum of the literature and focused on solid academic papers that we have found most relevant to relate to the current debate. We devote particular attention to the more recent academic articles from the last ten to fifteen years, but we also mention some earlier path-breaking articles. Second, we have followed a chronological description of the evolution of ideas and transformation of the debate and have tried to bring some structure to that evolution.

Third, it is important to be clear about what technology means. The literature has used indirect and as well direct measures of technology. Whereas direct measures of technology use data on computers, ICT capital, R&D investments and industrial robots etc., indirect measures use data on wages and output to infer what the underlying observed path of technology must have been. Clearly, direct measures of new technologies are preferable as results are then easier to interpret, but in some cases lack of data means researchers have had to resort to indirect measures. Fourth, it should be stressed that the surveyed papers almost exclusively consider the long run, which means a time period long enough to allow the economy to adjust to the introduction of new technologies. In some cases, evidence is also found for a medium run perspective, where partial equilibria at the industry level are reached. Fifth, for several reasons, a large chunk of the literature has focused on the US. We have done our best to provide a more international dimension to our survey, with a particular focus on Norther European countries, Denmark being especially targeted in comparison with similar economies. Finally, what we call technological development has had varying meanings throughout the period of analysis. We will often refer to it as adoption of information and communication technologies (ICT), and these technologies have been evolving over time. In the 1980's, the major tool that transformed the way firms were doing business was the computer; later, it was computer networks, software and enterprise resource planning; nowadays, it is all about industrial robots and machine learning. We will use special care in discussion the evolution of these technologies throughout the text.

Chapter 1 – Technological change and the labor market

This chapter provides a survey over how technological development has affected the labor market both in terms of wage inequality and the level and composition of employment. Section 1.1 starts out by noting that there is no unique comprehensive measure of technology and introduces the different measures used in the literature. The chapter then proceeds with a chronological account of how technological change has affected labor markets over the past 50 years starting in Section 1.2 with the earliest signs that the economy has been favoring the more skilled parts of the labor force disproportionately. Section 1.3 uses concrete measures of technology such as advanced manufacturing technology and computers, to show that this increase in inequality is tightly connected with technology. Sections 1.4 and 1.5 show that the most dramatic effects on employment and wages have been on those in the middle of the income distribution both in the US and in Europe. Having analyzed the effects on income inequality we turn to the effects of technology on the overall economy. Section 1.6. shows that technological improvements have no negative long-term impact on employment and Section 1.7. considers the business cycle. Section 1.8 turns to a few recent studies that consider the implications of automation and robotics for labor market outcomes and the overall employment level. Section 1.9 makes the point that automation ideally should be measured at the firm level in order to answer many policy relevant questions, but so far such evidence does not exist. Finally, Section 1.10 closes the chapter by noting that new technology may also affect labor markets indirectly through changes in globalization and international trade.

1.1. What is technological change technical change

This first section considers different measures of technology and sets the stage for the rest of the report

- There is no unique definition of technology, and several different approaches to have been used to assess the impact of technology on the economy. These can be grouped into four classes: indirect, direct physical measures, spending on innovation and residual measures of technology.

The biggest challenge in estimating the effects of technological change is how to measure it. Different aspects of technological change have been used in the literature and no single preferred measure exists. Consequently a number of different approaches have been taken (See box 1). The exact meaning of the term will depend on the context and the time period of interest, and in this report it will be measured in three distinct ways. The broadest meaning of the term is indirect and does not explicitly provide a measure. It is simply a matter of whether the broad trends in income inequality are consistent with a story of technological change. Katz and Murphy (1992) and Berman, Bound and Griliches (1994) are prominent examples. In such a context an increase in the relative payment of skilled workers simultaneous with an increase in the number of skilled workers will be taken as (indirect) evidence that broad technological change has favored skilled workers.

A second approach is the concrete measures of upgrades to production technology in terms of advanced production technology, computers or robots. Early examples are Doms, Dunne and Troske (1997) and Autor, Katz and Krueger (1998), whereas Krusell, Ohanian, Ríos-Rull and Violante (2000) provide the theoretical framework for this analysis (see Box 2). Such an approach has the advantage of precisely capturing a concrete aspect of technological improvement, but it will naturally be narrow in its focus.

A third approach measures spending on innovation and Research & Development directly. Although a very direct measure of how much firms spend on developing new technologies, it does not capture the contribution of the eventual product and many improvements to technology are of a more diffuse nature and are not directly captured by formal R&D spending.

A fourth approach takes a much broader view of technology. For individual firms the researcher considers a yearly increase in output and subtracts the part that can be explained by increased use of inputs. The rest is labeled as *total factor improvement* a broad concept that measures improvements in technology, management etc. We largely rely on this measure in Chapter 2.

Box 1 gives a list of these measures and Box 2 gives a detailed theoretical justification for the use of these measures.

Box 1. How Is Technology Measured?

No uniquely compelling measure of technological change exists, and the literature has employed a number of different approaches to quantify the impact of technological change. These can most easily be classified into four distinct categories:

Indirect measures: Katz and Murphy (1992) pioneer an “indirect” measure of technological change. They observe a rising ratio of college-educated to non-college educated workers over the period 1963-1987 at the same time as an overall increase in the relative pay of college-educated workers. In a relative-demand framework they couple the observed changes in the relative supply of college-educated workers and a linearly increasing demand for college-educated workers and show that this comes remarkably close to matching the actual college-premium. From this they conclude that technological change has been skill-biased during this period. More recent papers, such as Goos and Manning (2007) and Autor, Katz and Kearney (2008) use the polarization of employment along skill-lines to conclude that technological change has disproportionately affected middle-skill workers. Though such analysis is helpful in framing the big picture, the lack of more specific measures makes it difficult to test alternative theories against one another.

Direct physical measures: A more direct measure of technology is to look at a specific, more easily quantifiable, measures of the use of technology. Doms, Dunne and Troske (1997) count the use of advanced production technology in the manufacturing industry, whereas Autor, Katz and Krueger (1998) use computer equipment. More recently, Acemoglu and Restrepo (2017), Fort, Pierce and Schott (2018) and Graetz and Michaels (2017) have used the use of robotics in manufacturing to assess the impact of technology. Though, such measures allow for more fine-grained analysis – for instance, ICT equipment tend to replace middle-skill workers, whereas advanced manufacturing equipment tend to replace low-skill workers. Clearly, the usefulness of a particular measure depends on the context and time period: Whereas computers are now ubiquitous and therefore leave little variation to exploit, robots are still primarily employed in the auto industry and their use might say little about the rest of the economy.

Investments in R&D and innovation. Instead of measuring the employment or use of technology, researches can measure the investment in the development of new technology. Though not a direct measure of technology, investments in R&D have the virtue of being a concrete measure in dollars and can be more easily compared across firms and industries. In addition, investments in R&D are likely to respond more immediately to changes in firm environments than the implementation of new technology which can take years to fruition. Andersen (2016) show that Danish firms that are induced to offshore more by changing conditions in world markets have higher R&D expenditures, more product innovation and hire more R&D workers.

Residual measures of technological change: Solow (1957) originally proposed a residual measure of technological change: If we subtract the contribution to production from higher labor, capital and potentially input, and we still see a positive increase in production, then the residual must be due to improved productivity. In its modern reincarnation this is labeled *total factor productivity.* Autor and Salomons (2017) use such a measure to find that changes in total productivity have little impact on country-wide employment, but sectors that experience rapid productivity increases tend to have lower employment growth, employment that is then picked up by other sectors. Though, some stylized facts can be learned from such an analysis, the unknown nature of the residual makes interpretation difficult: besides physical improvements in technology, it can arise from changes in management approaches, liberalization of industries, increased competition from abroad and so on. Confounding all these effects makes direct interpretation difficult.

Box 2: A theoretical Framework

The theoretical literature has evolved in parallel with the empirical literature: The original framework used by Katz and Murphy (1992) was one of factor-augmenting technical change. It specified an aggregate production function as:

$$Y = \left((A_L L)^{\frac{(\sigma-1)}{\sigma}} + (A_H H)^{\frac{(\sigma-1)}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}},$$

Where L and H are the stock of low-skill and high-skill labor, respectively. A_L and A_H are technology parameters and σ is the elasticity of substitution between high-skill and low-skill labor, thought to be higher than 1 (usually 1.4-1.8). From this it follows that

$$\frac{w_H}{w_L} = \left(\frac{A_H}{A_L}\right)^{\frac{(\sigma-1)}{\sigma}} \left(\frac{H}{L}\right)^{-\frac{1}{\sigma}},$$

Where w_H/w_L is the skill-premium. It is affected positively be technological change that favors high-skill workers and negatively by the relative supply of high-skill workers. This relative demand / supply model framed the original literature and made the concept of skill-biased technical change clear: Even with a growing relative supply of skilled workers their relative pay is still rising: consequently, the underlying economy must gradually be requiring more skills (A_H/A_L is growing). Though elegant in its simplicity the framework leaves out a number of features. Besides only having two skill-groups and consequently being insufficient to address questions of wage – and employment polarization, it has no explicit role for automation: technology is a matter of making certain labor groups more productive. This feature forces all groups to benefit from technology, albeit unequally.

A second generation of theoretical models was originally introduced by Krusell, Ohanian, Rios-Rull and Violante (2000) where an explicit role for machines was made as an additional factor of production.

$$Y = \left((L)^{\frac{(\sigma-1)}{\sigma}} + \left[K^{\frac{\epsilon-1}{\epsilon}} + H^{\frac{\epsilon-1}{\epsilon}} \right]^{\frac{\epsilon}{(\epsilon-1)}\frac{(\sigma-1)}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}},$$

Where K is capital stock and ϵ is the elasticity of substitution between capital and high-skill labor. It is important that $\epsilon < \sigma$; that is capital complements high-skill labor and substitutes for low-skill labor. Consequently, increasing technological capabilities is modelled explicitly as an exogenous increase in the stock of capital – or almost equivalently as an exogenous decrease in the cost of capital with a resulting increase in its use – and the relative substitutability or complementarity with different skill groups depends on parameters of the model. This allows for the explicit inclusion of measurable technology and provides a theoretical framework for a large literature empirically examining the consequences of increases in ICT or other new technology and the skill – premium or ratio. However, in these models, although technology can increase income inequality, it cannot explicitly make any population worse off.

More recently, Acemoglu and Autor (2011) have emphasizes the need for an explicit "task-framework": It is important to realize that the role of new technology is not just that it is becoming cheaper, but that capabilities of technology is expanding and there are now certain tasks that technology can perform that previously could only be performed by humans. Acemoglu and Restrepo (2018) show that such a framework can be written such that production is:

$$Y = B\left(\frac{K}{I-N+1}\right)^{I-N+1}\left(\frac{L}{N-1}\right)^{N-I},$$

where $(N-I)$ is a measure between 0 and 1 of how automated the economy is (formally the share of tasks that can be performed by machines) and B is a measure of the level of technology. While these models continue to have positive overall effect on economic activity, they can potentially give much stronger predictions about negative consequences for certain parts of the population

Finally, a very recent theoretical literature emphasizes that technological change is not an exogenous process: economic agents decide whether they want to develop new products – and thereby increase economic productivity and create new employment – or whether they want to automate their production of existing products – and thereby reduce demand for certain subgroups of the population. Hemous and Olsen (2017) and Acemoglu and Restrepo (2018) are both examples of such models. They emphasize the crucial role of improving the productivity of low-skill labor: any sustained increase in the wages of low-skill workers without corresponding increases in labor productivity will continuously shift the innovate capabilities of the economy from the invention of new products to the automation of existing production.

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1.2. The early signs of skill-biased technical change

As an introduction, this section provides a brief account of how skill-biased technical change affected income inequality in the latter part of the 20th century.

- For most advanced economies there is strong evidence that technological change has increased the relative wage of college-educated workers relative to workers without a college degree.

Technology has profoundly altered the macroeconomy since the advent of the industrial economy. Although, there have been many dramatic transformations, for most of the twentieth century the benefits have been broadly shared by the whole economy. However, in the last decade of the 20th century income inequality has risen rather broadly across a number of developed countries. Figure 1. shows the increase in male income inequality, measured as the 90th to 10th ratio of hourly earnings (In the literature it is common to report on male wages not to confound changes to the wage distribution with the substantial changes in female employment over the past half a century). It is clear, that whereas there was little systematic increase in income inequality from 1980-1990 almost all countries have seen increases in income inequality during the period from 1990 to 2008. The central focus of the literature on income inequality is the source of this increase, and technological change is the favored candidate. As can be seen from Figures 1 and 2 this trend started earlier in the United States than elsewhere and work by Katz and Murphy (1992) showed that much of the overall increase in income inequality came as a result of increases in the skill-premium: the wage premium that college-educated receive over those not college-educated. The literature typically labels these high-skill and low-skill workers, respectively. Income of high skilled workers increased, whereas low skilled workers saw wages decline both absolutely and relative to high skilled workers.

This sparked a debate among commentators, policy makers and academics over the reasons behind this change. In the late 20th century the consensus was that skill-biased technological change (SBTC) was the main driver behind widening wage differentials, though other explanations such as international trade also have a role (see e.g. Feenstra and Hanson 2003). This conclusion was reached partly as a consequence of an increasing number of studies that found direct evidence of technological changes affecting the skill-premium, and partly due to a lack of convincing evidence that trade was of sufficient size to explain much of the increasing wage gap in the United States.

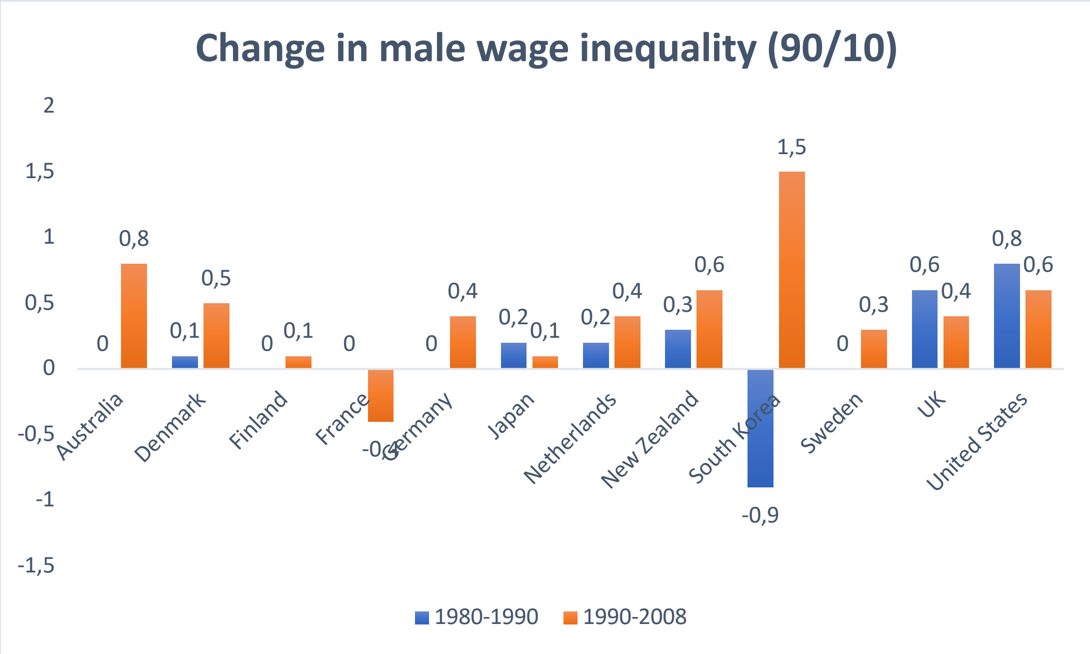

Figure 1. Source: OECD Stat Extracts website (where exact year not available we use nearest available year)

Although evidence in favor of a more prominent role for globalization in explaining the rise of income inequality has been mounting in recent years (see e.g. Autor, Dorn and Hanson, 2013), the consensus is still that the lion's share of income inequality is explained by technological change. [1]

[1] Technological change and globalization are often held up as alternative explanations for the increase in income inequality. Acemoglu (2003) argues that skill-biased technical change might be a consequence of globalization: with increased globalization developed nations will increase production in industries that employ more skilled labour. Consequently, innovation in such industries will become more profitable, and technological change will disproportionately favour industries that rely heavily on skilled labor. We will return to this question in Section 1.10.

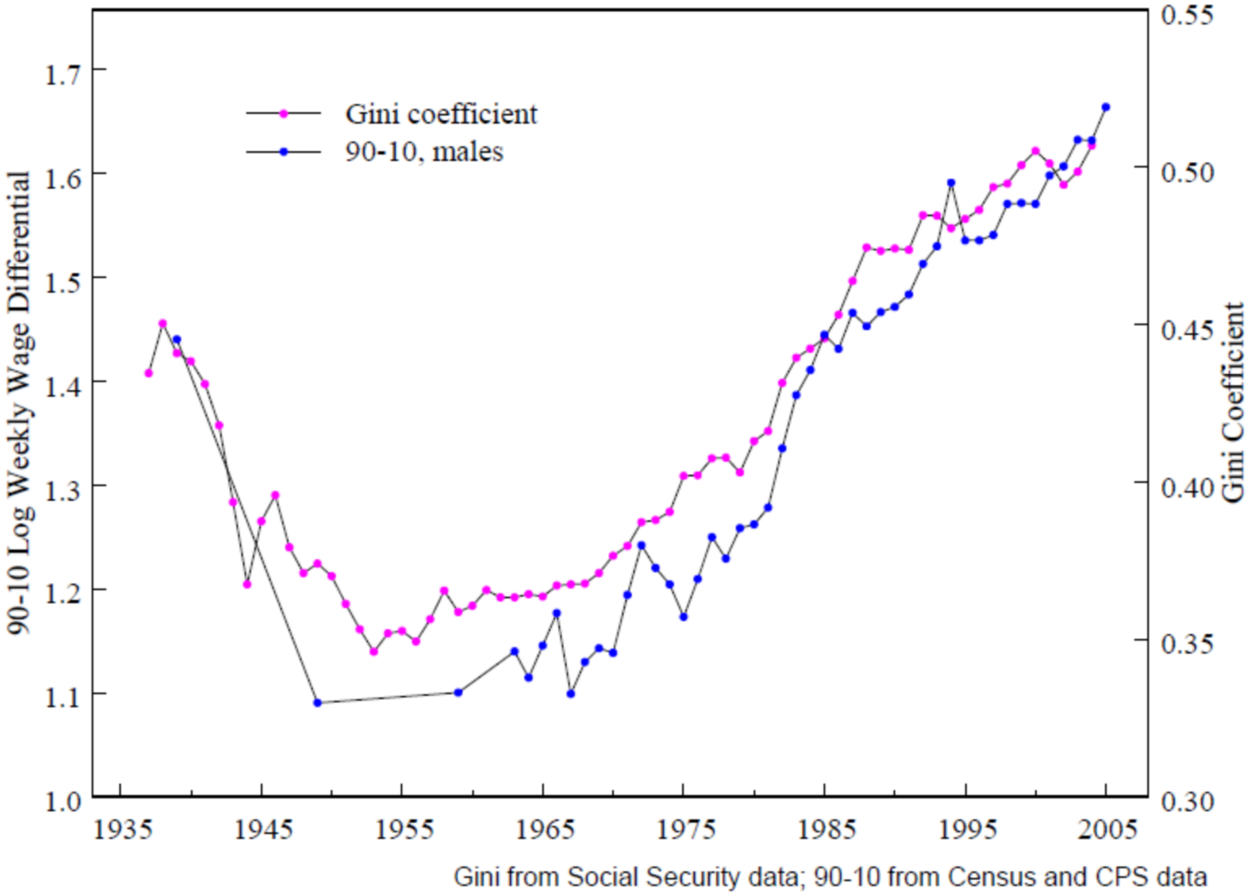

Figure 2. US male wage inequality, 1937-2005.

Source: Van Reenen (2011) using data from Goldin and Katz (2008)

Table 1.2. Studies of early signs of skill-biased technical change

Study	Country	Dataset	Method	Measure of technology	Effect
Katz and Murphy (1992)	USA	Individual level data on wages and industry of employment	Simple relative supply/demand framework: regress changes in skill-premium on the changes in skill ratio and a secular trend in skill-biased technical change	None. Inferred from changes in relative pay to skilled workers	A combined increase in the relative pay to skilled workers and an increase in the relative number of skilled workers is best explained by a secular technology-driven rise in relative demand for skill-biased worker

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1.3. The use of direct measures of technology

The first direct measures of technological change were the use of computers and advanced manufacturing techniques by firms.

- There is strong evidence for a correlation across firms in the use of advanced technology and the skill level of the workforce
- There is evidence that upgrading technology leads a given firm to upgrade the level of skill of its workforce.

Though the overall trends in income inequality are consistent with broad trends in technology that favors skilled workers (Katz and Murphy, 1992), a comprehensive picture requires the use of more specific measures of the use of technology. Doms et al. (1997) focus on the US manufacturing industry in 1988 and 1993. They measure technology as a count of the number of advanced technology, such as computer-aided design and automated sensors, a firm employs in its production facility. They find that whereas more technologically advanced companies tend to pay more and hire more skilled workers, there is no correlation between the adoption of new technology and the increase of skill in the work force. This suggests that it is not so much the adoption of new technology that leads firms to hire more skilled workers, but certain unobserved features of a firm – such as quality of management or productivity – induce it to both use more advanced technologies and hire more skilled workers. This is in sharp contrast to Autor et al. (1998), who focus on a broader set of firms from 1946 to 1996 and use investments in computer equipment as their measure of technology. They find that investments in computer equipment lead to the upgrade of the skill-composition of the work force. This is in line with a study by Bartel, Ichniowski and Shaw (2007) that obtain very detailed information on computer-controlled production and planning systems in the US valve industry. They find that firms that upgrade their technology require their production workers to have higher skills – though not more formal schooling – and that firms employ training programs to upgrade the skills of their workers.

Table 1.3 Early studies using various measures of technology

Study	Country	Dataset	Method	Measure of technology	Effect
Autor, Katz and Krueger (1998)	USA	Industry level data on employment and wages of college graduates 1960-1996. Data for computer use 1984-1993	Reduced form estimation of changes in wage bill share of college graduates on percentage of workers using a computer	Percentage of workers using a computer	Industries with high rates of skill upgrading showed higher rates of changes of computer usage and computer capital per worker.
Doms, Dunne and Troske (1997)	USA	Manufacturing survey. 1988 and 1993	Cross-sectional and panel data regressions using two waves of manufacturing surveys.	The use of advanced techniques in manufacturing.	Firms with more advanced technology employ more skilled and better educated workers and pay more. No effect of adopting better technology in skill-composition of work force.
Bartel, Ichniowski and Shaw (2007)	USA	Very detailed data on a narrow industry: valve manufacturing, including very detailed information on educational composition and productivity. 2002	Cross-sectional regression, but using retrospective survey so questions about changes can be addressed to some extent	Very detailed information about the use of advanced manufacturing technology	The adoption of new IT-enhanced capital equipment coincides with increases in the skill requirements of employees.

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1.4. The Routinization-hypothesis and job polarization

The routinization-hypothesis proposes that computers replace "routine" tasks, in the sense of tasks that can be described sufficiently well to be programmed. Comprehensive data on the type of tasks that different occupations perform exist for several countries, but this section reviews the findings for the U.S. labor market only.

- There is strong evidence that workers are affected by technology dependent on the type of tasks they perform.
- The tasks most easily automated are often found in the middle of the income distribution: jobs such as midlevel accounting, secretarial work and organizational work is relatively easy to automate and reduction in employment groups has been strongest in the middle of the income distribution.
- Jobs in the top and bottom of the income distribution are more difficult to automate: doctors and janitors are simple examples. Doctors because their cognitive work is difficult to replace, janitors because we cannot yet build machines that can perform the manual tasks the janitor performs.
- There is preliminary evidence of the increasing importance of social skills compared with classical math or abstract skills.

The early literature mentioned in the previous section was criticized for labelling more than explaining the positive correlation between technology and skills: It is all good calling it skill-biased technical change, but why does new technology complement skill? In their seminal contribution, Autor, Levy and Murnane (2003) take their starting point in *Polanyi's paradox* (Polanyi 1966): We know more than we can tell; that is humans are capable of a myriad of things that we cannot explain how we do. When we ride a bike, put up a drywall, or give a speech to an audience, we cannot write down the details of what we do in sufficient detail for a computer program to emulate the process. This is not the case with addition or much assembly work, which follows very precise rules. This led Autor, Levy and Murnane (2003) to propose the so-called routinization hypothesis. They extend the framework of Autor, Katz and Krueger (1998) and examine if computers have differential effects on workers depending on the tasks they perform. Several countries publish very detailed information on the types of tasks performed by hundreds of different occupations. Autor et al. (2003) classify these tasks in a two-dimensional matrix (See Box 3): for whether the occupation primarily performs manual (physical) tasks or cognitive tasks, and whether the tasks are sufficiently routine that they can be codified in a computer program. Consequently, an assembly line worker performs manual routine jobs, whereas a janitor performs manual non-routine jobs. Using this classification, they find that computerization raises demand for non-routine cognitive tasks, reduce demand for routine manual and routine cognitive tasks and appears to have little impact on demand for non-routine manual tasks.

Box 3. The Routinization Hypothesis

The characteristics of a job have proved essential to the ease with which technology can replace workers. A fruitful way of classifying jobs is through a 2-by-2 matrix first used by Autor, Levy and Murnane (2003). They use the U.S. Department of Labor's *Dictionary of Occupational Titles,* which contains detailed information on the characteristics of jobs, including the tasks performed on the job. They classify jobs according to the two-dimensional matrix seen below: *Routine* jobs are those that perform tasks that are possible to describe in sufficient detail that a computer can do them: some accounting tasks, calculations etc. The second dimension is whether the tasks are physical such as assembly line work. Though, say, janitorial work might seem routine to humans constructing artificial intelligence that can operate autonomously in a regular office building is beyond the capabilities of today's computer technology. Consequently, whereas routine jobs such as accounting and assembly work can and have been automated, non-routine tasks have proven much more difficult.

	Routine tasks	Non-routine tasks
	Analytic and interactive tasks	
Examples	Record-keeping, calculation, Repetitive customer service	Medical diagnosis, legal writing, persuading/selling
Computer impact	Substantial substitution	Strong complementarities
	Manual tasks	
Examples	Picking or sorting, repetitive assembly	Janitorial services, truck driving
Computer impact	Substantial substitution	Limited substitution or complementarity

Autor, Katz and Kearney (2006, 2008) use this framework to explain the subtle shift in income inequality in the last decades in the United States. They take as a starting point a plot like Figure 3 (updated from Acemoglu and Autor, 2011) that ranks occupations by their hourly earnings and look at the relative increase in earnings over the period 1974-1988 and 1988-2008. In the former period there was a monotonic increase in income inequality: those with the highest income saw the highest relative rises, whereas in the latter period there was wage polarization: those in the middle of the income distribution: midlevel accountants, secretaries, travel agents saw the lowest wage growth. Similar trends can be seen in employment trends. They label this wage (and job) polarization and attribute it to the different characteristics of automation in the late 20th century compared with the decades prior. Much of the automation in the decades before 1990 were automation of manual routine jobs, exemplified by assembly line work, whereas much of the technological change of the past 20 to 30 years has been automation of so-called routine cognitive tasks. These are exactly the type of jobs that people in the middle of the income distribution perform. The tasks carried out by people further down the income distribution, the cleaning lady, the barista, the janitor are much harder to describe in exact code and are consequently more difficult to automate:[2] This is consistent with the observation that changes in the wage structure after the 1980s increasingly affected employment by the middle-income groups negatively whereas employment in the top and bottom increased.

[2] Feng and Graetz (2017) offer a slightly different explanation: Consistent with the routine-hypothesis they show that the occupations that have seen declines in employment are the ones that are the easiest to automate from an engineering perspective, but also the ones with intermediate level of training requirements: They argue that jobs with higher training requirements typically pay substantially more and are therefore automated not because they are easier but because the benefit of doing so is higher.

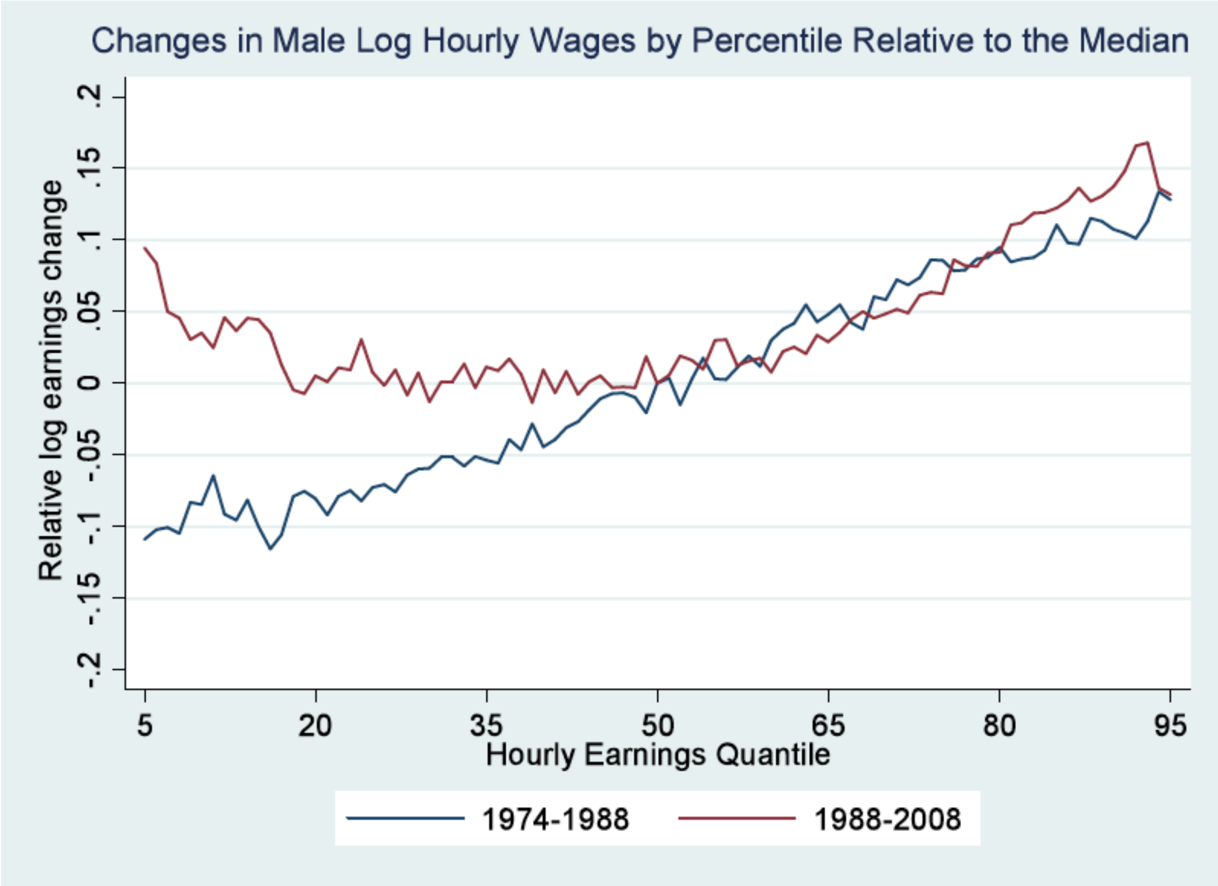

Figure 3: Source: Acemoglu and Autor (2011)

Consequently, the broad patterns of income and employment patterns are consistent with a subtler version of skill-biased technical change: In the 1970s and onwards a large part of technological change was automating the jobs performed by people working in routine manual professions. These observations are consistent with more detailed examinations of the consequences of ICT and advanced manufacturing technology on firms: firms with more advanced technologies tend to employ more skilled workers and there is some evidence that investing in new technology leads them to upgrade the skill-content of their work force as well. As these manual routine jobs have gradually disappeared and technology has improved the past decades have seen a substantial amount of automation of jobs performed by people in the middle of the income distribution.

There is preliminary evidence on what features of high-skill jobs makes them more difficult to automate. Deming (2017) finds that for the US there is a higher growth rate in jobs that require a high level of social skills compared with more math-intensive but less social jobs (classical science, technology, engineering and math).

Table 1.4 Studies of the Routinization hypothesis in the U.S. labor market

Study	Country	Dataset	Method	Measure of technology	Effect
Autor, Levy, and Murnane (2003)	USA	Industry level data on task composition for 1960-1998 and for computer use for 1984-1997	Reduced form estimation of changes in task composition (routineness and non-routineness) on change in percentage of workers using a computer	Percentage of workers using a computer / big contribution is to classify occupations in whether they are routine/non-routine	Increased computer use substantially reduces routine tasks and increases non-routine tasks
Autor, Katz and Kearney (2006)	USA	Employment and skill by occupation from Census Integrated Public Use Microsample for 1980, 1990 and 2000	Calculation of employment growth for 1980-1990 and 1990-2000 by percentile of skill distribution	None, inferred from income trends	Declining employment at the bottom and increasing employment at the top of the skill distribution in the 1980s. Employment growth in the 1990s polarized with the strongest increases the top and bottom, and slowest growth in middle of the skill distribution.
Autor, Katz and Krueger (1998)	USA	Industry level data on employment and wages of college graduates 1960-1996. Data for computer use 1984-1993	Reduced form estimation of changes in wage bill share of college graduates on percentage of workers using a computer	Percentage of workers using a computer	Industries with high rates of skill upgrading showed higher rates of changes of computer usage and computer capital per worker.
Autor, Katz and Kearney (2008)	USA	US micro survey of individuals. 1963 – 2005	Calculations of different moments of the overall wage distribution. Tabulating changes in income inequality across time. No regressions.	None, inferred from income trends	Monotonic increase in income inequality until late 1980s. Thereafter wage polarization: an increase in $90^{th}/50^{th}$ income ratio, decline in $50^{th}/10^{th}$ income ratio.
Deming (2017)	USA	US micro survey of individuals for 1980-2012. Interacted with job characteristics, and data on the occupational distribution of people with different social skills (from Army assessment tests)	Panel data regression: assess returns to occupations where more sociable people tend to work	None, inferred from income trends.	Labor market return to social skills was much greater in the 2000s than in the mid-1980s and 1990s

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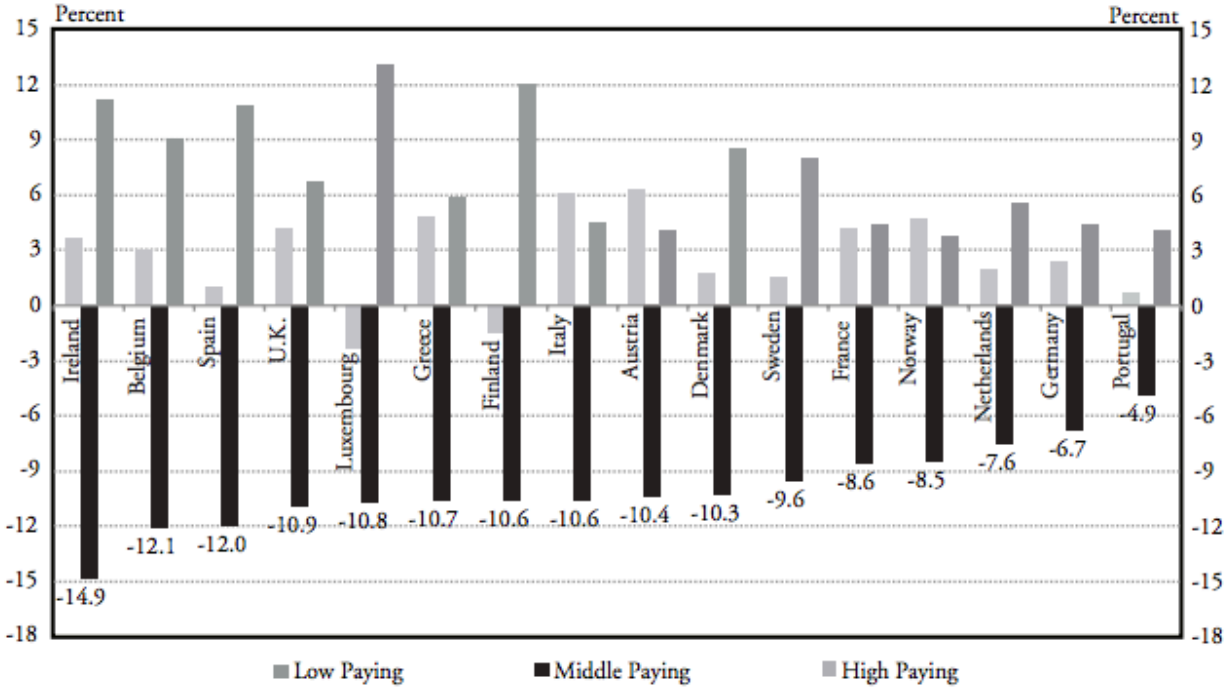
1.5. Job Polarization in Europe

A relatively large number of studies relying on different types of data sources have examined the extent to which similar job polarization patterns have occurred in European labor markets.

- Most European labor markets, including the Danish, have polarized in ways analogous to the US labor market.
- These findings are best explained by technological change as opposed to offshoring

Goos and Manning (2007) documented a similar job polarization of the U.K. labor market. They find employment growth in low-paying service jobs and high-paying professional and managerial jobs, and a decline in the number of jobs in the middle of the income distribution (e.g. clerical jobs and skilled manual jobs in manufacturing) over the period 1976-1995. Goos, Manning and Salomons (2009) broaden the perspective to include 16 European countries in their data and find similar job polarization patterns in almost all countries included, see Figure 4.



Notes: High-paying occupations are corporate managers; physical, mathematical and engineering professionals; life science and health professionals; other professionals; managers of small enterprises; physical, mathematical and engineering associate professionals; other associate professionals; life science and health associate professionals. Middle-paying occupations are stationary plant and related operators; metal, machinery and related trade work; drivers and mobile plant operators; office clerks; precision, handicraft, craft printing and related trade workers; extraction and building trades workers; customer service clerks; machine operators and assemblers; and other craft and related trade workers. Low-paying occupations are laborers in mining, construction, manufacturing and transport; personal and protective service workers; models, salespersons and demonstrators; and sales and service elementary occupations. Source: Goos, Manning and Salomons (2014, Table 2).

Figure 4: Job polarization in European countries.

Source: Autor (2014) with data from Goos et al. (2014)

For Denmark, the authors find employment growth in the highest paying occupations, employment contractions in the middling occupations and mildly declining employment in the lowest paying occupations. Goos, Manning and Salomons (2014) extend the data to include 2010 and find the same pattern, although for Denmark there is now a slight increase in the employment share of the lowest paying occupations (Figure 4). The main contribution of Goos, Manning and Salomons (2014) is to develop and test predictions of a model, which explains job polarization from changes in routineness and offshoring. Specifically, they use measures of the extent to which a job consists of routine tasks and the extent to which it consists of tasks that can be offshored and ask which of these features best predict reductions in number of hours worked. It is shown that routineness is the more important factor and that both within industry and between industry components are empirically important.

Spitz-Oener (2006) exploit survey data from West Germany, where the changing task content of occupations are observed (Autor, Levy and Murnane, 2003, cannot measure if tasks change within occupations over time due to e.g. technological change). She finds that occupations require more complex skills than earlier and that task changes mostly happen within as opposed to between occupations, again supporting the SBTC hypothesis. In addition, she shows that task changes are stronger in occupations where computers are more widely used. Dustmann, Ludsteck and Schönberg (2009) arrive at similar conclusions regarding job polarization using administrative data for West Germany.

Asplund, Barth and Lundborg (2011) use administrative microdata for Finland, Norway and Sweden for 1997-2005 and replicate similar patterns of job polarization as in Goos, Manning and Salomons (2009, 2014) for 22 occupations. They also find that relative wages have increased for the high-paying occupations and declined for low-paying occupations.

The findings for Sweden are echoed in Adermon and Gustavsson (2015), who use Swedish administrative data for 1975-2005. However, this is only the case for the latter part of the sample window, 1990-2005. They also document an expansion of jobs intensive in abstract tasks, a decline in jobs intensive in routine tasks, and no change for jobs intensive in service tasks. They do not find results for wage changes that are fully consistent with job polarization and routine biased technological change. They argue that wage formation in Sweden is more rigid than in Anglo-Saxon countries, which could explain why employment adjust more flexibly than wages.

Heyman (2016) uses Swedish matched worker-firm data for 1996-2013 to examine if job polarization also takes place at the firm level and whether any polarization can be attributed to occupation-based measures for routineness, offshorability or automation. Heyman (2016) finds that both the within-firm and between-firm components are important in explaining job polarization. However, job polarization at the firm level does not appear to be driven by offshorability or automation.[3]

[3] Sorgner (2017) uses a similar measure for (time invariant) occupation specific automation risk as Heyman (2016) to examine if this is related to the probability of individual worker transitions into unemployment in the German labor market. The author finds this to be the case, which may be taken

Harrigan, Reshef and Toubal (2017) uses matched worker-firm data for France to confirm that the French labor market has polarized. They also find that some of the polarization trend is due to within-firm changes, but most is driven by changes in the composition of firms. For the same time period (1994-2007) it is also documented that employment in technology related occupations increased and that firm-level trade increased. They examine how predetermined firm differences in the propensity to trade and adopt technology lead firms to change their size and employment mix over time. Firm-level measures of the capability to adopt technology is defined as the employment share of technology workers. They find that technology is the main driving force behind firm-level polarization as technology increases employment shares of top managers and mid-level managers while lowering shares of e.g. office and retail workers. Exporting is also found to explain polarization to some extent, while importing has a more traditional skill upgrading impact as skilled workers gain employment shares while unskilled shares fall.

Keller and Utar (2016) uses matched worker-firm data for Denmark to show that the Danish labor market also polarized during 1999-2009. They find that Chinese import competition caused employment to shrink in mid-wage jobs and to rise in low- and high-wage jobs. However, they do not employ any measure for technology to examine if technological change also explains job polarization in Denmark.

as evidence that higher risks of automation could be associated with adjustment costs in the labor market.

Table 1.5 European studies of job polarization

Study	Country	Dataset	Method	Measure of technology	Effect
Adermon and Gustavsson (2015)	Sweden	Administrative data for three years 1975, 1990 and 2005 with information about employment and wages by occupation and industry.	Calculation of employment growth for 1975-1990 and 1990-2005 by quintile of wage distribution. Reduced form regressions of job-specific changes in employment and wages on task measures for abstract, routine and service tasks.	None	High- and low-paying occupations expand employment shares relative to the middle for the 1990-2005 period but not for 1975-1990. Evidence for task biased technological change in wages is more mixed.
Asplund, Barth, Lundborg and Nilsen (2011)	Finland, Norway and Sweden	Administrative data for three years spanning 1997-2005 with information about employment and wages by occupation.	Calculation of employment and relative wage growth 22 two-digit occupations. Employment growth adjusted for wage changes in an extension.	None	High- and low-paying occupations expand employment shares relative to the middle. Relative wages have increased for the high-paying occupations and declined for low-paying occupations.
Dustmann, Ludsteck and Schönberg (2009)	West Germany	Administrative data on employment and wages by industry and occupation, 1975-2004	Calculation of employment growth for 1980-1990 and 1990-2000 by percentile of median wage in 340 occupations	None	High- and low-paying occupations expand employment shares relative to occupations in the middle in both the 1980s and the 1990s.
Goos and Manning (2007)	United Kingdom	Individual level survey data on employment by occupation, 1975-1999	Calculation of employment growth for 1976-1995 by percentile of median wage in three-digit occupations	None	Growth in low-paying service jobs and high-paying professional and managerial jobs, and a decline in the number of jobs in the middle of the income distribution (e.g. clerical jobs and skilled manual jobs in manufacturing).
Goos, Manning and Salomons (2009)	16 European countries including Denmark	Survey data on employment by occupation, 1993-2006	Calculation of employment growth for 1993-2006 by mean wage of occupations	None	High- and low-paying occupations expand employment shares relative to occupations paying close to the mean wage.
Goos, Manning and Salomons (2014)	16 European countries including Denmark	Survey data on employment by occupation, 1993-2010	Develop and test predictions of a model, which explains job polarization from changes in routineness and offshoring.	None	Routineness is more important than offshoring in explaining job polarization, and both within industry and between industry components are empirically important.
Harrigan, Resheff and Toubal (2017)	France	Matched worker-firm data for 1994-2007.	2SLS regression of firm-level employment growth on initial level of technology workers, imports and exports. Instruments are lagged values of endogenous variables.	Construct a measure for technology as the firm-level employment share of technology workers.	Job polarization is documented in the French labor market. Changes in the composition of firms is the main explanation behind polarization. Technology is the main driving force behind firm-level polarization, but importing and exporting also have influence.

Table 1.5 Continued

Study	Country	Dataset	Method	Measure of technology	Effect
Heyman (2016)	Sweden	Matched worker-firm data for 1996–2013 with occupational information at worker level. Measures for Routine Task Intensity, offshorability and automation risk at the occupation level are used.	Decomposition of overall change in occupation-level employment into within-firm and between-firm components, and reduced form firm-level regression of share of high, medium and low-wage workers on time dummies by initial routineness, offshorability and automation risk.	Use a measure for automation risk constructed from O*NET task data	Within firm and between firm components are both important in explaining job polarization. Offshorability and automation risk appear not to play a role for job polarization within firms.
Sorgner (2017)	Germany	Survey data (German Socio-Economic Panel) for households for 2005-2013 coupled with an occupational automation risk measure.	Cross section probit regression of transition out of employment on automation risk.	Use a measure for automation risk constructed from O*NET task data	Employment in occupations with high risk of automation is associated with higher unemployment risk
Spitz-Oener (2006)	West Germany	Survey data on skills, tasks and computer use, 1979-1999	Decomposition of overall change in task-level employment into within-occupation and between-occupation components, and reduced form estimation of occupation-level changes in task composition on changes in computer use.	Occupation-level data for computer use.	The within-industry component explains between 85 and 99% of the overall change in employment. Typically about half of the changes in task inputs are accounted for by computerization
Keller and Utar (2016)	Denmark	Administrative data for a panel of firms, 1999-2009 with information about Chinese import competition.	OLS and 2SLS regression of cumulated employment in low-, mid- and high-wage jobs on product-level Chinese import competition. Chinese import competition is instrumented with imports from China in other high-income countries.	None	Chinese import competition caused employment to shrink in mid-wage jobs and to rise in low- and high-wage jobs.

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1.6. The effects of technology on overall employment levels

As covered, technological change is responsible both for substantial shifts in the employment distribution and for increases in income inequality. However,

- There is no evidence that technological change affects overall employment
- Many workers in previous middle-skill occupation have not become unemployed but have been forced to move down the occupational ladder into services.
- These are results at the medium-to-long run level (at the horizon of a year or two and more).

It is important to note that whereas there have been dramatic shifts in the employment distribution over the past decades there is no reason to suspect that technological change will have reduced overall employment. Standard economic theory would predict that there is no fixed "lump of labor", i.e. not a fixed number of jobs. If a factory worker is replaced by new technology, then either these savings are passed on to consumers or kept by the factory owner. In either case somebody can spend more on new products and thereby create employment elsewhere. It is true that this employment need not be for the same people, in which wages should equilibrate to ensure close to full employment. Consistent with prediction, the empirical literature finds very little evidence that technology reduces overall employment. Gregory, Salomons and Zierahn (2016) and Autor and Salomons (2017) both use data for OECD countries to examine how technological change affect overall employment. Autor and Salomons (2017) use measures of total factor productivity as their measure of technological change (see box 1) and Gregory, Salomons and Zierahn (2016) use the extent to which industries were dominated by routine occupations – and hence more susceptible to routine-replacing technical change - in 1999. They both find that whereas improvements in productivity can substantially reduce employment in a given industry or region, there are strong countervailing effects: increases in productivity increase overall wealth of society and increases demand for the products of all other sectors.

These shifts in patterns are confirmed by Michaels, Natraj and Van Reenen (2014), who use data on the implementation of information and communication technologies (ICT) across 11 OCED countries. They take the importance of routine cognitive tasks suggested by Autor, Katz and Kearney (2008) seriously and first show that people with the highest level of education engage primarily in occupations that have mostly cognitive non-routine tasks, that people with middle level of education primarily engage in jobs of cognitive routine tasks, and that those with little schooling are primarily employed in occupations that are manual. They then use the substantial decline in prices of ICT from 1980 to 2004 and show that within each of these countries, industries for which ICT matters as lot, saw a disproportionate shift in employment from middle-educated employment to highly-educated employment with little relative change in the employment of people with low education, consistent with the hypothesis that ICT complements people with high education and is a substitute for people with middle levels of income.

So, although, overall employment seems to have suffered little, from the perspective of the workers not all jobs are created equally. Clearly a 50-year-old secretary with some college education cannot shift to a highly-skilled programming job, just because shifting technology upgrades the needs of his industry. However, most people are able to shift down the skill-distribution. Autor and Dorn (2013) first document that specific service occupations have shown substantial employment growth in the U.S. labor market between 1980 and 2005. By service occupations the authors have in mind for example food service workers, security guards, janitors, gardeners, cleaners, home health aides, child care workers and hairdressers. In other words, these are among the lowest paid and least educated job types, and they explain much of the lower tail of the job polarization process, i.e., the rise in employment shares in the bottom of income hierarchy. The authors then build a spatial model, where technological progress puts downward pressure on wages paid to routine tasks, which induces low-skilled workers to move into service occupations. Service occupations rely more heavily on manual tasks, and these are not influenced by computerization to the same extent. The model leads to some testable implications. Local labor markets that historically specialized in routine-task intensive industries should to a greater extent adopt computers, displace workers from routine task intensive occupations and push workers into service occupations. The authors confirm these predictions using data for U.S. local labor markets for the period 1950-2000.

In a follow up study, Autor, Dorn and Hanson (2015) build on the local labor market approach in Autor and Dorn (2013) and ask the question if international trade or technological change play the more important role for employment changes by examining the impact of Chinese import penetration and computerization on U.S. employment in a joint analysis. They find that Chinese imports play a larger role in the manufacturing employment decline after 2000, while local labor markets susceptible to computerization experience job polarization.

Table 1.6 Studies examining the impact of technology on overall employment

Study	Country	Dataset	Method	Measure of technology	Effect
Autor and Dorn (2013)	USA	Employment by occupation and commuting zones from Census Integrated Public Use Microsample for 1950, 1960, 1970, 1980, 1990 and 2000. Computer adoption is	Reduced form regressions of computer adoption and growth in service employment on initial share of routine employment at commuting zone level. Instrument for initial share of routine employment is a combination of local industry mix in 1950 and the occupational structure of industries nationally in 1950.	Computer adoption is measured by PCs per worker.	Commuting zones that historically specialized in routine-task intensive industries differentially adopt computers, displace workers from routine task intensive occupations and push workers into service occupations.
Autor, Dorn and Hanson (2015)	USA	Employment by occupation and commuting zones for 1980-2007.	Reduced form regressions of change in employment on initial share of routine employment and change in import exposure per worker at commuting zone level. Instrument for initial share of routine employment is a combination of local industry mix in 1950 and the occupational structure	None	Chinese imports play a larger role in the manufacturing employment decline after 2000, while local labor markets susceptible to computerization experience occupational polarization.
Gregory, Salomons and Zierahn (2016)	238 European regions	Industry/region specific measures of employment for 1999-2010	Panel data regression of employment on whether occupational distribution is routine.	Occupatioan-specific measures of routiness	Technological improvements can reduce employment in a given industry: however, these effects are compensated for by increases in employment demand by other industries
Autor and Salomons (2017)	Region/Industry level employment data for 19 European Countries	Industry/region specific measures of employemtn for 1970-2007.	Panel data regression of employment changes on TFP growth	Total Factor Productivity	Technological improvements can reduce employment in a given industry: however, these effects are compensated for by increases in employment demand by other industries
Michaels, Natraj and Van Reenen (2014)	11 OECD countries	Industry-level employment and industry-level reliance on ICT	Using data on employment and ICT spending on a panel data set of 11 countries from 1980-2004. Panel data regressions of employment changes on industry use of ICT	Use of ICT at the industry level	A 1 percentage point increase in use of ICT in industry is associated a 0.8 percentage point fall in prop. of middle-skilled workers (high-school – some college)
Autor, Katz, and Kearney (2008)	USA	US micro survey of individuals. 1963 – 2005	Calculations of different moments of the overall wage distribution. Tabulating changes in income inequality across time. No regressions.	None, inferred from income trends	Monotonic increase in income inequality until late 1980s. Thereafter wage polarization: an increase in $90^{th}/50^{th}$ income ratio, decline in $50^{th}/10^{th}$ income ratio.

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1.7. Business Cycles and Routine Tasks

This section reviews the evidence on the link between employment losses, job polarization and economic downturns.

- In the U.S. there is some evidence that the majority of the decline in employment in the middle-skill occupations has taken place during downturn and that the sluggish employment growth during the recovery is because these people struggle more finding new employment.
- These findings are not mirrored in Europe: there was no disproportionate drop in employment of “routine” occupations during the Great Recession and employment for these occupations has not recovered more slowly.

Jaimovich and Siu (2014) relate these findings to changes in employment over the business cycle. They show both that in the US a majority of the decline in employment in middle-skill occupations takes place during recessions and the persistent sluggishness of employment in recent upswings in the United States can be explained by slow growth for these middle-skill occupational groups. Graetz and Michaels (2017) show that these patterns do not in general translate to other OECD countries: industries that rely more heavily on routine tasks did not see a bigger decline during recessions and middle-skill employment have not recovered relatively slower over most OECD countries outside of the United States. It remains unclear why this is the case. Possible candidates for explanations are the slower adoption of ICT in the OECD than in the United States as discussed in Bloom, Draca, Kretschmer (2010) and Bloom, Sadun and van Reenen (2012) or the generally more flexible labor market in the United States.

The findings suggest important implications for the probability of finding a new job. A worker who loses his job due to technological change is typically able to find a job during normal economic times. However, during a downturn where many workers of similar skills find themselves looking for a new job this adjustment get be substantially longer. Since firms can more easily reduce their work force in the United States these effects are stronger there.

This is mirrored by the findings of Lordan and Neumark (2017) who examine the broad variation and changes in minimum wages across the United States. They replicate a common result of a persistent but small negative influence on overall employment, but show that this covers large variation across occupational groups. Amongst workers with little education those who are mostly harmed by minimum wage legislation are those who work in occupations with a high level of routine tasks They find that an increase in the minimum wage of $1 lowers the share of low-skilled automatable jobs by 0.43 percentage points. They interpret this as workers in routine tasks being more easily substitutable with capital.

Aaronson and Phelan (2017) extend this analysis: They show that minimum wage hikes only have a negative impact on employment for cognitive routine tasks and not for manual routine tasks. They interpret this as a higher substitutability of cognitive routine tasks with technology: regardless of the cost of a gardener at our current level of technology he is not easily substituted with technology.

Table 1.7 Business cycles and routine tasks

Study	Country	Dataset	Method	Measure of technology	Effect
Jaimovich and Siu (2014)	USA	Employment data for different occupations for the past 50 years	Time trends for employment recoveries across occupations	None	In the US a majority of the decline in employment in middle-skill occupations took place during recessions. These are the occupations that have recovered the slowest
Graetz and Michaels (2017)	17 developed countries	Employment data for different occupations for 1970-2011	Time trends for employment recoveries across occupations	None	Modern technology does not seem to be responsible for jobless recoveries outside the United States. The cause of the difference is unknown.
Lordan and Neumark (2017)	USA	Occupation-specific employment data for 1980-2015	Panel data regressions of employment on an interaction term of routine tasks in employment and minimum wage increases	None	Minimum wage increases have the biggest negative employment effects on occupations that are more routine
Aaronson and Phelan (2017)	USA	Occupation-specific employment data for 1980-2015	Panel data regressions of employment on an interaction term of routine tasks in employment and minimum wage increases	None	Minimum wage increases only affect workers working in cognitive routine tasks not those in routine manual tasks

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1.8. The use of robotics in production

Recently, automation and robotics have received much attention, but so far only a few studies have studied the consequences on labor market outcomes.

- Two studies find that increased usage of industrial robots is associated with higher industry-level productivity.
- One study finds that industrial robots have reduced overall employment in U.S. local labor markets, and one study show no impact on overall employment in German local labor markets.

A main driver of the wage and employment polarization that have been such a prominent feature of employment in all western countries is the introduction of ICT equipment. However, as of today, many of the associated productivity gains from ICT equipment are likely to have materialized. The question is whether future technologies such as artificial intelligence, self-driving cars and advanced robotics will show similar patterns. While there is naturally no empirical evidence on the consequences of self-driving cars, advanced robotics has been around sufficiently long to investigate the consequences empirically.

Graetz and Michaels (2018) are among the first to use a dataset from the International Federation of Robotics on the use of industrial robots across 14 industries and 17 developed countries (not including the United States). They estimate that the quality-adjusted price of robotics has fallen by around 80 per cent between 1990 and 2005, the period under consideration leading to an increase of the use of robotics of around 150 per cent. Perhaps not surprisingly the implementation of robotics leads to increases in productivity. More contentious is their effect on employment. While there appears to be no effect on overall hours worked, the implementation of robots reduces the number of hours worked by low-skilled workers compared with high-skilled workers. This result is robust to a number of different specifications, including an instrumental variable estimation using the susceptibility to robotics of industries in 1980 based on occupational composition. Kromann, Malchow-Møller, Skaksen and Sørensen (2016) find similar results in a study using the same data source for industrial robots at the industry-level, but where fewer countries, industries and years are included in the data. These findings are distinct from the results of Michaels, Natraj and Van Reenen

(2014) using ICT, which establishes that ICT disproportionately negatively affects middle-skill workers. The most plausible interpretation seems to be that the physical activities of industrial robots most readily substitutes for low-skill workers, whereas the computational activities of ICT most directly substitutes for middle-skill workers. While the effects of robotics are interesting, it is important to note that robots constitute around 2 percent of the total stock of capital.

Acemoglu and Restrepo (2017) attempt to estimate the direct effect of robots on employment and wages of low-skilled workers. Though robots - defined as reprogrammable automated production tools - are a focal point of much discussion of technology, they are still relatively limited in use. The international Federation of Robotics estimates that around 1.5 million robots are in use world-wide, slightly less than half of them in the auto-industry. Acemoglu and Restrepo (2017) exploit the fact that industries are diversely spread across economic areas of the United States. Some of the industries have benefitted much more extensively from increases in the use of robotics since 1990, and as a consequence some areas have been much more extensively impacted by the rise of robotics than others. The authors find that the use of one industrial robot per thousand employees has a negative influence on employment of around 0.2 percentage points and on wages by slightly less than 0.5 percent. The effect on employment implies that every industrial robot can perform the same amount of work as around 3-6 workers.

In a study examining the consequences of industrial robots in the German labor market, Dauth, Findeisen, Suedekum, and Woessner (2017) adopt the empirical approach of Acemoglu and Restrepo (2017) and document that robots are much more prevalent in Germany compared to the European average and the USA. In contrast to Acemoglu and Restrepo (2017) they find no effects of robots on total employment, but they do find a negative effect on manufacturing employment. The negative manufacturing employment effect is more than compensated for by increases in employment outside manufacturing. In a complementary analysis of the impact on individual wages they also find that high-skilled workers gain, while low-skilled and especially medium-skilled workers suffer in terms of lower wages when industry-level robot exposure rises.

Table 1.8 Studies examining the impact of industrial robots

Study	Country	Dataset	Method	Measure of technology	Effect
Graetz and Michaels (2018)	17 countries, 14 industries	IFR industry level dataset about the use of industrial robots for 1993-2007	Long difference analysis between the growth in labor productivity/TFP and robot adoption	Robot densification as number of robots per million hours worked	Growth of labor productivity and TFP strongly related to robot adoption
Acemoglu and Restrepo (2017)	USA	Industry-level variation in use of robotics and geographical in industry structure	Panel data regressions using employment across geography and industry. Test whether industry dependence on robots affects employment. Use robot use in Europe as instrument	Industrial robots defined as automated reprogrammable tools in production (IFR).	One industrial robot per thousand workers reduces employment by 0.2 percentage points and wages by 0.25-0.5 percent
Dauth, Findeisen, Suedekum, and Woessner (2017)	Germany	IFR (International Federation of Robotics) data on the use of industrial robots at the industry level and worker-employer matched data on 1 million workers in Germany for 1994-2014.	Same empirical approach as Acemoglu and Restrepo (2017).	Industry-level measure of the number of industrial robots per 1000 employees.	No impact on overall employment, but manufacturing employment falls. Every robot displaces around two manufacturing workers.
Michaels, Natraj and Van Reenen (2014)	11 OECD countries	Industry-level employment and industry-level reliance on ICT	Using data on employment and ICT spending on a panel data set of 11 countries from 1980-2004. Panel data regressions of employment changes on industry use of ICT	Use of ICT at the industry level	A 1 percentage point increase in use of ICT in industry is associated a 0.8 percentage point fall in prop. of middle-skilled workers (high-school – some college)
Kromann, Malchow-Møller, Skaksen and Sørensen (2016)	Nine European countries	IFR data on the use of industrial robots at the industry level and EUKLEMS data on value added, ICT capital, non-ICT capital, employment and the share of skilled workers at the industry level. The data covers 10 manufacturing industries and 2004-2007.	Estimation of the effect of industrial robots on productivity based on specification of production function.	Industry-level measures of the number of industrial robots relative to non-ICT capital and ICT capital per person.	More intensive use of industrial robots increases total factor productivity. Industrial robots are also associated with higher wages and unchanged employment.

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1.9. Automation at the firm level

Ideally one would want to examine the effects of automation on workers at the firm level.

- Due to data limitations there is almost no evidence to shed light on how automation affects workers at the firm level.

We reviewed a number of papers dealing with job polarization patterns using firm-level data above, but none of these ask questions about the implications of robotics and artificial intelligence because such data are not, at least until now, available at the firm level. In fact, Seamans and Raj (2018) argue that "…we lack an understanding about how and when robotics and AI contribute to firm-level productivity, the conditions under which robotics and AI complement or substitute for labor, how these technologies affect new firm formation, and how they shape regional economies. We lack an understanding of these issues because, to date, there is a lack of firm-level data on the use robotics and AI." In addition, a number of questions of importance for policy require even more detailed data, where workers are tracked across firms and over time. Such data would enable researchers to examine the extent and magnitude of worker-level adjustment costs to automation and AI, which would be valuable information for the design of optimal education and training policies.

One exception is the study by Fort, Pierce and Schott (2018), who use U.S. firm and plant data for 1977-2012 to document overall patterns in their adoption of new technologies. Interestingly, they can measure firms' adoption of new technologies in novel ways. There is information about computer purchase, use of electronic networks to control shipments, and imports of industrial robots at the firm level. In a series of descriptive exercises, they document that manufacturing firms' total employment, including employment in non-manufacturing plants, increase from 1977 to 2012, and that manufacturing firms, that adopt technologies, are larger and more productive. Plants within manufacturing firms that adopt new technology are also more likely to survive.

In ongoing work, Anders Humlum (2018) uses matched worker-firm data from Denmark, where firm-level purchase of robots is identified from imports of detailed product codes for industrial robots as in Fort, Pierce and Schott (2018). The research questions explored are precisely whether workers in firms introducing robots are adversely affected, and whether any adjustment costs depend on worker skills and tasks. In addition, this study aims to shed light on how robots have different effects from other types of capital and machinery.

Table 1.9 Studies using firm-level automation measures evaluating labor market outcomes

Study	Country	Dataset	Method	Measure of technology	Effect
Fort, Pierce and Schott (2017)	USA	Census data for manufacturing firms, 1977-2012, including three firm-level technology measures.	Size and productivity premia regressions on technology measures and importing.	Three firm-level technology measures: computer usage, use of electronic networks to control shipments and imports of industrial robots.	Manufacturing firms' total employment, including employment in non-manufactring plants, increase from 1977-2012. Manufacturing firms that adopt technologies are larger and more productive. Plants within manufacturing firms that adopt technology are more likely to survive
Humlum (2018)	Denmark	Matched worker-firm data, 1988-2015 coupled with firm-level foreign trade data.	Event study regressions of robot adoption on worker-level earnings and firm-level wage bill.	Firm-level import of industrial robots.	N/A

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1.10. International trade, technology and labor market outcomes

New technologies and international trade may both affect labor market outcomes directly, but there may also be indirect labor market implications as discussed in Section 1.2.

- There is solid evidence showing that new technologies indirectly affect labor markets through induced changes in international trade, and that increased trade indirectly affect labor market outcomes through the introduction of new technologies.

The increasing wage gap between high- and low-skilled workers in the 1980s and job polarization trends in the 1990s and later have mainly been attributed to technological change, but as mentioned above, some studies also examine if other explanations such as international trade play an important role (e.g. Feenstra and Hanson 2003, Goos, Manning and Salomons 2014 and Autor, Dorn and Hanson 2015). In fact, as argued by Fort, Pierce and Schott (2018) it is highly likely that trade and technology are jointly determined, making it difficult to claim that changes in labor market outcomes are exclusively caused by only one of these forces. For example, Bloom, Draca and Van Reenen (2016), find that British firms exposed to greater Chinese import competition are more likely to innovate, and Kromann and Sørensen (2017) show that Danish firms exposed to international competition from China invest more in automated production capital. In a similar vein, Andersen (2015) show that Danish firms that are induced to offshore more by changing conditions in world markets have higher R&D expenditures, more product innovation and hire more R&D workers. By contrast, Bøler, Moxnes and Ulltveit-Moe (2015) and Fort (2017) find that innovation induces trade for Norwegian and U.S. firms respectively.

Table 1.10 Studies examining the link between trade and technology

Study	Country	Dataset	Method	Measure of technology	Effect
Bloom, Draca and Van Reenen (2016)	Twelve European countries	Firm-level panel data from 1996 to 2007	OLS and 2SLS regression of changes in firm-level patents, IT intensity and TFP on Chinese import competition	Patenting, IT, and total factor productivity	Chinese import competition induces technical change within firms.
Andersen (2016)	Denmark	Administrative data for a panel of firms, 1995-2008 with information about R&D expenditures and imports of intermediate inputs.	OLS and 2SLS regression of R&D expenditures, product innovation and number of R&D workers on firm-level offshoring. Firm-level offshoring is instrumented by changes in world export supplies of products imported by Danish firms.	Firm-level R&D expenditures, product innovation and number of R&D workers.	Offshoring increases R&D expenditures, product innovation and the number of R&D workers in Danish firms.
Fort (2017)	USA	Census data for manufacturing firms, 2002-2007, including information about adoption of communication technology and purchase of contract manufacturing services (fragmentation).	Cross section regression of propensity to purchase manufacturing services on firm-level technology. Interaction of firm-level technology with industry-level electronic codifyability resemples a difference-in-difference regression.	Firm-level adoption of communication technology.	Adoption of communication technology is associated with higher probability of fragmentation.
Bøler, Moxnes and Ulltveit-Moe (2015)	Norway	Administrative data for a panel of firms, 1997-2005 with information about R&D expenditures and imports of intermediate inputs.	Difference-in-difference regression of R&D expenditure on number of imported products on a treatment indicator. Exploit reduced R&D costs from a R&D tax policy change in 2002.	Firm-leve R&D expenditures.	Lower R&D costs induce the affected firms to increase R&D expenditure and the number of imported products, including imported capital goods.
Kromann and Sørensen (2017)	Denmark	Firm-level survery dataset covering 474 manufacturing firms in 2005, 2007 and 2010.	Reduced form panel regressions of automated capital on Chinese trade competition and of value added on automated capital	Firm-level measure of automated capital stock based on percentage of new capital investments in machinery and equipment targeted at automation.	Increasing international competition from China increases investments in automated production capital and increasing automation increases productivity.

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Chapter 2 – Productivity and technological change

This chapter analyzes how new technologies have affected firm performance, with an emphasis on labor productivity – output by unit of labor - and total factor productivity – output corrected for all inputs.[4]

- The adoption of new technologies is expected to have profound effects on the activities performed by the firm and their performance and productivity. Yet, it is also associated with serious measurement issues. Given this well-documented problem, economists and statistical offices have developed new methods and new datasets to properly measure the IT revolution and its consequences on the measurement of productivity.

As laid out in Box 1, it should be noted that gains in productivity are themselves often taken as a measure of technological change. What is commonly referred to as total factor productivity is the part of output unexplained by inputs and can roughly be considered as a residual term of a regression (see Box 4 for a simplified technical explanation). In a seminal paper on growth accounting, Solow (1957) showed that about half of total growth in the United States could not be explained by the increase in the use of factors of production, labor and capital, and could therefore be related to technical improvements. (see Box 5 for a brief discussion of this approach). For this reason, it is often referred to as a measure of our ignorance, and the challenge for economists has been to reduce our ignorance by trying to reduce this noise.[5] Typically, this is done by adding more variables in the equation, such as labor quality, management quality or ICT use.

As discussed previously, what is considered as ICT tools has been evolving over time with the development of new tools and increased quality of datasets available to researchers. This constant process of researchers attempting to measure the latest technological improvements continues to this day with the increased use of industrial robots and the development of AI.[6]

[4] Tables in this section follow the same layout as a previous survey on the topic by Draca, Sadun and Van Reenen (2006). It adapts and updates their setup to account for new evidence.
[5] See e.g. the discussion in Syverson (2011) and Haltiwanger et al. (2018).
[6] See e.g. the discussion in Brynjolfsson, Rock and Syverson (2017) and later below.

Box 4: Production function estimation

Researchers in industrial organization have been estimating production functions for decades. The typical equation starts from a measure of output (in the natural logarithm) on the left-hand side, either real revenue or real value added. On the right-hand side, inputs (in logs) are labor, capital and material in the case of the real revenue specification. Capital can also be decomposed into ICT and non-ICT components when proper measures are available. The regression to be run therefore looks like:

$$\log(\text{Output}) = f\,(\log(\text{Input}); \beta) + \varepsilon$$

where β is a vector of coefficients to be estimated. The error term ε is the part of output level unexplained by inputs, and is called total factor productivity (in levels). The role of this exercise in the context of this study is to estimate if ICT capital positively contributes to output in a significant way.

One problem when estimating this equation is that the choice of inputs is potentially endogenous, so we cannot simply run the easiest estimation procedure, ordinary least squares (OLS). Various methods have been designed to deal with this endogeneity issue. The most commonly used methods use a so-called modified control function approach. Two leading references are Wooldridge (2009) and Ackerberg, Caves and Frazer (2015). Another problem is that very few datasets provide information about ICT capital stock. Capital stock is then proxied using the information about investment flows, which could generate severe measurement biases.

An important decision to take is which functional form should be chosen. The most popular one is the Cobb Douglas, where the inputs simply enter in a linear way. Another popular form is the translog production function, where a polynomial of second degree is used. The advantage is that it is a more flexible form, it allows to capture complementarities and output elasticity also varies by firm. Other functional forms allow even stronger complementarities such as the CES-translog.

Box 5: Growth accounting framework

The role of this exercise, made popular by Robert Solow in the 1950's, is to decompose output growth, either real production or value added, into the growth of inputs used for production, and an unexplained part. Typically, inputs considered are labor, capital and material in the case of the real production decomposition. Capital can also be decomposed into ICT and non ICT components when proper measures are available. Statistical offices have been improving the measurement of ICT capital over the years, so this variable is generally available at the aggregate and sector levels (see e.g. the EU KLEMS project).

The following equation provides a simplified version of the framework:

$$\Delta \text{ Output} = \alpha \, \Delta \text{ Input} + \varepsilon$$

where Δ indicate a change over a specific period (it can be 1 year, 5 years or even longer periods), α is a vector that measures the weights of the respective inputs in the production process, typically their expenditure share, and ε is the part of production growth that can't be explained by the growth of inputs. It is referred to as total factor productivity growth. This analysis can be conducted at the aggregate level, at the industry level and also at the firm level. No estimation is required, it is a straightforward computation once the variables are available and can be trusted to a reasonable level.

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2.1 Early sector level evidence from the US: the Solow paradox

This section examines the early attempts of relating the use of technology, notably IT, with increases in productivity. These papers used aggregate or industry-level data.

- For many years, economists and policy makers expected IT to generate productivity gains, but there was no evidence of it and little measures available to test it until the middle of the 1990's. Some early evidence at the sector level even indicated a negative contribution of IT capital to production or benefits below costs.
- However, researchers were concerned both about the measurement of output (Griliches, 1994) where quality is hard to measure and about the measurement of IT capital where deflators are hard to estimate.
- Studies focused on the manufacturing industry, while service sector was more likely to adopt these early IT tools.
- Also, several economists convincingly argued that firms are the economic players making IT investment, and therefore the econometric analysis should be conducted at the firm level and not at the aggregate or sector level.

This led Nobel prize winner Bob Solow to write the famous sentence in the New York Times that "*you can see the computer age everywhere but in the productivity statistics*", what is referred to as the Solow paradox (Solow, 1987). Since then, both statistical offices and empirical economists have tried to prove him wrong.

One important study by Berndt, Morrison and Rosemblum (1992) found that changes in high tech capital stock (computers, communication equipment, scientific instruments and photocopy equipment) were negatively related to labor productivity growth. Another study by Morrison and Berndt (1991) found that that marginal returns of investment in high tech capital were lower than the marginal costs, suggesting overinvestment in IT. The debate also centered on measurement issues and more importantly the unit of measurement.

Table 2.1: Studies about early evidence using industry level data

Study	Country	Type of Data / years	Method	Measure of Technology	Effect
Morrison and Berndt (1991)	US	2-digit manufacturing, 1952-1986	– cost function estimation using 3SLS and derivation of a shadow value of O capital and Tobin's Q ratio (benefit/cost)	"high-tech" office and information technology equipment (0) from BLS	estimated marginal revenue of O capital lower than marginal cost
Berndt, Morrison & Rosenblum (1992)	US	2-digit manufacturing, 1968-1986	– Labor productivity and profitability equations	"high-tech" capital aggregate of office and information technology equipment (0F) from BEA	changes in labor productivity are negatively related with changes in OF capital

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2.2 Firm level evidence from the US

- A first wave of papers used private survey data about computer stocks as a measure of IT capital. Altogether, despite their limitations and small sample size, these early studies suggested a positive effect of IT on productivity and contradicted the so-called Solow productivity paradox.
- When firms invest in new tools, it takes time for them to reap the fruits of their investment, as they must learn how to use these tools and might also need complementary inputs such as skilled labor.
- Economists in cooperation with statistical agencies have designed new surveys to capture the adoption of IT in production rather than computer adoption. Studies using these datasets have found strong correlations between the use of ICT in production and firm productivity, but mostly explained by selection.

The first papers in the modern age to analyze the effect of IT on productivity used survey data collected by the International Data Group on IT Capital, covering 367 large Fortune 500 firms at the end of the 1980's and the beginning of the 1990's. These researchers were able to distinguish between computer capital and non-computer capital, and to identify clean price deflators for these specific inputs. They were also able to identify how many workers were working in IT. When estimating the production function, they were therefore able to compute a measure of the marginal product of IT capital and IT labor. The first papers used a simple Cobb Douglas specification and simple OLS, ISUR or 2SLS regressions as robustness checks.

Brynjolfsson and Hitt (1996) found that both IT capital and IT labor were significantly related to output, and their marginal products were larger than their non-IT counterparts. Every additional dollar spent in computer capital was measured to be associated to 81 cents per year on the margin, compared to a little more than 6 cents for non-computer capital. On the other hand, the net marginal product of IT staffs was 1.62 dollars per dollar used. Returns to IT capital also declined over time, as it was estimated lower in 1990-1991 compared to the period 1987-1989. It also varied by industry, the gross marginal product of returns being the highest in non durable manufacturing, and negative in mining. It was however difficult to establish that the benefits outweighed the costs, although they showed that investing in IT capital was more profitable than investing in non IT capital.

Discussion followed on the right specification for the estimation of the production function, in particular regarding the choice between a Cobb Douglas and a more flexible translog functional form that allows for complementarity between factors of production. There was also some discussion about interpreting the significance of this relationship. Indeed, there was very little care devoted to the endogeneity of the IT investment decision in these initial papers. One way to try to capture the "selection effect" (i.e. the fact that more productive firms are more likely to invest in IT in the first place) is to estimate the production function with a firm fixed effect (we will discuss the criticism of this approach later in this section). Brynjolfsson and Hitt (1995) find that using a translog instead of a Cobb Douglas does not affect the measurement of the output elasticity of IT capital. They used the same datasets with an additional year. However, their new calculations of the marginal product of IT stock dropped to 53% in the Cobb Douglas specification. Interestingly, they also found that the elasticity of IT capital dropped by around half when using a fixed effect in the specification, indicating that unchanged firm characteristics explain about half of the IT effect. This is a strong indication of selection, although it does not really control for endogeneity

Lichtenberg (1995) used similar data published in two computer magazines (Computerworld that overlaps with the IDG dataset used by Brynjolfsson and Hitt and Informationweek that provides less precise measures of IT capital) for the period 1989-1993. The sample size varies a lot depending on the year considered, from 209 firms in 1988 to 441 in 1992 in the ComputerWorld data (similarly from 190 firms to 245 in the InformationWeek dataset), suggesting a composition effect that might affect the estimation strategy (another problem of selection). However, keeping these limitations in mind, the study found large and significant effects of IT capital using both datasets using a Cobb Douglas OLS specification. The coefficient was around 0.1, suggesting that 1 dollar invested in IT yields a return of 10 cents in output. They also establish evidence of substantial excess returns to investment in computer capital. IT labor was also established to positively affect output in a significant way. They moreover found that the marginal rate of substitution between IT and non IT employees was equal to 6, i.e. 6 non IT employees would be needed to substitute one IT worker.

Dewan and Min (1997) used the same data as Brynjolfsson and Hitt and estimated a CES-translog, an even more flexible form. They found that IT capital was a net substitute for non IT capital and non IT labor, as well as evidence of positive returns to IT investment. Their mean elasticity of IT capital was found to be 0.1 similar to previous studies, but the implied gross marginal product for the median firm was found to be higher, at 117%, but with substantial dispersion implied by the choice of functional form for the production function. IT output elasticity was also found not to differ between manufacturing and service firms, but the elasticity of substitution between computers and labor was higher in manufacturing than in services (1.35 vs. 0.91). However, firms with higher IT intensity (i.e. a higher share of IT expenses) had higher IT output elasticity, but not higher marginal product of IT.

In a follow up paper, Brynjolfsson and Hitt (2003) use a slightly larger sample of US firms (524 firms for the period 1987-1994) provided by Computer Intelligence InfoCorp (CII), but more interestingly adopt a new methodology for computing short (1 year) and long (5 and 7 years) differences in total factor productivity. The measure of productivity growth obtained can then be regressed on a measure of computer growth in short and long difference as well. They find that IT capital makes a significant contribution to productivity and output growth in the short run, but the contribution is 5 times larger in the long run. This suggests that IT might take some time and require some adaptation and investment in complementary inputs, as we discuss in the next section. Of course, one problem with this long run analysis is that it restricts the sample to firms present over the entire period.

McGuckin et al. (1996) used the new Surveys of Manufacturing Technology (SMT) as described in Box 1 to analyse how the adoption of new IT technologies in production was associated with labor productivity, defined as the log of value added per worker. This information came from another database, the Longitudinal Research Database (LRD), containing accounting data. They ran a simple OLS regression where labor productivity is related to capital intensity and use of technologies. They find that firms adopting more of these technologies had higher productivity growth, but they acknowledge that this result is mostly explained by a selection effect: better firms adopted better technologies, so they documented a correlation between technology and productivity, not a causal effect.

A more recent paper by Aral, Brynjolfsson and Wu (2006) defines IT as the use of Enterprise Resource Planning (ERP), Supply Chain Management (SCM), and Customer Relationship Management (CRM). They obtained the data from one large enterprise systems vendor from 1998 to 2005, covering all their customers. The dataset covered 2,428 establishments from 725 firms, 623 of which could be matched with Compustat to obtain performance data. They find evidence of strong association between labor productivity and all three IT measures.

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Table 2.2: Studies about early firm level evidence from the US

Study	Country	Type of Data / years	Method	Measure of Technology	Effect
Brynjolfsson & Hitt (1996)	US	367 large Compustat firms 1987-1991	OLS, ISUR and 2SLS	Computer capital stock CII (Harte Hanks) value of total IT stock; IDG (firms stated value of mainframes plus no. PCs)	– both IT capital and IT labor significantly related to output – marginal return of IT capital larger than non IT capital
Brynjolfsson & Hitt (1995)	US	large Compustat firms 1987-19923; 1,185 observations	translog OLS	Computer capital stock CII (Harte Hanks) value of total IT stock; IDG (firms stated value of mainframes plus no. PCs)	– estimates of IT elasticity with translog little changed compared to Cobb Douglas settting – firm fixed effect explains around half of the returns to IT – marginal product of IT at least as large in firms that did not grow as in firms that grew
Lichtenberg (1995)	US	190 to 450 firms	OLS Cobb Douglas	Computer and non-computer capital stock, ICT and non-ICT labour	evidence of excess returns of IT capital and IT labor
Dewan & Min (1997)	US	Computerworld data matched to Compustat.	CES-Translog production functions	Market value of computer hardware and labour expenses for IT staff	- IT capital net substitute for non IT capital and non IT labor - evidence of positive returns to IT investment
Brynjolfsson & Hitt (2003)	US	527 large Compustat firms 1987-94	OLS, short and long differences. Production function and TFP equation	Computer capital stock CII (Harte Hanks) value of total IT stock; IDG (firms stated value of mainframes plus no. PCs)	– computerization makes a contribution to measured productivity and output growth in the short term (using 1-year differences) – productivity and output contributions associated with computerization are up to 5 times greater over long periods (using 5- to 7-year differences).
McGuckin et al. (1996)	US	Surveys of Manufacturing Technology (SMT), 1988 and 1993	OLS regression where labor productivity is related to capital intensity and use of technologies in manufacturing production	17 questions on technologies "generally associated with the use of computers and information technology to design, develop, and control manufacturing production"	– firms adopting more IT technologies in production had higher productivity growth – result mostly explained by a selection effect
Aral, Brynjolfsson & Wu (2006)	US	data from one large enterprise systems vendor, 1998-2005	OLS regression of labor productivity on IT measures	use of ERP, SCM and CRM	strong association between labor productivity and all three IT measures.

2.3 Revised aggregate and sector level evidence from the US

- Cleaner and more reliable measures of ICT capital became available at the industry and aggregate level at the end of the 1990s.
- At the aggregate and sector level, IT started to show up more clearly as a contributor to economic growth and labor productivity.

Jorgenson and Stiroh (2000) discussed how the "remarkable transformation" of the US economy could be related to decreasing price of IT, leading to an explosion in investment by firms (see also Jorgenson, 2001). Using a standard growth accounting approach but improved data (in particular regarding the deflators of capital, software and communication equipment), they estimated (table 2, p. 143 and figure 4 p. 145) that average labor productivity grew at a rate of more than 1 percentage points faster than the initial 5-year period between 1995 and 1998, mostly explained by an increase in capital deepening, especially IT capital (contributing to half a percentage point) and faster TFP growth (contributing to 0.6%). Initially, the gains were estimated to come mostly from IT producing industries, although not entirely (p. 159), but it was argued that they would quickly spill over to the rest of the economy, in particular the service sector.[7] Using different data but a similar approach, Oliner and Sichel (2000) argued in their review that it took time for computing equipment to become large enough to make a contribution. But by the end of the 1990's, they estimated that ICT capital accounted for 2/3 of the acceleration in labor productivity in the US non-farm business sector.

Using more disaggregated data at the industry level and for a slightly longer period, Stiroh (2002) argues that more recent evidence suggests that the increased rate of productivity growth in the US since the mid 1990s had come from the joint contribution of the IT production sector and IT use in the rest of the economy, leading to a new consensus. He showed that 2/3 of the industries considered had experienced acceleration in productivity. When excluding the IT sector, there was still strong evidence of stronger productivity growth in the rest of the economy. Using a novel

[7] See also Gordon (2000) and Gordon (2003) who argues that there was no structural acceleration in TFP, which was mainly a cyclical phenomenon. His consideration was however quite isolated compared to the mainstream view discussed above.

method of decomposition of aggregate labor productivity growth, he showed that IT-producing and IT-using firms accounted for all of the contribution to the growth acceleration, with a respective importance of 0.17 and 0.87.

The productivity growth accelerated in the period 2001-2003. As mentioned in Brynjolfsson and Saunders (2010), companies were able to “reap and harvest” after the investments made over the previous few years. Experts agreed that the gains had come from the ICT producing sector and the sectors relying on ICT (see e.g. Oliner and Sichel, 2002; Fernald and Ramnath, 2004; Jorgenson et al., 2008).

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Table 2.3: Studies about revised aggregate and sector level evidence in the US

Study	Country	Type of Data / years	Method	Measure of Technology	Effect
Jorgenson & Stiroh (2000)	US	National Income and Product Accounts (NIPA), 1959-1999	– growth accounting decomposition	Computer capital investment and capital, software investment and capital, communication equipment and capital	– aggregate labor productivity (ALP) grew 2.4 percent per year during 1995–1998, more than a percentage point faster than during 1990–1995 – capital deepening added 0.49 percentage point to ALP growth; faster TFP growth contributed an additional 0.63 percentage point
Oliner & Sichel (2000)	US	BEA & BLS, 1972-1999	– Detailed growth accounting – Breaks down contribution to output growth according to income shares and input growth rates	computer hardware, software & communication equipment Productive stocks are calculated for hardware using detailed BLS equipment data	– IT capital contributed for almost 25% of output growth rate during 1996-1999 (1.1% of the 4.8%) – IT contribution for the period 1974-1995 was 0.5-0.6% – IT producing sectors experienced acceleration at 40% of total TFP growth for 1996-1999.
Gordon (2000)	US	Same as Oliner and Sichel (2000)	– growth accounting, decomposing output/hour according to (i) cyclical effects; (ii) contribution of IT- producing sector	Same as Oliner and Sichel (2000)	– no evidence of structural acceleration in productivity during 1995-1999 (once controlling for cyclical and IT producing sector effects)
Gordon (2003)	US	quarterly BLS data on 4 sectors: non- farm private business, manufacturing, durables, non- durables, 1972-2002	– similar growth accounting decomposition – further business cycle decomposition	Same as Oliner and Sichel (2000)	– Oliner & Sichel (2000) assume an unrealistic instant pay-off to IT investment – Micro evidence in retail suggests productivity revival is uneven – concentrated in new establishments only – Cross-state comparisons do not exhibit the expected relationship between IT intensity and state productivity
Oliner & Sichel (2002)	US	BEA & BLS, 1974-2001	– Growth accounting as in Oliner and Sichel (2000) – multi- sector growth model to assess sustainability of IT-driven growth to make projections.	Same as Oliner and Sichel (2000)	– Earlier results on contribution of IT using and producing sectors still valid despite the dot.com bubble. – Model projections of 2 - 2.75% labour productivity growth/year over the next decade

2.4 International evidence: Preliminary aggregate and sector-level evidence from the UK

The above-mentioned studies so far have only concerned the US. During those years, European policy makers developed some fears that European companies had missed the opportunity to upgrade their capital and were losing competitiveness compared to their US counterparts.

- A first set of European studies focused on the UK. They showed that UK firms were apparently less efficient at using IT, and that might have contributed to the productivity gap between Europe and the US.
- Lack of data was limiting a better understanding of the poor performance in the UK relative to the US, not to mention other European countries. In particular, there were no firm level analyses of the role of ICT to explain firm performance.
- An important contribution by Bloom, Sadun and Van Reenen (2012) showed that subsidiaries of US multinationals in Europe benefitted from stronger returns to IT than UK firms. They interpreted these results as evidence that Americans do IT better, probably because they have also adopted better management practices that are complementary to IT.

Using aggregated data, Oulton (2002) generated a series of stylized facts about differences between the UK and the US during the 1990's. First, ICT investment followed a similar trend, increasing significantly in both countries, with an acceleration in the 2nd half of the 1990s. Second, the contribution of IT capital to growth was much larger in the US than in the UK. ICT definitely contributed a lot to GDP growth (around a fifth over the period 1989-1998), capital deepening (higher capital per hour worked, especially ICT capital - it contributed to 90% for the last 5 years), and by extension labor productivity (close to half over the last 5 years of the study, 1994-1998, and around 25% for the entire decade). But it was in a context of decreasing TFP growth and labor productivity. The author suggests in his conclusion that it would be more informative to break down the aggregate estimates by sector.

Basu et al. (2004) followed Oulton's suggestion and provided a disaggregated analysis at the sector level. They also compared the relative productivity performance of the US and the UK, and the contribution of ICT in both countries. For this, they first had to construct an industry-level dataset that included information about ICT investment and capital. They stress the role of ICT as a general purpose technology (GPT) which suggests that complementary investments are necessary to fully get the benefits of ICT investments. To test this, they look at the correlation between ICT capital growth rates and TFP growth by sector in the US and in the UK. In the US, they find a strong relationship, and relatively mixed results for the UK. They argue that this can be explained by stronger unmeasured investments in intangible assets (complementary to ICT capital) in the US compared to the UK as discussed in Chapter 3.

Bloom, Sadun and Van Reenen (2012) were among the first to propose a novel test for the hypothesis of lower IT use and performance in Europe compared to the US: they look at US subsidiaries in Europe and compare them with establishments owned by non US multinationals and purely domestic establishments. They use two main datasets: one covers only UK based establishments and is provided by the Office of National Statistics (ONS), the UK statistical institute. The second source comes from a combination of a self conducted survey in European countries by the authors and IT data from a marketing and information company Harte-Hanks. They find that subsidiaries of US multinationals have both higher IT and generate more benefits from their IT investment in both their datasets. For the UK only experiment, they also show that UK firms acquired by US multinationals did not have higher contribution to output from IT investment from their non-acquired counterparts, but that changed after their acquisition, as IT started to contribute more to output. This suggests that US owners modified the way IT was used, going against the selection story, and suggesting that US acquisition **causes** more efficiency in IT use. From their European sample, they are also able to include management practices in their analysis. They show that management practices explain why US firms have higher IT output elasticity. Once creating an interaction between IT and quality of people management, the US premium on IT use disappeared.

Table 2.4: Studies about evidence in the UK.

Study	Country	Type of Data / years	Method	Measure of Technology	Effect
Oulton (2002)	UK	ONS data for national accounts. US producer price indices (adjusted for exchange rates) used to value ICT. Value of software adjusted upwards.	Growth accounting	Computers, software, telecoms equipment, semi-conductors.	– ICT contribution to GDP growth increased from 13.5% in 1979-1989 to 20.7% in 1989-1998. – ICT contributed 55% of capital deepening during 1989-1998 and 90% for the period 1994-1998.
Basu et al. (2004)	UK	34 industries, 1979-2000. (BE, Bank of England dataset).	Look for unmeasured complementary investments and presence of TFP gains amongst IT- using and non- using sectors. (test of the GPT hypothesis)	Value of IT hardware and computer equipment	– Investments in IT stock affect a firm's market valuation ten times more than investments in other tangible assets like capital stock. – ICT capital services growth positively correlated with TFP. – ICT investment also positively correlated with TFP suggesting scope for the GPT hypothesis (given shorter lags in the UK).
Bloom, Sadun and Van Reenen (2012)	U.K., 21,746 clean observations European countries, 720 firms, 2,555 observations	ONS survey and e-commerce survey, 1995-2003 CiDB database, 1999-2006	OLS and fixed effect regression of an augmented production function including IT capital	IT expenditures; number of workers using a computer; proportion of college workers	– IT capital has strong effect on output – IT capital in subsidiaries of US firms has a stronger impact on output

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2.5 International evidence: The EU KLEMS Project

In the early 2000s very little was known about the impacts of ICT on firms productivity in Europe in general. As a consequence, great effort was made to improve the quality of data.

- Frustrated with the lack of available information about ICT use and investment, the European Commission launched a large scale effort to collect data, sponsoring a team of well-known experts in growth accounting to coordinate with Eurostat and national statistical institutes to create a sector level database. This database would include very precise measures of IT capital and investment, comparable across countries, taking great care at the measurement of price and proper deflators by type of capital, something that had clearly been lacking before.
- A large number of studies using this new database indicated significant contribution of ICT to labor productivity growth, but lower than in the US.

van Ark et al. (2002) discussed and analyzed the construction and exploitation of a new European wide sector level dataset for 12 European countries before enlargement, originally for the years 1980-2000, including measures of ICT investments and capital. They document that investment rates increased as quickly in Europe as in the US, while the share of ICT was between half and 2/3 of the US. As a consequence, ICT contribution to labor productivity growth was about half of the US equivalent (see Box 5). In addition, spillovers from investment in ICT and non-ICT were found to be much lower. In more recent years, this situation has improved, but labor productivity itself has stagnated. Ark et al. (2002) also documented substantial differences between countries. Ireland for example showed higher ICT contribution than the US (although possibly due to US FDI in Ireland). There were differences in the composition of ICT as well: Nordic countries had relatively higher share of the software component. They also suggested a few structural reasons behind this decline in aggregate productivity, in particular product- and labor market rigidities, and the lack of competition and capability to redeploy resources to their best use.

This is how the EU KLEMS project was initiated. The period of analysis was later extended to longer period (1970-2005, and more recently updated to 2016), and the number of countries covered increased from 12 to 29. Thanks to this wealth of new data, a thorough in-depth analysis followed, and a few conclusions quickly came to light. First, most of the explanation of why Europe lagged behind the US in terms of labor productivity in the 1990's and afterwards can be attributed to lower contribution of ICT to growth. The most convincing explanation for this result is mostly that ICT is put to a better use in the US compared to Europe. Second, there was no evidence, neither in the US nor in Europe of positive spillovers of ICT on TFP. These results are discussed in details in van Ark and Inklaar (2005), O'Mahony and Timmer (2008), or van Ark, O'Mahony and Timmer (2008). For Denmark, it showed an increase in average yearly labor productivity over the period 1995-2005 of 1.6 percentage points for the market economy, of which 1.3 percentage points could be attributed to the knowledge economy, a figure similar for the EU, but much smaller than the US where labor productivity increased by 2.9% at an annual rate, and almost all of 2.7 percentage points could be explained by the growth in ICT capital, labor composition and TFP.

Using data from the EU KLEMS project, Lind (2008) analyzed the role of ICT on the development of labor productivity in Sweden and Finland with a particular focus on ICT producing sectors. The analysis is particularly relevant given that comparative advantage in communication equipment manufacturing over the period of analysis, with Eriksson and Nokia being global players at the time. Sweden had a considerable higher labor productivity compared to Finland at the beginning of the period, but the author observed a convergence since the beginning of the 1990's.

Schreyer (2000) followed a similar growth accounting framework for G7 countries for the period 1980-1996. He used an original dataset to measure ICT investment outside of the US in a comparable way. He found that ICT capital goods have been important contributors to economic growth in all countries, but the effect was particularly large in the US. Colecchia and Schreyer (2002) provided an update and extended the definition of ICT capital to include software. They also used official statistics instead of private data. Finally, two countries were added to the list: Australia and Finland. At the aggregate level, Gust and Marquez (2004) construct two alternative measures of ICT capital and investment in 13 large economies from 1992 to 1999. The first measure is the country's IT production as a share of GDP, constructed from STAN, the OECD sector level dataset (so the analysis uses sector level analysis to construct an economy wide measure of IT capital). The second measure is the ratio of spending in information technologies to GDP. The spending information comes mostly from the World Information Technology Service Alliance, measuring spending in computer hardware, software and other IT equipment. They find that their measures of IT explain most of the productivity divergence observed over the period of analysis, and also relate differences in the adoption of IT to differences employment protection legislation laws.

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Table 2.5: Studies about sector level evidence from Europe

Study	Country	Type of Data / years	Method	Measure of Technology	Effect
van Ark et al. (2002)	12 EU countries and US	National accounts and input- output tables, 1980-2000 build comparable ICT investment and ICT capital data across EU and US	– standard growth accounting and labour productivity equations	(1) Broad definition of ICT as comprising the whole category of office and computer equipment - including peripherals (2) Separate investment series on ICT investments used where available (3) Used a Commodity Flow Method to fill gaps. This supply side method first computes total amount of ICT commodities available in a specific year as value of total ICT production less ICT exports plus ICT imports.	– Similar growth rates ICT real capital formation and capital services for US and EU. – ICT investment share levels lower in the EU- 2/3 of US level throughout the period. – Relative contribution of ICT to EU labour productivity growth close to US but slowdown in EU growth reduces the absolute contribution. – Stronger TFP effects for ICT-producing sectors in the US during the 1990s.
van Ark & Inklaar (2005)	US and European industries (France, Germany, Netherlands, UK)	Updated version of van Ark et al. (2002); 60 industries, 1987-2004.	– Growth accounting equations for macro-level data. – Labour productivity equations for industry data – TFP equation to test for spillovers.	Investment series for different types of IT-related capital expenditure. Specially constructed GGDC dataset.	– Lower IT- contribution to EU growth has continued through early 2000s. – US-EU differential increased following strong labour productivity gains in US market services (i.e. non- government sector). – No evidence of IT spillovers to TFP.
Lind (2008)	Sweden and Finland	EU KLEMS, 1975-2004	– evolution of labor productivity	As in EU KLEMS distinction between ICT-producing and non-ICT producing sectors	– convergence in labor productivity between Sweden and Finland, mostly due to relatively larger productivity growth in the ICT producing sector in Finland
Schreyer (2000)	G7 countries	OECD database, 1980-1996	– Growth accounting framework	IT hardware and telecommunications spending from IDC	– ICT capital goods have been important contributors to economic growth in all countries, but especially large in the US
Colecchia and Schreyer (2002)	9 OECD countries	OECD database, 1980-2000	– Growth accounting framework	IT and Telecommunications Equipment: Software purchases	– dispersion in IT expenditures per employee explains around 8% of the productivity dispersion – growth of labor productivity and TFP strongly related to robot adoption
Gust & Marquez (2004)	13 OECD countries, 1993-2000	OECD national data and regulations database	– Models labour productivity growth as a function of IT and other controls – Also look at IT investment equations	2 measures: (a) Share of IT producing sectors in GDP (OECD); (b) IT expenditure: GDP ratio (World IT Service Alliance)	– IT production and (to a lesser extent) IT expenditure are associated with higher productivity growth. Labour and start-up regulation significantly retards IT (although no controls for country fixed effects)

2.6 International evidence: firm level studies

While EU KLEMS allowed for the use of high-quality sector level data, the use of firm level data adds additional insights. However, only few papers have been able to use European firm level datasets to look at the link between productivity and ICT.

- A first wave of papers merely replicated previous US studies with little methodological or data innovation, and were therefore less visible and less well published. Results generally show evidence of a relationship between ICT and productivity, but less strong than in the US.
- In Denmark, to the best of our knowledge, there are only two studies looking at the relationship between productivity and IT focusing only on Danish firms.[8] Both find a positive contribution of ICT to productivity growth.

Preliminary evidence from France made innovative use of worker level survey (Greenan and Mairesse, 1996) collected at the end of the 180's and beginning of the 1990's by the Ministry of Employment. Using an employee based survey on the techniques and organization of work, they were able to compute the share of employees using a computer in the firm (based on a sample of employees). When connecting this survey to standard accounting data and work composition information (share of white and blue collar workers), they found that their IT variable was strongly connected to productivity (except in the bank and insurance sector). They also found that the share of blue collar workers was negatively correlated with IT use. A few years later, Greenan et al. (2001) used more precise measure of IT capital coming from accounting data and the shares of employees employed as researchers or IT employees from an employment structure survey. They ran both cross sectional and time series regression (to control for firm fixed effect). They found evidence of significant contribution of IT to output in the cross section estimations, but not when including a fixed effect, suggesting selection of the best firms into IT adoption.

[8] A new study is currently under progress (Smeets and Warzynski, 2018).

Haltiwanger, Jarmin and Schank (2003) compared the adoption of advanced technologies and workforce adaptation between US and German firms. The research centre at the Ministry of Employment in Germany (IAB) runs yearly surveys at large German plants asking among other things their use of ICT tools. The measures used are the share of employees with internet access, and computer investment. They find that ICT tools have a strong effect on performance in both countries. However, the effects are estimated to be larger in the US than in Germany.

In 2004, the OECD published a report called "The Economic Impact of ICT" that contained several contributions from researchers in several countries using firm-level data: Finland, Switzerland, Australia, Italy, the Netherlands. Most of these papers used early measures of IT and IT use surveys.

The Finnish study by Malirata and Rouvinen (2004) showed how the Finnish economy had experienced large gains in productivity since the late 1980's and how this evolution relates to investments in ICT, that started increasing around 1995. Given the size of the Finnish economy, the ICT producing sector during those years was very much dominated by one company, Nokia, and its network of subcontractors and suppliers. ICT use also spread to the other sectors of the economy, just as in the US. Using internet and e-commerce surveys, they measured IT as using email, internet, intranet, extranet and EDI, as well as the share of workers having access to a computer and to internet (similar measures were collected by Statistics Denmark). They then estimated by OLS an augmented production function adding these shares in their regression. They found that the share of workers having access to a computer was strongly related to output, although the coefficient was much higher in services than in manufacturing. When using the share of workers having access to internet instead, they found a negative coefficient for manufacturing, mostly driven by the effect in large firms. It was positive however in services. Lastly, the effect of ICT on output appeared to be much larger in ICT producing sectors than in other sectors (labelled a Nokia effect). Their analysis stopped in 2000, and the authors claimed that it might take some time for firms to benefit from their investments.]

The Australian study by Gratton et al. (2004) is less convincing, as the database does not provide a measure of capital, but their results indicate a positive relationship between labor productivity growth and measures of IT that include dummy variables for the use of computers, internet access and web presence for the period 1993-2001.

The chapter by Atrostic et al. (2004) looks at a comparison between three countries, including Denmark, about the effect of the adoption of networks in firms. For both Japan and the US, positive returns to the use of networks are found using an augmented production function approach. There was no such analysis for Denmark. They also looked at the relationship between the use of networks and productivity growth instead of level. For Denmark, the authors found that firms adopting networks achieved higher growth in value added but also higher growth in employment, leading to a lower growth in labor productivity. However, the authors used a pilot survey by Statistics Denmark in 1999 about the use of IT in firms for a cross section of firms. The measures of IT used, as in the other papers, were quite preliminary measurements of IT use.

Engelstätter (2013) mostly replicated the Aral, Brynjolfsson and Wu (2006) paper previously discussed for Germany using similar data obtained by phone interview to correlate labor productivity and various measures of IT such as the share of computer workers, the use of ERP, SCM and CRM. All variables were positively related to productivity and IT. The author also showed evidence of complementarity between different measures, as a combination of them led to larger effects. The mechanisms through which IT (selection vs. causal effect) were not properly addressed but recognized by the authors as a shortcoming in the conclusion.

Hall, Lotti and Mairesse (2013) use survey data run by Unicredit, an Italian commercial bank to look at how R&D and IT decisions affect productivity and innovation for a panel of 9,850 Italian firms. They find that R&D and ICT are both strongly associated with innovation and productivity, but the sensitivity of innovation to R&D is larger, while the sensitivity of productivity to ICT investment is more important. Rates of return to both investments are extremely high, indicating underinvestment in both these activities. They also find little evidence of complementarity between R&D and ICT in innovation and production.

In Denmark, a CEBR study by Fosse, Jacobsen and Sørensen (2013) used rich firm level ICT use and ICT spending survey data, as well as R&D surveys collected by Statistics Denmark for the period 2007-2010 to look at the link between ICT investment and productivity growth, as well as with innovation. They find that ICT intensive firms had on average 2.4% higher annual productivity growth. Moreover, they argue that these gains can be attributed to the innovations that ICT facilitated.

Kromann and Sørensen (2017) run a survey on automation for 567 Danish manufacturing firms in order to collect new measures of ICT use in production in 2012, asking retrospective questions for the years 2005, 2007 and 2010. Among the questions asked was the share of new investment in machinery and equipment targeted for automation; subjective questions about the extent of mechanization and automation of the production process at various stages; and subjective questions about the evolution of various measures of performance related to the production process itself (run time, setup time, quantity produced per worker, etc…). This survey is then merged with other datasets to allow for the estimation of the production function. This allows them to distinguish between three types of capital and to build an automation index based on the answers to 8 specific questions on automation scope. They find that their index of automation is highly related to value added, and their measures of IT and automated capital positively contributes to output. However, there was little care devoted to the problem of selection or endogeneity.

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Table 2.6: Studies about international firm level evidence

Study	Country	Type of Data / years	Method	Measure of Technology	Effect
Greenan & Mairesse (1996)	Around 3,000 manufacturing firms and 2,500 in services.	TOTTO (survey on the techniques and organization of work) matched to INSEE firm database for 1987, 1991, 1993.	– Production function estimation. – OLS Cobb- Douglas production function, no fixed effects	Share of workers using computers at work	– Share of blue- collar workers falls with increase in IT (for all indicators). – IT coefficient stable across models for all 3 years. Coefficient of approximately 0.20.
Greenan, Mairesse, & Topiol- Bensaid (2001)	French firms, 1986-1994	SUSE (System of Unified Statitics on Enterprises) and ESE (Employment Structure Survey)	– examines correlations between IT, R&D and skills.	Value of office and computing equipment, No. of specialized workers (computer, electronics, research and analysis staff)	– IT effect is not significant when firm fixed effects are included.
Haltiwanger, Jarmin, & Schank (2003)	US and Germany	Matched ASM and CNUS for the US, 1999-2000. 22,000 observations. IAB manufacturing sector panel for Germany, 2000-1. 3,500 observations used in regression analysis.	– Compare the productivity outcomes for similar IT intensive firms in both countries.	Total investment in computers and peripheral equipment (US). Total investment in information and communication technology in previous business year (Germany) Proportion of employees with internet access (US and Germany)	– IT-intensive US firms exhibit greater productivity dispersion, particularly amongst younger businesses.
Malirata and Rouvinen (2004)	Finland	Survey on internet use and e-commerce use in enterprises, 1992-2000	– divide firms in three groups based on ICT intensity; then looks at aggregate growth for these three groups – OLS estimation of production function augmented with ICT use measures	IT use measures: email, internet, intranet, extranet and EDI share of the workforce use of computer, LAN and internet equipment	– no major difference in productivity growth between the three groups of firms – share of workers using computers strongly related to output; effect stronger in services – share of workers using internet strongly related to output in services, but negative in manufacturing, especially for old firms – impact of ICT higher in IT producing sectors than IT using sectors
Gretton et al. (2004)	Australia	ABS survey on business use of IT, 1993-2001	– estimation of an autoregressive labor productivity function and some measures of IT use (no measure of physical capital!)	computer use, internet access, web presence	– evidence of positive contribution of ICT in manufacturing, retail and wholesale

Table 2.6 (ctd)

Atrostic et al. (2004)	US, Japan and Denmark	CNUS survey matched with Annual Survey of Manufacturers (ASM) and Economic Census, 1999 (US; ICT workplace survey matched with the Basic Survey of Business Structure and Activity (BSBSA), 1997 (Japan); IT use survey matched with account statiistics and linked employer employee dataset (IDA), 1998 (Denmark)	– estimation of augmented production function with use of network as additional variable – comparison of value added, employment and labor productivity growth between ICT using firms and non ICT using firms	use of networks in firms	– positive contribution to output of having a computer network – positive contribution to output of intra firm network, inter firm network, use of EDI, CAD/CAM and open network – firms adopting networks achieved higher growth in value added but also higher growth in employment
Engelstätter (2009)	Germany	own run survey, 2004 and 2007, 927 obs.	– regression of labor productivity on various measures of IT	share of computers and use of IT in production (ERP, SCM and CRM) obtained through phone surveys	– all measures of IT positively correlated to labor productivity
Hall, Lotti and Mairesse (2013)	Italy	survey of manufacturing firms by a commercial bank (Unicredit) 4 waves: 1998, 2001, 2004, and 2007	– augmented CDM model considering both R&D and ICT investment	Dummy for investment in ICT	– R&D and ICT are both strongly associated with innovation and productivity
Fosse, Jacobsen and Sørensen (2013)	Denmark	IT use in firms, IT spending in firms and innovation surveys from DST, 2007-2010	– OLS estimation of a growth in value added regression over the growth of inputs and ICT and innovation dummies	ICT spending per employee divides firms as ICT intensive if ICT spending per employee is above the median	– ICT intensive firms had 2.4% higher annual productivity growth than non ICT intensive firms – ICT strongly correlated with innovative activities
Kromann and Sørensen (2017)	Denmark	own survey measuring use of industrial robots by firms, 2005-2010	– OLS estimation of augmented production functions with different types of capital both in level and first difference	index of automation and ICT capital stock	– index of automation highly related to value added; measures of IT and automated capital positively contributes to output

2.7 New Measures of ICT: Industrial Robots

- There is some new evidence that industrial robots have had strong effects on productivity

As complement to the EU KLEMS project, several recent papers have made use of additional data on the use of robots at the industry level by the International Federation of Robotics (IFR). The IFR provides measures of several types of industrial and service robots by industry in a large number of countries. It aims to capture the universe of robot suppliers.

Graetz and Michaels (2015) use data from 17 countries (among them 14 being European, including Denmark) in 14 industries over the period 1993-2007 to look at the relationship between productivity and industrial robots – controlling for other IT factors. Their results suggest that increased robotization contributed to 0.36 % to annual labor productivity growth, raising total factor productivity and lowering output prices.

Kromann et al. (2016) used a similar approach for 9 countries (also including Denmark), 10 industries and 4 years of data (2004-2007). Instead of using a long difference, they run a production function estimation in level specification in OLS and FE. They find that robot intensity strongly contributes to output. However, little is done to deal with the endogeneity of robot intensity, so that it is hard to understand the mechanisms behind the relationship (selection vs. productivity enhancing robotization).

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Table 2.7: Studies about the link between productivity and industrial robots

Study	Country	Type of Data / years	Method	Measure of Technology	Effect
Graetz and Michaels (2015)	17 countries, 14 industries, 1993-2007	IFR industry level dataset about the use of industrial robots Matched with EU KLEMS	– long difference analysis between the growth in labor productivity/TFP and robot adoption – control for endogeneity of robot adoption	Robot densification as number of robots per million hours worked	– growth of labor productivity and TFP strongly related to robot adoption – increased robotization contributed to 0.36 % to annual labor productivity growth, raising total factor productivity and lowering output prices – controlling for endogeneity leads to a 50% increase in coefficients
Kromann et al. (2016)	9 countries, 10 industries, 2004-2007	IFR industry level dataset about the use of industrial robots Matched with EU KLEMS	– OLS estimation of augmented production with IT capital and robot intensity	IT capital and robot intensity	robot intensity strongly contributes to output

2.8 Evidence from more recent years

- In recent years, productivity growth has significantly slowed down (see Byrne et al, 2016; Syverson, 2017; Fernald et al., 2017). Also, the strength of the relationship between productivity and ICT has appeared to decrease, puzzling most economists (Byrne et al., 2013).
- Some have questioned whether the strong IT effect that had been detected in the past was mostly driven by a few specific sectors, the IT producing sectors. Others have claimed that we are facing a return of the IT paradox. Again, measurement issues are playing a central role.
- There is still no evidence of a positive contribution of AI or machine learning on productivity. The development of this technology is still at its infancy and we lack proper measurements. Once we get a proper measurement, we will be able to estimate the marginal product of AI.
- More recent studies have made use of more innovative datasets and have been more careful with the endogeneity issue. They confirm that ICT adoption correlates strongly with productivity.

In a provocative paper, Acemoglu et al. (2014) revisit the Solow paradox. Their view is that the measured contribution of IT to productivity observed in US manufacturing in the period 1977-2007 is biased, as it can mostly be attributed to a few IT-producing sectors, namely the computer producing sector (as we have seen previously, this debate is not new). Using measures of IT use in non IT producing sectors leads to a different picture. IT has absolutely no effect on output per worker outside of the computer producing industry. When using other measures of IT such as advanced manufacturing technologies (as measured by the Survey of Manufacturing Technology discussed previously), they observe a positive effect of these technologies until the end of the 1990s, but then a flattening of the relationship, i.e. a slowdown in the relationship between output per worker and advanced manufacturing technologies. But more importantly, the gain in labor productivity can be explained by the fact that employment fell more than output, and both fell!

In a recent paper, Brynjolfsson, Rock and Syverson (2017) evaluate four potential explanations for the productivity slowdown despite the recent technological developments. The first one is false hopes. New tools did not deliver on their promises, and they have not improved productivity. The second one is bad measurement. We do not yet have proper measures of new ICT tools and therefore can not assess their effects. It is hard to measure the value of Facebook posts or Google searches for society. The third one is redistribution and increased concentration: only a few firms really benefit from new technologies and the average firm hasn't taken advantage of new technologies, creating increasing "inequality" in productivity. Finally, the authors' favorite explanation, for which they argue in length, is that it takes time for the new tools to be put at their best use (implementation lags). In particular, AI, especially machine learning, has not been diffused on a large scale yet, and the necessary complementary changes to organizations take time to be designed and implemented. Machine learning has much deeper and potentially huge consequences for society and productivity compared to the adoption of computers in the late 80's. To quote them: "*There really is a good reason to be optimistic about the future productivity growth potential of new technologies, while at the same time recognizing that recent productivity growth has been low*". The deeper the disruption and the more there is to gain, the longer it takes for society and the economy to adapt and reap the benefits of these new technologies. One the one hand, the total size of this new type of capital has to be large enough to have an effect on aggregate productivity. On the other hand, many complementary practices have to be adopted and complementary investments, in particular in human capital and organizational form (see next section for more discussion about this issue), and there might be some frictions and adjustment costs behind these actions.

One important reason is that AI is a general purpose technology (GPT), i.e. "*a new method of producing and inventing that is important enough to have a protracted aggregate impact*" (Jovanovic and Rousseau, 2005), just like the steam engine or electricity, just to name a couple. They should be 1) pervasive and adapt to all sectors; 2) be able to improve over time; and 3) be innovation spawning, i.e. make it easier to create other types of innovation. These characteristics fit perfectly to AI. Thanks to its existence, it creates the conditions for numerous additional innovations with their own implications. Machine learning tools are designed to become better over time, so that gains accumulate at an increasing speed. Self-driving cars are a good example of these additional gains, and could generate direct aggregate productivity gains estimated at 1.7% over a decade.

Historically, GPTs have taken time to deliver productivity gains, because new ideas take time to grow, and existing firms are reluctant to adopt them because they consider they have been successful without them. Syverson (2013) discusses how the effects of portable power (the combination of electrification and internal combustion technology) can be compared to the IT revolution. It took 25 years for both GPTs to start having an effect on labor productivity growth. The productivity growth slowdown that followed (1924-1932 for portable power, 2004-??? for IT) was then followed by another increased rate of growth (a second wave).

Labor productivity growth is by definition the combination of two forces: increased capital intensity or deepening (each human can produce more with the help of capital, AI and non AI); and growth in total factor productivity (TFP), which can itself be affected by AI. To properly assess both effects, one needs proper measurement of AI capital, and this is where we face a similar task to what has been discussed previously: how to value it, how to define the value that it generates, and how to define the price and the depreciation rate. This is a major challenge for statistical agencies and economists. But it will have to be met if we want to be able to inform policy makers and society about the consequences of AI. Part of the problem is that it is extremely difficult to quantify the intangible part of AI, although it should be reflected in the value of the of the company. Without a proper valuation, our estimate of productivity will be biased.[9]

More recent studies have been trying to compare the contribution of IT to productivity dispersion using more innovative data. The motivation in the study by Bloom et al. (2017) is mostly to document the importance of management quality to understand productivity dispersion, but one

[9] TFP growth will be underestimated if the real capital stock (not measured, including wrongly valued AI) is growing faster than output. This is equivalent to wrongly considering those resources that we can measure properly as the only factors used for production and can be labeled as "lost potential output". The mismeasurement is composed of a "hidden" capital effect and a "hidden" investment effect. These two effects eventually tend to disappear over time, leading to a so called "Mismeasurement J-curve" for the economy. This is the input equivalent (capital in this case) to the problem of measuring new goods in price indices, a common difficulty for statistical agencies.

of the exercises in the paper is to compare the fraction of dispersion explained by management quality compared to IT or R&D. Using a recent survey of 32,000 US manufacturing firms, run in partnership with the Census Bureau, they find that dispersion in IT expenditures per employee explains around 8% of the productivity dispersion, while management quality explains around 17% of the spread in TFP.

Dhyne et al. (2017) use a novel measure of IT investment as provided by a dataset of all VAT transactions by Belgian firms over a decade. They define IT investment as all purchases from firms in the computer and peripheral equipment, the wholesale of computers and software, the retail sale of computers and software, and the "other software publishing" sectors. The define the stock of capital using the perpetual inventory method and proxy the initial stock as the average ratio of IT investment over total investment during a period of 4 years multiplied by total capital, as standard in the literature. They find that the marginal product of IT capital is larger in the manufacturing industry than in services (1.58 vs. 0.80). This can be explained by the fact that manufacturing is less IT intensive. They also show that the marginal product of IT capital is higher for larger firms, a finding that they interpret as evidence that IT capital is complementary with management quality (assuming management quality is higher in larger firms), in line with Bloom et al. (2010). The authors therefore claim that their results go against the revival of the Solow paradox hypothesis mentioned previously, since they observe positive and large marginal returns of IT capital across industries. Finally, they test, as in Bloom et al. (2017) how much of the observed dispersion in TFP can be explained by differences in IT investment. They find that IT investment per worker explains around 20% of TFP dispersion, compared to 8% in the US.

Table 2.8: studies from more recent years

Study	Country	Type of Data / years	Method	Measure of Technology	Effect
Bloom et al. (2017)	US	Own run survey, around 32,000 firms run as supplement to the ASM	– Estimation of an augmented production function distinguishing between IT and non-IT capital	Investment in computers per employee	– dispersion in IT expenditures per employee explains around 8% of the productivity dispersion
Dhyne et al. (2017)	Belgium	Business to Business (B2B) transaction data from VAT records, 2002-2013	– Estimation of an augmented production function distinguishing between IT and non-IT capital – Deal with endogeneity following Ackerberg, Caves and Frazier (2016) method – adopt an estimation method that controls for the mismeasurement of capital. (Collard-Wexler and De Loecker, 2016).	Spending in IT from B2B dataset	– The marginal product of IT capital is 1.24 – The marginal product of IT is larger in manufacturing than in services – Larger firms have a higher marginal product of IT – IT investments explain around 20% of the productivity dispersion

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Chapter 3. Technology Adoption and Firm (Re)Organization

Previous sections have documented important relationships between technology adoption, labour demand and productivity, at the economy, industry and firm level. While recent research relying on firm-level data has opened up the black box of production in an environment dominated by an increasing reliance on technology, little is known about the way firms reorganize following new technology adoptions. Changes in information or communication technology may lead firms to adjust their work organization or the nature of work, which may ultimately affect the labour demand of various types of workers, occupations and skills. Not accounting for firms' reorganizational responses to changes in technology may therefore understate the economic contribution of technology, both at the aggregate level but also when relying on microeconomics studies using firm or plant level data. This section describes the emerging literature on the relationship between technology adoption and firm organization, and its impact on firm performance and labour demand.

3.1 Complementarities between Technology Adoption, Organizational Transformation and Firm Performance

A large set of studies shows that to maximize the benefits of technology adoption, firms need to adopt simultaneously complementary work practices. Most papers rely on data available for U.S. firms, only one study relies on a set of European firms. The main findings are:

- The practices that appear to be especially relevant are people management practices like selection, incentives, the flexibility of hiring and firing decisions, and the empowerment of workers, indicating that strong human resources practices are crucial to leverage the benefits of technology adoption.
- Those effects are present in all studies, despite relying on different types of technology measures like computer use, hardware investment or data-driven software.

One of the early papers to investigate the complementarity between technology adoption, organizational transformation and firm performance is Brynjolfsson and Hitt (2000). They primarily rely on case studies, but also on preliminary research performed by the same authors using U.S.

firm-level data and on indirect evidence provided by earlier studies. They document that computerization without changes in work practices usually fails at delivering an increase in efficiency. For example, technology aiming at facilitating the interactions between a firm and its suppliers will be efficient only if the entire supply chain is reorganized accordingly; consumer-driven computer-based technologies will lead to increase in sales only if they are supported by practices fostering interactions between a firm's customer service and its customers. The authors conclude that relying only on the direct effect of investments in technology - or computers - on firms' outcomes without considering any complementarities with other decisions understate the impact of technology – or computerization - by a factor of ten.

Brynjolfsson, Hitt and Yang (2002) further investigate the complementarity between IT and firm's organization, and how it impacts firm's performance, focusing this time on the relationship between intangible organizational assets and a firm's market value as assessed by financial markets. In their paper, intangibles organizational assets are defined as organizational practices like the decentralization of decision rights, team-oriented production and demand for certain types of worker skills. Their measure of IT is computer assets, which include IT hardware and computer equipment. They use stock market valuation data from Compustat which is available for around 1,200 large U.S. firms over 1987-1997. Data on organizational practices come from a survey that took place between 1995 and 1996, so those data are a snapshot of firms' organization in the middle of the 1990s. When combining IT, firm valuation and the cross-sectional survey of organizational practices, the matched sample consists of 272 firms. They find that investments in IT stock affect a firm's market valuation ten times more than investments in other tangible assets like capital stock. They also find that intensive IT firms are more likely to adopt a specific cluster of organizational practices, including greater use of teams more decentralization of decision rights and increased worker training. Combining complementarity organizational practices with IT investments leads to firm value gains that are beyond the contribution of both factors taken separately. Interestingly, there appears to be no complementarity between organizational practices and tangible assets on a firm's market value. While most estimations rely on OLS, the authors also perform fixed-effects specifications and experiment with different timing assumption to make sure their results are not contaminated by unobserved firm heterogeneity or short-run correlated shocks between market value and IT investment.

Bloom, Sadun and Van Reenen (2012) and Bloom et al. (2014) revisit the complementarity of organizational practices and IT investments using more recent surveys on management and organizational practices. Those surveys report information on management practices, like monitoring, targets and incentives, information on organization, like decentralization, the number of direct reports of managers and decision making, and information on workforce characteristics. Both papers use the stock of computer equipment as their measure of IT investments. Bloom, Sadun and Van Reenen (2012) use the initial World Management Survey (WMS) developed by Bloom and Van Reenen (2007). Their data consists of a cross-section of over 1600 establishments in 2006, either affiliates of U.S or European firms, or purely domestic. The WMS data are combined with computer usage and accounting data at the firm-level, running from 1995 to 2003. They find that U.S. affiliates are more productive than European firms, as measured by higher levels of labour productivity. They show that the U.S. productivity advantage is mostly due to the joint association of IT investments and internal organization practices. The IT related productivity advantage of U.S. affiliates is explained by more decentralization, a higher rate of change of organization structure and tougher "people management" practices, defined in terms of promotions, rewards, hiring, and firing. The authors present a series of tests showing the robustness of the main results to selection, unobserved heterogeneity, inputs endogeneity, industry effects and alternative production function specifications.

Bloom et al. (2014) use the recent survey on management and organizational practices (MOPS) developed by the U.S. Census Bureau and the U.S. National Science Foundation, following the World Management Survey developed by Bloom and Van Reenen (2007). The survey they use covers around 37,000 manufacturing establishments in 2010 and is matched with IT and performance data from Census and non-Census data sets. They report that more structured management practices, i.e. the quality of their systems of monitoring, targets and incentives, are tightly linked to higher level of expenditures on IT. Moreover, more structured management is strongly associated with superior performance, like multi-factor productivity, profitability, rates of innovation and employment growth. Those results confirm the previous findings that organizational structures matter for the contribution of IT investments on firms' outcomes.

Brynjolfsson, and McElheran (2016) go one step further in analysing the complementarity between IT and firms' organization, and focus on the relationship between IT investments, the use of data-driven decision making (DDD) and management practices. The emergence of big data for firms as well as the increased reliance on analytics have shaped the way firms organize their workforce and make decisions. They use the management and organizational practices survey, as in Bloom et al. (2014), and separate managements practices questions from questions related to the use of data-driven decision making. They use the 2010 answers as well as retroactive answers for 2005, so that their sample has a quasi-panel structure. They constraint their sample to establishments present in both 2005 and 2010. Their final sample is around 18,000 establishments. They match this information with investments in information technology, which in their case is capital stock in terms of both hardware and software. They find a dramatic increase of data-driven decision making over the period, as the share of manufacturing plants adopting those new decisions nearly triples between 2005 and 2010. Adoption of DDD is uneven and the authors provide evidence that DDD adoption is driven by the complementarities between DDD and both IT and worker education. Again, this study supports the finding that management practices, IT and firms' labour demand are all interconnected and suggests the need for an omniscient approach towards analysing the benefits of technology for the economy, firms and workers.

Aral, Brynjolfsson and Wu (2012) focus on the relationships between IT, performance pay and the reliance on human resources analytics. They argue that the complementarity between IT and performance pay can only be achieved through the introduction of HR analytics, as those systems are crucial to effectively monitor, manage and reward employee performance accurately. The authors collected data on enterprise resources planning (ERP) purchases and adoption of 189 firms that adopted HR analytics systems between 1995 and 2006. Because purchase and adoption occur at different times, they can directly assess the causality in the relationship between IT adoption and firm's performance. A survey on human resources practices was conducted between 2005 and 2006 on the same set of firms, with subsets of questions used to define the reliance of firms on HR analytics and performance pay. Financial performance of firms (sales) was obtained thought Compustat. They find a strong correlation between ERP, performance pay and HR analytics. Relying on a simple multi-factor productivity analysis, they show that implementing those practices simultaneously generate disproportionate performance gains for firms, highlighting again the fact that complementarities are key when assessing the impact of firms’ technology adoption.

Table 3.1. Studies about complementarities between technology adoption, organizational transformation and firm performance

Study	**Country**	**Type of Data / years**	**Measure of Technology**	**Effect**
Brynjolfsson and Hitt (2000)	USA	Case studies.	Computer usage (computer/worker)	– Computerization without changes in work practices usually fails at delivering an increase in efficiency. – Not considering complementarities between computerization and other decisions understate the impact of technology, by a factor of 10.
Brynjolfsson, Hitt and Yang (2002)	USA	As in Bresnahan, Brynjolfsson and Hitt (2002).	Value of IT hardware and computer equipment	– Investments in IT stock affect a firm's market valuation ten times more than investments in other tangible assets like capital stock. – Complementarity organizational practices with IT investments lead to firm's value gains that are beyond the contribution of both factors taken separately. – No complementarity between organizational practices and tangible assets.
Bloom, Sadun and Van Reenen (2012)	Europe	World Management Survey, 1633 establishments, 2006 Compustat, Harte-Hanks data, 1999-2006.	Computer usage (computer/worker)	– U.S. affiliates are more productive than European firms. – U.S. productivity advantage comes from the joint association of IT investments and internal organization practices. – U.S. affiliates have more decentralization, a higher rate of change of organization structure and tougher "people management" practices, defined as promotions, rewards, hiring, and firing.
Bloom, Brynjolfsson, Foster, Jarmin, Patnaik, Saporta-Eksten and Van Reenen (2014)	USA	Survey on management and organizational practices for 37,000 manufacturing plants. U.S. Census data. 2010.	Value of IT hardware and computer equipment	– More structured management practices, i.e. the quality of their systems of monitoring, targets and incentives, are tightly linked to higher level of expenditures on IT. – More structured management is strongly associated with superior performance. – Organizational structures matter for the contribution of IT investments on firms' outcomes.
Brynjolfsson and McElheran (2016)	USA	Survey on management and organizational practices for 18,000 manufacturing plants. U.S. Census data. 2005 + 2010.	Capital stock of hardware and software	– Data-driven decision (DDD) triples between 2005 and 2010. – DDD adoption is driven by the complementarities between DDD, IT and worker education. – Supports the finding that management practices, IT and firms' labour demand are all interconnected.
Aral, Brynjolfsson and Wu (2012)	USA	Survey on 189 firms about HRM practices, HR analytics, ERP and performance pay. Compustat. 1995-2006.	Enterprise resources planning purchases and adoption	– Strong complementarity between ERP, performance pay and HR analytics. – Implementing those practices simultaneously generate disproportionate productivity gains for firms.

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3.2 Hierarchies, Knowledge and Technology Adoption

The introduction of information and communication technologies flattens firms' hierarchies and changes the way firms are organized internally. Due to the lack of appropriate data, this subset of the literature has mostly been so far either very descriptive or theoretical. The exceptions are the two studies described below that rely on rich survey data on European and U.S. firms. Their main conclusions are:

- Information technologies decentralize decisions, while communication technologies move decisions higher up in the firm.
- The theory predicts that information technology will increase the skills content of all workers, while communication technology will decrease the skills content of workers located at the bottom of the firm. If workers are paid according to their set of skills, the adoption of some type of technology adoption will reinforce wage inequality within firms. Due to the lack of appropriate data, there is no evidence about the direct link between IT and wage inequality at the firm-level at this stage.

Most of the literature on the link between IT adoption, the internal organization of firms and work practices rely mostly on empirical analysis using firm or plant-level data. Few attempts have been made to theoretically address the relationship between technology and within-firm (re)organization. A notable exception is Garicano (2000) and Garicano and Rossi-Hansberg (2006) who define the concept of firms as knowledge-based hierarchies. A recent survey about this strand of literature is summarized in Garicano and Rossi-Hansberg (2015). Firms use hierarchies to organize knowledge optimally and to solve coordination problems. Each individual has to solve a given set of tasks. Different tasks require a different set of knowledge. Individuals are embedded with some level of knowledge, which helps them to solve the tasks they have been assigned to. If they fail to solve a given task, they can ask more knowledgeable individuals in the firm for help. Hierarchies are designed to partition workers' knowledge as each hierarchical layer focuses on a certain group of tasks. In the model, easy or routine tasks are performed at the bottom, and require little knowledge, while upper levels (i.e. managerial layers) concentrate on more complex tasks, which require more knowledge. Hierarchies protect more knowledgeable individuals from being involved into routine or easy-to-solve decisions. The efficient allocation of knowledge depends on the expertise of managers, the knowledge of workers, and the transfer of knowledge within the organization. The model considers two types of technological improvements and their impacts on a firm's organization: information technology, which make information or knowledge cheaper to access, and communication technology which increases communication within the firm. Improvements in information technology (IT) lead managers to have larger teams (as subordinates can deal with more tasks) and require a lower number of hierarchical layers needed to solve a given set of tasks so that it leads to a flattening of the firm. Decisions also become more decentralized and are moved down in the firm's hierarchy. On the other hand, improvements in communication technology (CT) make it easy for managers to communicate with their subordinates. They can therefore manage larger teams. Managers become more involved into decision making so that decisions are moved higher up the firm. Lower level workers may therefore not need as many skills as before.

Garicano and Rossi-Hansberg (2006) also show that technology adoption can affect workers' earnings and wage inequality within firms and within the economy. Interestingly, the effect of technology on wage dispersion varies depending on the type of technology adopted. When firms adopt new information technology, as it becomes easy to acquire information or knowledge for everyone in the firm. Therefore, if individuals are compensated based on their set of skills, workers and managers will benefit from a wage increase following a positive IT shock. On the other side, when firms adopt new communication technology, knowledge embedded in higher layers can be easily transmitted down to lower layers, and the amount of skills needed for low level jobs decrease. If individuals are compensated based on their set of skills, a positive CT shock will in this case lead to more within-firm wage inequality, as the gains from CT will only be captured by workers higher up in the firm. The authors the illustrate that the mechanisms at play in their model fit the different evolution of wage inequality in the 1980s versus the late 1990s in the United States, two distinctive periods in term of the technological improvements introduced. They conclude that – to understand the determinants of wage inequality - it is necessary to understand the internal structure of firms and the organization of production properly.

Delmastro (2002) tests whether various types of technology adoption impact the hierarchical organization of the firm. Using data from a sample of 438 Italian manufacturing plants, he investigates the relationship between the depth of firms (or the number of hierarchical layers) and the adoption of new technology. The analysis is based on a cross-section of 1997. Two types of technology are considered: (1) technological improvements related to production such as various types of advanced manufacturing technology (AMT) and (2) communication enhancing technology like the adoption of intra-firm and/or inter-firm networks. The results show that the adoption of manufacturing-enhancing technology – if adopted jointly – significantly decrease the depth of firms, leading to a flattening of the firm. Communication enhancing technologies have heterogeneous effects, as intra-firm networks are associated to an increase in depth while inter-firm networks are associated to a decrease in depth. The author cannot rule out the reverse causality of technology adoption, and concludes that the counterintuitive result of the positive relationship between communication technology and depth could be simply due to the fact that “tall” firms (i.e. with many hierarchical layers) may be the ones deciding to adopt within firm communication enhancing technology.

Bloom, Garicano, Sadun and Van Reenen (2014) study the link between technology adoption and a firm’s organization, however their analysis is mostly about the impact of new software adoption. They consider information improvements, such as enterprise resource planning (ERP), computer aided design (CAD) and computer aided manufacturing (CAM) and communication improvements such as intra-firm networks. They use data about firms’ organization from the World Management Survey (as in Bloom, Brynjolfsson et al. (2014)) and ICT data from the Harte-Hanks ICT panel. Their sample consists of U.S. and European manufacturing firms, for a cross-section of 2006. They find that information technologies are associated with the adoption of larger teams and more decentralization, while communication technologies decrease the autonomy of lower-level workers, consistent with the theory.

Table 3.2. Studies about hierarchies, knowledge and technology adoption

Study	Country	Type of Data / years	Measure of Technology	Effect
Delmastro (2009)	Italy	Survey on 438 manufacturing plants about organization and ICT adoption. 1997.	Advanced manufacturing technologies, intra-firm and inter-firm networks	– Joint adoption of manufacturing-enhancing technologies decreases firm's depth of firms, leading to a flattening of the firm. – Communication enhancing technologies have heterogeneous effects: intra-firm networks associated to increase in firm's depth while inter-firm networks associated to a decrease in firm's depth. – Possible reverse causality issue.
Bloom, Garicano, Sadun and Van Reenen (2014)	U.S. + Europe	World Management Survey of about 1,000 firms in 2006. Harte-Hanks data.	Enterprise resource planning, computer aided design, computer aided manufacturing, intra-firm networks	– Information technologies associated with the adoption of larger teams and more decentralization. – Communication technologies decrease the autonomy of lower-level workers. – Consistent with the knowledge-based hierarchy theory (Garicano (2000)).

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3.3 Workers Skills, Training and Technology Adoption

High skills are complementary to technology adoption and needed to secure increased firm's performance and workers' labour market outcomes. Those relationships have been identified in a small set of studies only due to the lack of available data (two studies use data on U.S. firms, one on French firms and one on Norwegian firms). Their main conclusions are:

- To maximize the benefits of IT adoption on firm performance, firms need to simultaneously adopt specific work practices that foster the development of their workers' skills.
- Following the introduction of new technologies, firms heavily rely on training to upgrade the skills of their workforce, especially in the manufacturing industry (supported by one study only).

Bresnahan, Brynjolfsson and Hitt (2002) investigate the existence of complementarity between information technology investments, work organization and human capital; and whether it impacts firm's performance and firm's labour demand. They rely on the same organizational practices survey as in Brynjolfsson, Hitt and Yang (2002). Organization data are complemented by firm level value of IT stock, defined as the total value of IT hardware and computer equipment. Firm-level inputs (as employment and capital stock) and output (as value-added) are retrieved using Compustat. Looking at simple OLS regressions, the authors find that investments in technology are associated with more decentralization, more pre-employment screening, and a higher level of skills, like education or training. They also find strong correlations between those work practices indicating a complementary system. To estimate the effect of the complementarity between IT, organization and human capital on firm productivity, they regress firm output (proxy by value-added) on labour, capital stock, IT capital stock, and measures of workplace organization and skills, using a simple OLS estimation of multi-factor productivity with industry and year dummies. They find that, conditioning on other inputs like labour and capital stock, larger IT stocks lead to more output, confirming previous findings about productivity that IT is positively associated with higher firm performance. However, their novel result is the quite sizeable effect of the interactions between IT, skills and workplace organization on firm performance. Firms scoring high on those three dimensions experience a productivity 7 percent higher than what would the average firm experience. Being unbalanced in those three dimensions also reveal losses in term of productivity, highlighting the importance of complementarity. Finally, they find that a stronger impact of IT on labour demand when combined with the adoption of organizational practices, suggesting the importance of IT-enabled organizational change.

Bartel, Ichniowski and Shaw (2007) take the unique approach to focus on one very narrow industry which is valve manufacturing. The choice of a narrow industry allows to obtain industry-specific measures of IT, that are much more detailed than the measures of technology used in previous studies. The technology used in valve manufacturing consists of the adoption of computer numerically controlled (CNC) machines, flexible manufacturing systems (FMS), IT procedures reducing inspection time and 3D computer-aided design. The authors conducted a customized industry survey for valve plants in 2002. The survey covers 416 valve-making plants, or 51% of plants with more than 20 employees in the U.S. valve manufacturing industry. Retroactive questions about 1997 allow the authors to build a quasi-panel structure. The survey questions ask about HRM policies, the technology used in each plant, production process efficiency measures (such as setup time, run time, and inspection time) and product customization measure. A simple OLS estimation of the effect of various technology improvements on the change in production time reveals a sharp decrease in production time between 1997 and 2002 due to plants adopting new IT-related technologies. Plants that introduce simultaneously HRM policies aiming at improving the workers' skills required for a given technology are the ones benefitting the most from technology adoption. Skills that appear particularly relevant for machine operators are technical skills (like programming, computer or engineering skills) and problem-solving skills. This result is consistent with previous findings of Levy and Mundane (2004) that IT adoption leads to an increased demand for non-routine skills at the cost of a decreased demand in routine skills.

Akerman, Gaarder and Mogstad (2015) revisit the complementary between skills and firms' adoption of new technologies. Their context is the adoption of broadband internet by firms in Norway during the first half of the 2000s. One of their contribution is the identification strategy they rely on in their paper. They use a national public program aimed at ensuring broadband access at a reasonable price throughout the country during the 2000s as a source of exogenous variation in broadband availability, so that their results can be interpreted as causal. They combine various datasets from Statistics Norway for the period 2000-2008. They match linked employer-employee data with firm-level accounting information, firm-level broadband subscription and the availability of broadband internet at a given time in a given location. Their sample consists of around 17,000 firms. Worker-level results reveal that increased availability of broadband internet improves the labour market outcomes of skilled individuals (as measured by employment or wages), while the opposite is true for low-skilled individuals. Firm-level evidence shows also that increased availability of broadband internet is associated with a substantial increase in the output elasticity of skilled labour and that firms that adopt broadband technology benefit from an increase in productivity mostly driven by the complementarity between high-skilled workforce and technology adoption. They also report that workers who appear to benefit the most from broadband technology are workers who perform abstract tasks, while workers performing routine tasks are affected negatively, suggesting a task-based approach to skilled-biased technological change as in Levy and Mundane (2004) and Bartel, Ichniowski and Shaw (2007).

Behagel, Caroli and Walkowiak (2012) analyse the effect of technology adoption on skill upgrading. They especially focus on the channels through which upgrading occurs, differentiating between policies aiming at retraining current workers versus hiring new skilled workers. They use data from France at the end of the 1990s, a period when technology adoption was still spreading for French firms. Their ICT measure comes from a survey on nearly 3,000 establishments implemented in 1998 where they provide information on the proportion of workers using the Intranet and the Internet. That information is matched with worker flows information such as entry and exit, and establishment-level data on training, both broken down by various occupational categories (managers and professionals, technicians and supervisors, clerks, blue-collar workers). Their matched sample consists of around 1,100 establishments. They document correlations between ICT adoption and the strategies used by firms to upgrade the skills of their workforce. The use of Internet and Intranet is positively correlated with an upward shift in the occupational structure, especially an increase in managers and high-level professionals. Interestingly, this upgrading occurs mostly via internal promotions as opposed to external hiring. Firms also heavily rely on training to upgrade the skills of their workforce, as for most occupational categories, the introduction of new technologies is associated with a greater access to training. The correlations are further broken down by industry, as firms in manufacturing may exhibit very different behaviour than firms in services. A striking difference between manufacturing and services is the role of training. While it appears negligible for services, it is crucial for workers in manufacturing firms, across all occupational groups. Finally, the authors acknowledge that their paper does not address the endogeneity of technology adoption and that their results should be interpreted as partial correlations.

Table 3.3. Studies about workers skills, training and technology adoption

Study	Country	Type of Data / years	Measure of Technology	Effect
Bresnahan, Brynjolfsson and Hitt (2002)	USA	Survey on organizational practices for 379 large U.S. firms, 1995-1996. Compustat. Computer Intelligence Infocorp.	Value of IT hardware and computer equipment	– Investments in technology are associated with more decentralization, more pre-employment screening, and a higher level of skills. – Large complementarity effects of IT, skills, workplace organization on firm performance, losses for firms not adopting complementary practices. – Strong impact of IT on labour demand when combined with the adoption of organizational practices.
Bartel, Ichniowski and Shaw (2007)	USA	Survey of 416 U.S. valve-making plants about HRM practices, technology and production process efficiency measures. 1997+2002.	Computer numerically controlled machines, flexible manufacturing systems, IT inspection time and 3D computer-aided design	– Sharp decrease in production time between 1997 and 2002 due to plants adopting new IT-related technologies. – Plants introducing simultaneously HRM policies aiming at improving workers' skills benefit the most from technology adoption. – Relevant skills for machine operators are technical skills and problem-solving skills.
Akerman, Gaarder and Mogstad (2015)	Norway	Various datasets from Statistics Norway for 2000-2008. Linked employer-employee data; firm-level accounting information; internet adoption. Around 17,000 firms	Firm-level broadband subscription and availability	– Increased availability of broadband internet improves the labour market outcomes of skilled individuals (as measured by employment or wages), while the opposite is true for low-skilled individuals. – Increased availability of broadband internet is associated with a substantial increase in the output elasticity of skilled labour – Firms that adopt broadband technology benefit from an increase in productivity mostly driven by the complementarity between high-skilled workforce and technology adoption – Workers who appear to benefit the most from broadband technology are workers who perform abstract tasks, while workers performing routine tasks are affected negatively.
Behagel, Caroli and Walkowiak (2012)	France	Survey of establishment-level ICT use in 1998 matched with worker flows and training by occupational groups. Around 1,100 establishments.	Use of Internet and Intranet	– Use of Internet and Intranet positively correlated with an upward shift in the occupational structure (managers and high-level professionals) – Upgrading occurs mostly via internal promotions as opposed to external hiring – Firms heavily rely on training to upgrade the skills of their workforce, following the introduction of new technologies – Training is especially important for firms in the manufacturing industry

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