JRC TECHNICAL REPORTS

The Routine Biased Technical Change hypothesis: a critical review

Sebastian, Raquel

Biagi, Federico

2018

Contents

Acknowledgements

Authors

Biagi, F., European Commission, Joint Research Centre, Human Capital and Employment Unit.

Sebastian, R., San Pablo CEU University (Madrid, Spain).

Abstract

In this report we contribute to the growing debate about how the introduction of technology affects labour demand.

First, we provide some background of the main theoretical frameworks (SBTC and RBTC) used by researchers to explain recent changes in the employment distribution.

Second, we review the most important empirical studies using the RBTC model. Overall, the prevailing economic literature provides empirical support to the RBTC model: cheaper computerisation progressively replaces human labour in routine tasks, thereby leading to an increase in the relative demand for workers performing non-routine tasks.

Third, we show that the RBTC captures quite well the changes in the employment distribution, but we argue that it presents challenges from a conceptual, operational, and empirical point of view. These challenges are discussed in the report.

Finally, we argue that the literature has yet to converge to a model that consistently explains how technology affects the labour demand. The RBTC has the merit of providing an explanation of why cheaper computerisation progressively replaces human labour in routine tasks, leading to an increase in the relative demand for workers performing non-routine tasks. However, it is not immune to severe challenges, especially on the empirical ground. Future research should focus on the development of a measurement framework that addresses the challenges raised in this report.

1 Introduction

In recent years, the topic of inequality has gain major interest both in policy and academic circles. There is evidence of an increase of wage inequality in the United States and in most of the European countries. On wage inequality, mainstream economic literature highlights the role of demand shocks, particularly those driven by technological change. The conventional wisdom is what Acemoglu and Autor (2011) refer to as the Skill Biased Technical Change (hereafter, SBTC): highly skilled workers benefit from new technologies (complementarity between high skills and ICT), while low-skilled tend to be substituted by them, which appears as a "skill-bias" in the evolution of labour demand (Katz and Murphy, 1992). In this model technology has a monotonically upgrading effect on the occupational structure in terms of skills: the higher is the level of skill, the higher is the increase in labour demand. The implication is that we should observe an increase in employment for highly-skilled individuals, while low skilled would suffer employment losses. As for wages, no unique indications emerge since the "price" implications of such technological shock depend upon the evolution of supply (the race between education and technology, to which we should add the demographic evolution). However, if demand shifts faster than supply, we expect to observe rising wage premia for higher skills as well.

The SBTC hypothesis has been proved empirically successful in accounting for the growth in the skill premia and employment in the United States as well as among advanced nations throughout the twentieth century.

However, despite its virtue, SBTC alone cannot explain a prominent and relatively recent phenomenon: the decline in the share of middle wage occupations relative to high and low wage occupations. This phenomenon has been defined as "job polarisation" (Goos and Manning, 2007).

While the main drivers behind job polarisation are still subject to debate, the main candidate is the so-called Routine Biased Technological Change hypothesis (Autor et al., 2003, hereafter called RBTC). The basic idea is that technological developments, including artificial intelligence, robotics, and, more generally, advancements in ICT, have made possible the replacement of workers performing routine tasks by machines. This process is driven by the declining price of computer capital. This labour-capital substitution reduces the relative demand of labour in middle-wage occupations due to the increasing ability of machines to perform routine tasks, which characterise these occupations. The innovative aspect of this model is that it predicts that computerization has a non-linear effect on labour demand.

Despite the importance of RBTC, the conceptual and operational framework is still not fully developed (Fernández-Macías and Hurley, 2016). First, there are some problems with the definition of routine occupations. For instance, in workers' surveys, questions about the routine content of occupations are really meant to measure how repetitive are the tasks performed by workers, and not the possibility of expressing those tasks into a computer code. In other words, the interpretation of the word "routine" is not the same among economists and sociologists on the one hand and among workers or employers on the other one. In fact, researchers are really interested in the extent to which tasks are routinizable (can be expressed in computer codes). Even if everyone would agree on the definition, workers would have difficulties in knowing whether their job might be performed by a computer or by some other machine. Second, there is no common agreement of what the main categories of job tasks should be: often researchers juxtapose the routine to the cognitive dimension, but some argue that cognitive tasks can be routine as well, so that a preferable distinction is between routine and non-routine tasks. Others stress the cognitive/analytical vs. manual tasks distinction (Goos et al., 2009; Autor and Dorn, 2013; Autor and Handel, 2013), where each of them could be more or less routine. Others have added the interpersonal dimension of tasks or the service dimension (Goos et al., 2010), both of which tend to be interpreted as non-

routine. And third, the RBTC is very difficult to operationalize as there is no perfect data source (Fernández-Macías and Bisello, 2017).

In the light of the above remarks, this paper critically examines the RBTC literature in order to: i) provide an overview of the theoretical and empirical debates that surround the notion of how technology affects the labour demand; ii) define areas where consensus among researchers is still not prevalent. This paper is structured as follows: Section 2 provides a summary of the main theoretical frameworks used by researchers to interpret the relationship between technological change and labour demand. Section 3 looks at the empirical evidence on the same matter. Section 4 addresses the main conceptual problems that researchers face when framing the relationship between digitalization and the labour market. In Section 5 we discuss the main problems encountered when bringing theory to the data, with a special focus on the definitions and the variables used. Section 6 discusses the data sources used in the empirical studies on the Routine Biased Technological Change hypothesis. A summary and conclusions are presented in Section 7.

2 Theoretical framework

Technological progress is often considered as the dominant factor driving the changes in labour demand observed in many developed countries (Manning, 2004; Goos and Manning, 2007). It is well known that technological innovations affect labour demand in an important way. Over time, workers might be substituted by technology and displaced from jobs and sectors in which technological advance has a pervasive impact. For example, during the first Industrial Revolution, major technological advances like the mechanization of textiles, lead to a significant substitution of artisans for unskilled labour, resulting in an occupational downgrading. In contrast, in the modern age, information and communication technologies have stimulated the demand for managerial and professional jobs but might have had a negative effect on medium-low skilled jobs in sectors especially affected by the Digital Revolution (Goldin and Katz, 1996). Overall, from the second Industrial Revolution until the end of the 1990s, technology has fostered an increasing demand for more qualified workers (Goldin and Katz, 2007). The following section gives an overview of two of the more prominent theories trying to explain the relationship between technology and the labour market.

2.1 Canonical model: Skill Biased Technical Change

According to Acemoglu and Autor (2011), the Skill-Biased Technological Change hypothesis –and the so-called canonical model– bases the interpretation of the effects of technological change on labour markets on two main assumptions. First, jobs can be classified accordingly with workers' skills, typically by selecting two distinct categories: skilled (high-educated) and unskilled (low-educated). In particular, this classification implies that any given job is assigned to a given category, and workers from the other category cannot perform it (i.e. a job is either a high or a low skill job). Second, in the canonical model, technology is often interpreted as exogenous, meaning that the forms innovations take are not influenced by the skill composition of the workforce itself. However, this assumption is abandoned in more complex General Equilibrium models, in which the adoption of technology is endogenous.

The basic idea behind SBTC is that new technologies that foster productivity are "skill-biased", meaning that high-skilled workers are more able to use new technologies than low-skilled workers (Tinbergen, 1974, 1975), who, in fact, are at risk of being substituted by them. Indeed, Information and Communication Technologies (ICT) are typically interpreted as being complementary to skilled labour and substitute of unskilled labour. This non-neutral technological change increases the relative (to low-skilled) productivity of high-skilled workers and therefore increases their relative labour demand. In conclusion, the model predicts a positive monotonic relation between skills and employment growth (Acemoglu, 2002). The hypothesis that ICT and digitalisation induce an increase in the demand for skilled labour relative to unskilled labour suggests, other things being equal ([1]), an increase in the return to education, and higher wage and employment/unemployment differentials between skilled and unskilled. Many empirical studies have provided estimates for the increase in the (pre-tax) wage premium for higher education ([2]) or the increase in (pre-tax) wage inequality ([3]).

([1])   In practice, the ceteris paribus condition is not exactly satisfied because of changes in the educational composition of the workforce

([2])   While some studies have looked simply at the characterisation of the wage premium (Katz and Murphy, 1992; Juhn et al., 1993; MaCurdy and Mroz, 1995; Beaudry and Green, 2000; Brunello et al., 2009) others have tried to separately estimate the impacts of labour demand changes from those arising from the labour supply (demographic change and changes in education composition; see Card and Lemieux 2001).

([3])   See for example ILO (2015) World Employment and Social Outlook - Trends 2015.

Evidence of such relationship is provided when skills are measured in terms of education. First, at the aggregate level of the economy, both employment (quantities) and wages (prices) of college workers in the US have strongly risen since the early 1980s and through the 1990 in comparison with these magnitudes for less educated workers (Katz and Murphy, 1992). Second, at the firm and industry level, there is a striking correlation between the adoption of computer-based technologies and increased demand for high-skilled workers (Fernandez, 2001). Finally, ample micro-econometric research and several case studies document a statistical positive correlation between the use of new technologies, such as computers, and the employment share of skilled workers (Bartel and Lichtenberg, 1987) or their wage share across industries (Autor, Katz and Krueger, 1998). These studies firmly establish that the new technologies are deployed with better-qualified and better-paid labour and support the SBTC prediction. Hence, during the 90s, SBTC became the standard explanation in labour economics to account for the wage and employment patterns observed for less qualified workers.

The Skill-Biased Technological Change hypothesis can be summarised as follows:

- improvements in technology in the ICT-producing sector affect the whole economy through direct and indirect mechanisms;

- this generates an increase in the returns to ICT capital accumulation and to the accumulation of complementary factors such as skilled labour, which in turn can induce investment in human capital;

- depending on the 'race' between ICT-induced technological change and investment in human capital (Goldin and Katz, 2007), these labour demand and labour supply effects will determine the evolution of the skill premium and wage inequality (inequality and the returns to education would increase if demand factors prevail);

- labour demand and supply evolution will also determine employment patterns; however in this case both supply and demand factors go in the same direction and lead to higher employment of skilled workers;

- the increased demand for skills and competences brought about by the ICT revolution is compatible with the increase in residual wage inequality ([4]) observed in many countries.

The SBTC hypothesis could account for most of the wage and employment patterns observed in the US in the 1980s. However, the hypothesis does not appear to fully explain wage and employment patterns observed in other countries or other periods. In particular, the SBTC hypothesis cannot account for the wage and employment patterns observed in the US after 1990, and particularly the fall in the wage differential between the first and the fifth decile ([5]) recorded during the 1990's. It also cannot explain the drop in employment in middle-skilled jobs and the increase in high-skill and low-skill occupations observed during the same decade (Wright and Dwyer, 2003, Autor et al., 2006, Goos and Manning, 2007). Moreover, from a theoretical perspective, the SBTC relies on a simplistic classification of skilled and unskilled jobs. This classification is unable to capture the interrelations between the labour market and technological progress (feedbacks) and, identifies skills with education, while overseeing the importance of tasks and their relationship with skills. For these reasons, some authors started to investigate not only skill requirements, but also how the task content of jobs is relevant in explaining the effect of technological change on the demand for labour.

([4]) The part of inequality that cannot be accounted for by the observable variables such as education, experience, age, gender, type of occupation etc..

([5]) This is the ratio between the median real wage and the average real wage of the 1st decile. It is often used as a measure of lower tail inequality. Similarly, the ratio of the average real wage in the 9th decile and the median real wage (p90/p50) is considered a measure of upper tail inequality.

2.2 From Skill Biased Technical Change to Routine Biased Technical Change

A more nuanced and refined version of the SBTC was put forward to explain changes in the employment structure, focusing on the impact of computerization on the different tasks performed by workers on the job. The main purpose of this effort is to develop a theory –with testable implications– that takes into account the fact that technology, globalizations and labour market institutions determine the extent to which production tasks are allocated to labour and capital. In other words, while labour and capital remain the basic inputs into production, the production function is expressed in terms of tasks. Tasks are allocated to labour or capital depending on their comparative advantages. This flexible approach is, in principle, able to capture the fact that some tasks –broadly defined as routine or routinizable and historically allocated to low and middle skilled workers- following the digital revolution can now be allocated to capital.

Autor, Levy and Murnane (2003) (hereafter, ALM) put forth this revised version of the SBTC hypothesis, often referred to as Routine Biased Technical Change (RBTC), later refined by Acemoglu and Autor (2011). According to the RBTC hypothesis, the production process is defined in terms of tasks. Job tasks are allocated to workers or to capital ('machines') depending on: 1) the degree to which they are automatable (repetitive and replaceable by code and machines); 2) their separability from other tasks; and 3) the relative costs of using 'machines' versus humans (^{6}). In this context, 'machines' includes hardware, software and combinations of the two, such as robots. One of the most important characteristics in this framework is the distinction between tasks and skills. According to Acemoglu and Autor (2011, p. 1045), a task is defined as a "*unit of work activity that produces output (good and services)*" whereas a skill is a "*worker's endowment of capabilities for performing various tasks*". Tasks are actions that workers perform in their jobs and they might change, due to technical changes and to the relative price of labour versus capital.

One of the main challenges of this approach is the link between the theoretical underpinning, well described in Acemoglu and Autor (2011), and the empirical analysis. In the theoretical model tasks are the basic elements of the production function, and they can be allocated to workers of different skill levels (including offshoring some of them) or to machines, depending on their comparative advantage (ultimately labour and capital services remain the inputs into the production function). However, within this framework, the typical empirical analysis of tasks uses information from workers' surveys or from datasets describing occupational tasks such as O*NET (as opposed to firms' surveys), which really focus on jobs (i.e. those tasks that are actually performed by workers). By imposing a structure on these surveys –such as assigning a measure for the routine abstract/cognitive, manual and interactive content of a given job– it becomes possible to rank occupations as being more or less intensive in routine or in cognitive/abstract or manual or interactive activities. This information can then be aggregated at the level of occupations (more or less refined and including sectors) and countries to get aggregate indices.

ALM propose a classification based on a two-dimensional typology: routine, as opposed to non-routine, and manual, as opposed to cognitive, content. The cognitive element can be further divided into analytical and interactive (Table 1 for details). Overall, the authors identify five categories of tasks:

- *Routine manual tasks*: repetitive physical labour that can be easily replicated by machines and automated. These tasks are typical of production and operative occupations. It includes occupations like assemblers and machine operators.

(^{6})   There is clear distinction between tasks (which arise from the demand side) and skills (which are possessed by workers).

- *Routine cognitive tasks*: repetitive labour involving the processing of information. These tasks are characteristic of clerical and administrative occupations, for example, a bank teller or a telephone switchboard operator. The IT revolution of the 1980s and 1990's made many of these tasks easily performed by computers.

- *Non-routine cognitive tasks*: non-repetitive or non-codifiable work involving the production, processing and manipulation of information. These tasks, which are carried out mainly within managerial, professional and creative occupations, are usually performed by high-skilled workers. Examples of occupations with non-routine cognitive tasks are judges, psychologists, lawyers or medical doctors. According to ALM hypothesis, these occupations are not only difficult to replace with machines, but technologies like personal computers are even considered to play a complementarity role.

In turn, non-routine cognitive tasks are divided in two groups:

- *Non-routine interactive*: tasks that demand creativity, flexibility and complex communication (managerial and interpersonal tasks).

- *Non-routine analytic*: tasks requiring problem solving, and quantitative reasoning.

- *Non-routine manual tasks*: non-repetitive tasks of a physical nature. It includes occupations such as bus driver, cabinet makers or plumbers. The ALM framework does not explicitly predict neither strong substitution by nor strong complementarity with computers, because this category is not directly affected by technological change. Indeed, non-routine manual tasks are typical of service occupations, and are difficult to automate as they require direct physical proximity or flexible interpersonal communication and rely on dexterity. At the same time, they do not need problem solving or managerial skills to be carried out, hence there is limited room for complementarity.

Table 1. Categories of workplace tasks according to Autor et al. (2003)

	Routine tasks	Non routine tasks
	Analytic and interactive tasks	
Examples	Record-keeping	Forming/testing hypothesis
	Calculation	Medical diagnosis
	Repetitive customer service	Legal writing
		Persuading/selling
		Managing others
Computer impact	Substantial substitution	Strong complementarities
	Manual tasks	
Examples	Picking or sorting	Janitorial services
	Repetitive assembly	Truck Driving
Computer impact	Substantial substitution	Limited opportunities for substitution or complementarity

Source: Autor et al. (2003; p. 1286).

In summary, the RBTC hypothesis predicts that ICT developments and digitalisation lead to a decline in jobs that are rich in the routine component (manual or cognitive) and an increase in the number of jobs that are rich in the cognitive non-routine component. The theory does not make clear predictions about employment in jobs that are mostly manual and non-routine, as these are not directly affected by the digital revolution. The effects of ICT-driven technological change on the demand for tasks are magnified by globalisation and free trade, since the ability to separate tasks and the availability of a technology through global trade allows for their outsourcing ([7]). The innovative aspect of this model is that it predicts that computerization has a non-linear effect on labour demand.

([7]) Research has shown that these factors combined make outsourcing of middle-skilled occupation cheap and easy (e.g. Blinder, 2009).

3 Empirical evidence on RBTC

We review twelve studies which build on the ALM model to measure the effect of computerisation and technical change on the structure of labour demand, paying attention to the type of tasks that each study identifies as the most important. Table 2 presents the main results of each paper, together with the specification of the domains considered, and the identified relationship between technology and routinisation. The list does not pretend to be exhaustive as there are more studies applying the task approach to specific countries. The aim here is to show: i) how the literature has evolved from the original ALM model based on five task categories to the three tasks framework introduced by Autor, Katz and Kearney (2006) and formalized in Autor and Dorn (2013), which has become mainstream in the economics literature; ii) present recent and alternative models that challenge such a framework.

Table 2. Task categories

Name of the study	Year	Country	Task categories	Technology displace routine tasks
Autor, Levy and Murnane	2003	US	Routine manual Routine cognitive Non-routine analytic Non-routine interactive Non-routine manual	Yes
Autor, Katz, and Kearney	2006	US	Abstract Routine Manual	Yes
Spitz-Oener	2006	Germany	Follow ALM (2003)	Yes
Goos and Manning	2007	UK	Follow ALM (2003)	Yes
Autor and Handel	2013	US	Follow AKK (2006)	Yes
Autor and Dorn	2013	US	Follow AKK (2006)	Yes
Matthes et al.	2014	Germany	Analytic Interactive Manual Routine Autonomy	Yes
Goos, Manning and Salomons	2014	EU-15	Follow AKK (2006)	Yes
Fernández-Macías and Hurley	2016	EU-15	Cognitive Routine Social Interaction Trade intensity	Yes

Marcolin, Miroudot and Squicciarini	2016	EU-15	Routine task intensity	Yes
Fernández-Macías and Bisello	2017	EU-15	Work (Physical, Intellectual, Social) and tools (work organisation and technology)	Yes
Sebastian	2018	Spain	Follow AKK (2006)	Yes

Source: Author's analysis from the references quoted in the table.

As can be seen in Table 2, there are just two studies that follow the original ALM taxonomy (Goos and Manning, 2007; and Spitz-Oener, 2006). Five papers consider a three-fold classification of tasks by bringing together the two routine categories. To be more precise, Autor, et al. (2006), Autor and Handel (2013), Autor and Dorn (2013), Goos et al. (2014) and Sebastian (2018) classify tasks into abstract, routine and manual. In this case, routine captures both the routine manual and routine cognitive categories of ALM, whereas the abstract category refers to tasks that require problem-solving and managerial tasks with high cognitive demand. Manual tasks are those requiring physical effort and adaptability and flexibility, making them difficult to automate (and are hence not routinary by definition) (8).

Different from most studies in the literature, Matthes et al. (2014), Fernández-Macías and Hurley (2016), Marcolin et al. (2016), and Fernández-Macías and Bisello (2017) propose four new frameworks to measure tasks (9). Matthes et al. (2014) define five domains: analytic, interactive, manual, routine and autonomy. The most innovative idea is that they define routine *ex negativo*, that is, by asking respondents whether their jobs are in some ways non-routine. This is motivated by the fact that, in a survey, direct questions on whether their job implies routinary tasks or not would likely be interpreted by workers as inquires on the repetitiveness of their tasks (not on their codifiability in computer language). Moreover, what is routinary (in the sense of codifiable) or not changes in time (due to technological improvements) and this means that the concept of routine needs to be expressed in an abstract and flexible way. But this increases the measurement problems in workers' surveys, since workers are typically not used to answer abstract questions. Hence, Matthes et al. (2014) propose to define as not-routine tasks those that involve learning of new things, solve difficult problems, react to unanticipated situations or to work on varying assignments. As for autonomy, which is a new category and different from those proposed by Autor and his co-authors, it measures how workers contribute to the definition of their work schedule or pace of work, to the definition of new assignments and to their involvement in decision making processes. While this is a very interesting aspect that has been overlooked by the previous literature, we think that the degree of autonomy is really a feature of the organization of work more than of the technological content of tasks (i.e. it is really about how tasks can be performed and not on their content).

Fernández-Macías and Hurley (2016) maintain the routine and cognitive dimensions but also add the 'social interaction' one, arguing that the latter is by definition of human nature, and hence in principle resilient to computerization.

---

(8) In an earlier version, Goos et al. (2010) introduce the concept of service tasks (instead of manual) alongside abstract and routine. In here, service tasks are defined as taking care of others, and tend to be located in the low-skilled and non-routine quadrant.

(9) It must be noted that Matthes et al. (2014) and Fernández-Macías and Bisello (2017) present new frameworks and hence do not exactly investigate the RBTC hypothesis.

Marcolin et al. (2016) focuses on the measurement of occupational routine intensity, living on the side the issue of how to measure cognitive/abstract/interpersonal and manual tasks.

Finally, Fernández-Macías and Bisello (2017), taking stock of the various contributions here reviewed, propose an approach that distinguishes between the content of tasks (the "*what*") and the ways in which they are carried out (the "*how*"). As for the "*what*", they propose to distinguish between the physical, intellectual and social dimensions, while for the "*how*" they propose to look at both methods and tools (which include the use of machines and ICT). Notice that in this framework, the routine dimension is a sub-category of the methods, reflecting the idea that the extent to which jobs are routinised depends both on technology and on the organization of work. This approach is hence broader than the one proposed by the RBTC and looks at a number of factors affecting the composition of the occupational structure ([10]).

The RBTC model has been used by several studies as a conceptual framework to investigate changes in the employment structure at the occupational and sectorial level, specifically the phenomenon of job polarisation (e.g. Goos and Manning, 2007; Autor, Katz and Kearney, 2006; Goos et al., 2014; Autor and Dorn, 2013; and Autor, 2015). Job polarisation refers to a situation in which employment growth is concentrated at the extremes of the wage distribution ([11]). In other words, over a certain period of time employment in high and low-wage jobs grows faster than employment in the centre of the wage distribution. The rationale of the job polarisation hypothesis is as follows:

- workers employed in jobs that involve manual routine tasks are likely to be replaced by machines. They typically have lower education and wages;

- more generally, workers employed in jobs that require highly routine and standardised tasks are more likely to be replaced by technology. These workers tend to have an intermediate level of education and wages;

- workers employed in highly cognitive, non-routine and non-standardised jobs perform tasks that are difficult to replace by technology. In fact, in many cases their productivity is enhanced by ICT. These workers typically have higher education and higher wages, and the demand for such workers is increasing;

- workers involved in tasks that -in spite of being manual- are not easily performed or replaced by machines (such as those related to people care and education) will not be negatively affected by digitalisation. These may be workers with lower or intermediate education but the demand for such non-routine tasks appears to be growing. This demand is partly due to population ageing, partly due to the increased demand for personal services from the richer part of the population (Mazzolari and Ragusa, 2013) and partly due to the general equilibrium effects of ICT-induced technological change (Autor and Dorn, 2013) ([12]).

Goos and Maning (2007) are the first to formalise the relationship between the substitution of routine tasks and job polarisation. They look at the relationship between the median wage of occupations, their task content, and the evolution of the UK employment structure since the 1970s. They find that the UK exhibits a pattern of

---

([10]) The framework proposed by Fernández-Macías and Bisello (2017) is really about characterizing tasks across occupations/jobs, in the sense that for each individual it is possible to create an index of how much the job performed by her/him is rich in physical, intellectual, and social activities (i.e. tasks) and on how the job is organized in terms of methods and tools. This implies that it is possible to compare jobs in terms of their intensity in physical (i.e. manual), intellectual (i.e. cognitive) and social tasks.

([11]) Other alternative dimensions/distributions to consider include job quality or education. However, the wage dimension is the one most often used to order jobs as it is continuous and it allows for a comparison of wage and job polarisation.

([12]) Technological change will increase productivity and reduce prices, which will affect positively purchasing power, providing a demand-driver push to growth and employment. Applying a spatial equilibrium model, the authors find that local labour markets specialized in routine tasks adopted information technology, reallocated low-skill labour into service occupations (employment polarisation), experienced earnings growth at the tails of the distribution (wage polarisation), and received inflows of skilled labour.

polarisation, with rises in employment shares for the top and bottom of the wage distribution relative to the middle, for the period 1979-1999. Furthermore, they are able to link low-wage occupations with non-routine manual tasks, middle-wage occupations with the routine tasks and high-wage jobs with cognitive non-manual tasks. Hence, their work suggests that job polarisation naturally emerges from substantial substitution, and subsequent displacement, of workers performing routine tasks and from complementarity between digital technologies and cognitive non-routine activities, as predicted by ALM.

Following Goos and Manning (2007), Autor et al. (2006) shows that the US labour market experienced a polarising trend as well, with routine tasks losing ground relative to non-routine tasks. In a more recent work, Goos et al. (2014), using European Labour Force Survey (EU-LFS) data for the period 1993-2010, find evidence that job polarisation has been occurring in all the EU countries considered, with the exception of Finland and Luxembourg, where hours worked by low-wage workers have actually declined. They also find that employment between 1993 and 2006 is positively correlated with the importance of abstract and service tasks, and negatively correlated with the relevance of routine tasks. Naticchioni et al. (2014) suggest that ICT investment is positively correlated with job polarisation. The OECD (2017) also confirms the job polarisation hypothesis for selected OECD countries in the period 1990-2012, but predicts that such effects will disappear in the long run. Evidence supporting job polarisation is also found by Michaels et al. (2014), who use EUKLEMS data over the period 1980-2004 for US, Japan and nine EU countries. Their results indicate that industries that experienced the fastest growth in ICT investment also experienced the fastest growth in the demand for high-skilled workers and a fall in the demand for workers with intermediate levels of education. On the contrary, Fernández-Macías (2012) find very heterogeneous results among European countries and do not show evidence of job polarisation ([13]). Finally, evidence for job polarisation is found in Germany by different authors from 1979 to 1999 (Spitz-Oener, 2006) and from mid-1980s until 2008 (Kampelmann and Rycx, 2011).

While the RBTC might offer a convincing explanation to recent developments in the demand for labour and skills in many industrialised economies, it still presents some serious challenges from a conceptual, empirical, and operational point of view as it is discussed in the next sections.

---

[13]   It should be emphasised that the methodology used in these analyses is not the same.

4 Conceptual problems: capturing routine

The RBTC, introduced by ALM, has replaced SBTC as the most conventional approach to explain changes in the labour market structure induced by technological change. However, as discussed above, differences exist among researchers that have adopted the task framework and some unresolved issues persist.

The first problem is related to the definition of routine tasks, which, according to ALM, comprise those that are programmable, expressible in rules, codifiable and imply a methodological repetition of procedures. This definition is very much technology driven, and implies that technology will replace the jobs with high-routine content. However, it is someway problematic in itself as what is perceived as routine from a worker's point of view may not be so from the perspective of machine execution, and this poses a further challenge to the operationalisation of the concept, as highlighted by Matthes et al. (2014). For instance, driving a motor vehicle is often considered as a non-routine task, because even though it implies the repetition of the same basic activities and might be considered as monotonous (i.e. routine from the workers perspective), it also requires the use of some skills for which humans –but things are rapidly changing- tend to have a comparative advantage (see Matthes et al., 2014, p.279). Along the same line, Green (2012) also raises some doubts on the validity of the distinction between routine and non-routine tasks, arguing that in many cases it is not possible to determine *a priori* which activities are routine and therefore programmable. Finally, limitations in data availability and lack of uniformity among surveys questionnaires inevitably lead to different choices of variables actually used for the analyses, which add to the difficulty in comparing different studies (Autor and Handel, 2013; see also Biagi and Sebastian, 2018).

Another conceptual problem is the distinction between routine and cognitive tasks. Ideally, we would like to measure tasks along orthogonal dimensions. However, and almost by definition, a routine task is often interpreted as a task performed with little cognitive effort and vice versa (Eurofound, 2014), making the addition of a second axis unnecessary or misleading. Part of this problem may lie in the term "cognitive". Whereas the concept of routine is quite precisely defined (at least in theory), the cognitive dimension is more vague. In some cases, cognitive tasks are related to problem solving, and in this case routine and cognitive end up as being two extremes of the same axe (i.e. if a task is routine, it does not require problem solving). In other cases, cognitive tasks are defined as tasks involving information processing. In this case, the overlap is not necessary since there are information processing tasks that are routinary (Eurofound, 2014). The non-orthogonality of the model also relates to some operational problems, which will be discussed in the next section.

Moreover, the ALM model does not distinguish between domestic and foreign labour, and hence does not consider explicitly the possibility that routine tasks performed by domestic workers are offshored abroad for a lower economic cost. Blinder (2009) and Acemoglu and Autor (2011) provide a unified framework which incorporates globalisation and international trade (particularly, offshoring), allowing for the possibility of trade in tasks.

Finally, both the SBTC and the RBTC approaches tend to focus on within-industry shifts in occupational composition and dismiss the importance of the redistribution of jobs between industries (in particular from manufacturing to services). An exception is Autor and Dorn (2013), who point to the need to have a better understanding of the rapid rise of employment and wages in service occupations. Similarly, Handel (2012) argues that this increase is mainly due to three factors: i) population aging contributing to employment growth in the health care sector; ii) the growth of female labour force participation, which stimulates market demand for services previously produced mostly in the home, such as meals or childcare; iii) the growth of the Welfare State.

5 The operationalization of the RBTC

Another relevant issue is the relationship between the definitions of tasks and the operationalization of the theoretical concepts. Indeed, not only is the classification of tasks into different typologies inconsistent between the original work by ALM (2003) and following papers, but also the choice and the number of variables used to create task indices is often completely arbitrary.

Table 3 summarizes the operationalization of the RBTC in eleven relevant papers that are based on the RBTC/polarisation hypothesis (the list is not exhaustive but we focus on the mostly cited publications in the area of RBTC or on studies that introduce novel approaches). As previous argued, the ALM model is bi-dimensional, which leads to the consideration of four broad categories: routine-manual, routine-cognitive, non-routine manual, non-routine cognitive (in turn, subdivided into non-routine cognitive interactive and analytical). Of these eleven papers, two follow the ALM classification ([14]): Goos and Manning (2007), and Spitz-Oener (2006). However, in other four papers, the two routine (cognitive and non-cognitive) categories are conflated into one, leading to a three-fold classification: abstract, routine, and manual (Autor, et al., 2006; Autor and Handel, 2013; Autor and Dorn, 2013; and Goos et al. 2014 ([15]). One paper (Marcolin et al., 2016) focuses on the measurement of routine intensity of occupation. Matthes et al. (2014) develops a new measurement of job tasks, based on five categories that include autonomy. Finally, two papers present new frameworks using (and combining) existing data: Fernández-Macías and Hurley (2016) and Fernández-Macías and Bisello (2017).

The main problem in its operationalization is that the RBTC approach does not provide a unique framework for data analysis. For example, "managerial tasks" are included in the abstract or cognitive category. Indeed, while it seems reasonable to assume that cognitive effort is required in order to perform managerial tasks, the precise identification of what are managerial tasks in a given time and place depends on the social organization of work. The same can be said about "quality control" as an indicator of routine. Quality control might be routine and repetitive in traditional production line jobs that involve mostly manual work and basic tasks with machines, but not necessary in other activities. This naturally creates measurement errors.

In addition, different authors use different data sources and classify tasks based on the information available in the survey they use. This creates additional difficulties when interpreting and comparing the results across studies. For instance, Autor and Handel (2013) introduce the "*absence of face-to-face interactions with customer*" as a parameter to identifying routine. This is arguable; whether there is interaction or not with customers does not necessarily affect the routine content of the occupation. However, the absence of face-to-face interaction is often an indicator of middle-level jobs (Blinder, 2009). As a result, jobs that are high in routine content tend to be performed by middle-skilled workers and therefore, the hollowing out of middle-skilled jobs results from the definition of routine tasks. A similar case happens when "*social interactions and care*" is used to classify non-routine non-cognitive category at the bottom of the wage distribution.

As we can observe in Table 3, there are also some inconsistencies between different applications of the same RBTC hypothesis. For example, the category of "non-routine manual" is measured as: "*hand-eye-foot coordination*" in three papers (Autor, et al., 2003, Goos and Manning, 2007 and Goos et al., 2014); "*time spent performing physical activities*" in Autor and Handel (2013); or "*repairing or renovating houses/apartments/machines/vehicles, restoring art/monuments, and serving and accommodating*" in Spitz-Oener (2006). Another good example is "routine manual". In two papers (Autor, et al., 2003, and Goos and Manning, 2007) is measured as "*finger*

---

[14]   Outside this list we also have Kampelmann and Rycz (2011) and Cortes et al. (2014) following ALM.

[15]   In an earlier version, Goos et al. (2010) introduce the concept of service tasks (instead of manual) alongside abstract and routine. In here, service tasks are defined as taking care of others, tending to be in the low-skilled and non-routine quadrant.

dexterity", Goos et al. (2014) also include "*set limits, tolerances and standards*". In the paper by Autor and Handel (2013), the variables are completely different: "*short repetitive tasks, absences of face-to-face interactions with customers*". However, they all refer to the same categories of the RBTC framework: "non-routine manual" in the first case and "routine manual" in the second one.

More problematic is perhaps the classification of cognitive (as opposed to manual) tasks. These are usually split into analytical and interactive (or interpersonal) activities. In some cases the cognitive dimension is more about problem-solving and analytic skills, in others is related to information-processing tasks. Also, managerial tasks (such as direction, evaluation and planning) sometimes are included in the analytical category (e.g., Spitz Oener, 2006) and other times in the interactive one (e.g. ALM, 2003).

Fernández-Macías and Hurley (2016) provide a new framework to measure the RBTC hypothesis arguing that, in the ALM setup, cognitive tasks and routine tasks overlap in reverse. Different from previous cases, routine (as a noun) is here interpreted as referring to a sequence of actions that is carried out regularly and identically.

Finally, we also include Fernández-Macías and Bisello (2017), with the caveat that it provides a new framework in part alternative to the RBTC one.

Table 3. Operationalization of the RBTC in 11 relevant papers

1. Autor, Levy and Murnane, 2003 (p. 1283)

Typologies	Non-routine analytic, non-routine interactive, routine cognitive, routine manual, non-routine manual.
Definitions	Routine: 'tasks that require the methodical repetition of an unwavering procedure'. No definition of analytic or cognitive; only of non-routine cognitive tasks: 'tasks demanding flexibility, creativity, generalized problem-solving and complex communications'.
Variables used	Non-routine analytic: quantitative reasoning requirements. Non-routine interactive: direction, control and planning (managerial and interpersonal tasks). Routine cognitive: adaptability to work requiring set limits, tolerances and standards. Routine manual: finger dexterity. Non-routine manual: eye-hand-foot coordination.

2. Goos and Manning 2007 (p. 119) - Follow Autor, Levy and Murnane (2003)

3. Autor, Katz and Kearney, 2006 (p. 192)

Typologies	Abstract, routine, manual.
Definitions	Abstract: 'problem-solving and managerial tasks. These are not well structured and require non-routine cognitive skills'.
	Routine: 'cognitive or physical tasks that follow closely prescribed sets of rules and procedures and are executed in a well-controlled environment'.
	Manual: 'do not require abstract problem-solving or managerial skills but are nevertheless difficult to automate because they require some flexibility in a less than fully predictable environment'.
Variables used	Not specified.

4. Spitz-Oener, 2006 (pp. 239-240; 243)

Typologies	Nonroutine analytical, nonroutine interactive, routine cognitive, routine manual, non-routine manual
Definitions	Routine (both manual and cognitive): "are well defined in the sense that they are expressible in rules such that they are easily programmable and can be performed by computers at economically feasible costs (Levy and Murnane 1996)".
	Non-routine tasks: "are not well defined and programmable and, as things currently stand, cannot be accomplished by computers".
	Analytical: "refers to the ability of workers to think, reason, and solve problems encountered in the workplace".
	Interactive: "refers not only to communication skills—that is, the ability to communicate effectively with others through speech and writing—but also to the ability to work with others, including coworkers and customers".
Variables used	Non-routine analytical: researching, analyzing, evaluating and planning, making plans/constructions, designing, sketching, working out rules/prescriptions, and using and interpreting rules.
	Non-routine interactive: negotiating, lobbying, coordinating, organizing, teaching or training, selling, buying, advising customers, advertising, entertaining or presenting, and employing or managing personnel.
	Routine cognitive: calculating, bookkeeping, correcting texts/data, and measuring length/weight/temperature.
	Routine manual: operating or controlling machines and equipping machines.
	Non-routine manual: repairing or renovating houses/apartments/machines/vehicles, restoring art/monuments, and serving or accommodating.

5. Goos, Manning and Salomons, 2014 (p. 9)

Typologies	Three categories: abstract, routine and manual tasks
Definitions	Routine: 'those which computers can perform with relative ease, such as jobs that require the input of repetitive physical strength or motion, as well as jobs requiring repetitive and non-complex cognitive skills'.
	The non-routine dimension is split into abstract and manual. No definition of abstract tasks, just examples: 'complex problem-solving' ([such as] … needed by engineers and medical doctors)'. Examples of service tasks are 'caring for others ([such as] … needed by hairdressers and medical doctors)'.
Variables used	Routine: "set limits, tolerances and standards" and "finger dexterity".
	Abstract: "direction control and planning" and "GED Math".
	Manual: "eye-hand-foot coordination".

6. Autor and Handel, 2013 (pp. S70-71)

Typologies	Abstract, routine, manual tasks
Definitions	Abstract: 'abstract problem-solving, and creative, organisational and managerial tasks'.
	Routine: 'routine, codifiable cognitive and manual tasks that follow explicit procedures'.
	Manual: 'non-routine manual job tasks that require physical adaptability'.

Variables used	Abstract: document-reading, mathematics, problem-solving of at least 30 minutes, supervision of other workers.
	Routine: short repetitive tasks, absence of face-to-face interactions with customers.
	Manual: time spent performing physical tasks.

7. Autor and Dorn, 2013 – Follow Autor, Katz, and Kearney (2006)

8. Matthes, Christoph, Janik and Ruland (2014)

Typologies	Analytic, Interactive, Manual, Non routine, Autonomy
Definitions	Analytic: tasks that involve thinking of reasoning (such as reading, writing and calculating)
	Interactive: tasks that involve communication with others (such as dealing with customers or clients, supporting others, teaching or dealing with applicants)
	Manual: tasks that involve physical strain (such as stand, walk, lift or assume uncomfortable body positions or exposure to cold or heat)
	Non routine: task complexity, including learning new things, solve difficult problems, react to unanticipated situations, work on varying assignments)
	Autonomy: captures the degree to which workers have a voice in setting the order and pace of job tasks, are free to make decisions, free to express their voice in decisions making processes and free to decide the procedures and methods to be applied in their work.
Variables used	Analytic: reading (number of pages), writing (number of pages), mathematics (difficulty)
	Interactive: how often does a worker: i) deal with customers, ii) provide people with simple information or general advice; iii) provides counselling to others; iv) support or assist others; v) teach or train others; vi) deal with applicants
	Manual: how often does a worker (per average working day): i) have to stand continuously for at least two hours; ii) cover longer distances by foot or by bike; iii) have to lift or carry something that weights at least 10 Kg; iv) work while assuming uncomfortable body posture; v) is exposed to great heat or great cold
	Non routine: how often (as part of her work) does a worker: i) have to solve difficult problems; ii) have to learn new things; iii) is assigned new tasks; v) have to react to unforeseen situations; vi) face changes in work assignment; vi) perform new tasks.
	Autonomy: how often does a worker: i) may schedule work activities all by herself; ii) choose new task assignments all by herself; iii) choose work pace all by herself; iv) personally involved in important strategic decisions of the company.

9. Marcolin, Miroudot and Squicciarini (2016)

Typologies	Sequentiability, Flexibility, organise your own, and plan your own.
Definitions	Sequentiability: choose the sequence of the tasks involved by the job.
	Flexibility: change the content of work or how this is carried out.
	Organise your own: plan their own work activities.
	Plan your own: organise their own working time.

Variables used	Sequentiability: D_Q11a: "To what extent can you choose or change the sequence of your tasks?" (Not at all, Very little, To some extent, To a high extent, To a very high extent)
	Flexibility: "To what extent can you choose or change how you do your work?" (Not at all, Very little, To some extent, To a high extent, To a very high extent)
	Organise your own: "How often your current job involves planning your own activities?" (Never; Less than once a month; Less than once a week but at least once a month; At least once a week but not every day; Every day)
	Plan your own: "How often your current job involves organising your own time?"(Never; Less than once a month; Less than once a week but at least once a month; At least once a week but not every day; Every day)

10. Fernández-Macías and Hurley (2016)

Typologies	Non-manual non-routine, Non-manual routine, Manual non-routine and manual routine
Definitions	Cognitive: "Adaptability to work requiring set limits, tolerances and standards".
	Routine: Refers to a sequence of actions that is carried out regularly and identically; as an adjective, it is synonym of *repetitive* and *standardized.*
	Social Interaction: No definition.
	Trade intensity: No definition.
Variables used	Cognitive: (a) complex tasks; (b) use of computers at work; (c) use of internet at work; (d) number of years of formal education necessary to perform the job adequately
	Routine Manual: (a) repetitive hand or arm movements; (b) repetitive hand movements of less than 1 or 10 min; (c) monotonous tasks; (d) dealing with unforeseen problems (reverse coded)
	Social Interaction: (a) whether the current job requires direct interaction with non-colleagues; (b) whether the pace of work is determined by the demands from customers.
	Trade intensity: the index comes from the 1995–2007 average of domestic value-added of exports (that is, eliminating the value of intermediate imports) and the 1995–2007 average of the gross value added of imports relative to gross output.

11. Fernández-Macías and Bisello (2017)

Typologies	Physical tasks, Intellectual tasks, Social tasks, Methods and Tools
Definitions	Physical tasks: strength (tasks which primarily require the exertion of energy and strength) and dexterity (tasks which primarily require a fine physical skill and coordination, particularly in the hands)
	Intellectual tasks: tasks aimed at the manipulation and transformation of information, and the active resolution of complex problems. It is further divided into Information processing, differentiating between literacy (verbal information) and numeracy (numeric information), and Problem solving (distinguishing between information gathering and evaluation of complex information) and creativity and resolution).
	Social tasks: tasks that primarily consist in interacting with other people,. They differentiate between serving or attending customers, training and coaching others, persuading and influencing others, supervising and coordinating others.
	Methods: forms of work organization used in performing the tasks, differentiating

	between autonomy, teamwork and routine
	Tools: type of technology used at work, distinguishing between use of machines and use of ICT.
Variables used	Items from EWCS, PIAAC, O*NET are used. The full list of variables used is available at https://www.eurofound.europa.eu/sites/default/files/ef1617en2.pdf

Source: Author's analysis from the references quoted in the table.

6 Empirical measurements: data sources

When we look at empirical specifications, we can see (Table 4) that there are two main options for measuring the task content of different types of jobs: (1) direct measures, drawing from occupational databases based on the assessment of experts (e.g. O*Net), and (2) self-reported, aggregating the answers of individual workers to surveys on skills and working conditions (e.g. IAB/BIBB, BBS, PDII, PIAAC, and EWCS).

One of the main problems in ALM's empirical approach has to do with their exclusive reliance on O*Net, which does not allow for a comparison over time, even if this database is regularly updated. Thus, studies using this database are limited to analyse exclusively changes in the extensive margin (i.e. between occupation/job variation), and assume that the task-content is fixed within occupations/jobs. As can be seen in Table 4, O*Net has been used in eight out of seventeen studies. Other surveys used for this purpose in the literature are the IAB/BIBB for Germany (see, e.g., Spitz-Oener, 2006), NEPS for Germany (Matthes et al., 2014), the Princeton Data Improvement Initiative (PDII) for the US (see e.g. Autor and Handel, 2013), the British Skills Surveys for the UK (see, e.g., Green, 2012, and Akcomak et al., 2013), the Programme for the International Assessment of Adult Competencies (PIACC) for 24 OECD countries (see, e.g., Fernández-Macías and Bisello, 2017; Marcolin et al. 2016) and the European Working Condition Survey for 15 European countries (Fernández-Macías and Hurley, 2016, Fernández-Macías and Bisello, 2017) and for Spain (Sebastian, 2018).

Using workers´ surveys to infer the task content of jobs and occupations has advantages and disadvantages. On the one hand, it allows studying the variability in task content within each occupation or job type. As discussed in Section 2.2, jobs can be interpreted as coherent bundles of tasks, implying that workers in the same occupation or type of job should carry out similar tasks. But there is also some within-occupation variation that can be explicitly analysed only using workers´ surveys. Since not all workers within the same job carry out exactly the same tasks, it is worth exploring the extent of dispersion in task content within jobs and the reasons behind it. On the other hand, gathering information on tasks from workers introduces a potential measurement bias, since workers´ answers may reflect other things beside the task content in strict terms.

Table 4. Empirical measurement of the RBTC in 17 papers

Name of study	Year	Dataset	Country	Data
Autor Levy and Murnane	2003	O*Net	US	1977 and 1991
Goos and Manning	2007	O*Net	UK	1977
Autor, Katz and Kearney	2006	O*Net	UK	Not specified
Spitz-Oener	2006	BIBB/IAB	Germany	1979, 1985/86, 1991/92, 1998/99, 2006, 2012
Kampelmann and Rycz	2011	SOEP	Germany	Information on tasks was collected in 1985, 1987, 1989, 1995 and 2001
Green	2012	BBS	UK	1997, 2001, 2006
Autor and Dorn	2013	O*NET	US	1977

Autor and Handel	2013	PDII	US	19
Akcomak, Kok, and Rojas-Romagosa.	2013	British Skill Survey	UK	1997, 2001, 2006
Goos, Manning and Salomons	2014	O*Net	EU-15	1977
Matthes, Christoph, Janik and Ruland	2014	NEPS	Germany	2012
Anghel et al.	2014	O*Net	Spain	*same as GMS
Marcolin, Miroudot and Squicciarini	2016	PIAAC	20 OECD countries	2012
Fernández-Macías and Hurley	2016	EWCS	EU-15	2010
Fernández-Macías and Bisello	2017	O*Net, EWCS, PIAAC	EU-15	2006-2012
Fonseca, Lima and Pereira	2018	O*Net	Portugal	Not specified
Sebastian	2018	EWCS	Spain	1995-2010

Notes: BBS (British Skill Survey), BIBB/IAB (German Federal Institute for Vocational Training/Research Institute of the Federal Employment Service), EWCS (European Working Condition Survey), NEPS (National Education Panel Study), O*Net (Occupational Information Network), PIAAC (Programme for the International Assessment of Adult Competencies), PDII (Princeton Data Improvement Initiative), and SOEP (German Socio-Economic Panel).
Source: Author's analysis from the references quoted in the table.

7 Summary and conclusions

In this report we contribute to the growing debate about how the introduction of technology affects labour demand. First, we provide some background of the main theoretical frameworks used by researchers to explain recent changes in the employment distribution. In here, we discuss the main drawbacks of the SBTC and why the RBTC might better account for the decline in the share of middle wage occupations (relative to high and low wage occupations).

Second, we review the most important empirical studies using the RBTC model. Overall, the prevailing economic literature provides empirical support to the RBTC model: cheaper computerisation progressively replaces human labour in routine tasks, thereby leading to an increase in the relative demand for workers performing non-routine tasks.

Third, we show that the RBTC captures quite well the changes in the employment distribution, but we argue that it presents challenges from a conceptual, operational, and empirical point of view. The first relevant issue is the conceptual problems that arise when trying to capture the concept of routine tasks. In the RBTC model, they are defined as codifiable tasks that can be performed by machines. However, a measure of codifiability is hardly found in existing databases: what is perceived as routine for workers (everyday task) may not be so from the perspective of machine execution. Another conceptual problem is the possible overlap (in reverse) between routine and cognitive tasks. Many routine (i.e. codifiable) tasks require, by definition, fewer cognitive tasks.

Moreover, we find inconsistencies between the theory and its operationalization. This is particularly true in the case of the operationalization of routine and cognitive tasks, which often include measures that do not correspond to a precise theoretical framework. For example, routine task indices sometimes include measures of quality controls, but this item is unrelated to the theoretical definition. Analogous issues arise for cognitive task measurement: whereas the definition involves problem solving and information processing tasks, cognitive task indices often include measures of managerial responsibilities.

Finally, it is clear than no perfect database exists. On the one hand, self-reported sources allow studying the variability in task content within each occupation or job type, which cannot be studied using occupational database. On the other hand, self-reported sources are prone to introduce potential bias in the measurement, which tend to be lower in occupational databases.

In conclusion, the literature has yet to converge to a model that consistently explains how technology affects the labour demand. As already stated, the RBTC has the merit of providing an explanation of why cheaper computerisation progressively replaces human labour in routine tasks, leading to an increase in the relative demand for workers performing non-routine tasks. However, it is not immune to severe challenges, especially on the empirical ground. Future research should focus on the development of a measurement framework that addresses the challenges that we have raised here. This might require the development of ad-hoc items or surveys.

References

Acemoglu, D. (2002). "Technical Change, Inequality, and the Labor Market", *Journal of Economic Literature*, 40(1), 7-72.

Acemoglu, D. and Autor, D. H. (2011). *Skills, Tasks and Technologies: Implications for Employment and Earnings*, in: O. Ashenfelter and D.E. Card (eds.) Handbook of Labor Economics, Vol. 4B, Amsterdam: Elsevier, pp. 1043-1171.

Akcomak, S., Kok, S., and Rojas-Romagosa, H. (2013). The effects of technology and offshoring on changes in employment and task-content of occupations. Technical report, CPB Netherlands Bureau for Economic Policy Analysis.

Anghel, B., De la Rica, S., and Lacuesta, A. (2014). "The impact of the Great Recession on employment polarization in Spain", *SERIEs*, 5(2-3):143-171.

Autor, D. H (2015) "Why are there still so many jobs? The history and future of workplace automation", Journal of Economic Perspectives, 29(3): 3-30.

Autor, D. H and Dorn, D. (2013). "The Growth of Low-Skill Service Jobs and the Polarization of the US Labor Market", *American Economic Review*, 103(5): 1553–1597.

Autor, D. and Handel, M. (2013). "Putting tasks to the test: Human capital, job tasks, and wages", *Journal of Labor Economics*, 31(2), 59–96.

Autor, D. H., Katz, L. F. and Kearney, M. S. (2006). "The Polarization of the U.S. Labor Market", *American Economic Review Papers and Proceedings*, 96(2), 189-194.

Autor, D. H., Katz, L. F. and Krueger, A. (1998) "Computing Inequality: Have Computers Changed the Labor Market?", *Quarterly Journal of Economics*, 113(1), 1169-1214.

Autor, D. H., Levy, F., and Murnane, R. J. (2003). "The Skill Content of Recent Technological Change: An Empirical Exploration", *Quarterly Journal of Economics*, 118(4), 1279-1334.

Bartel, A. P., and Lichtenberg, F., R. (1987). "The Comparative Advantage of Educated Workers in Implementing New Technology: Some Empirical Evidence," *Review of Economics and Statistics*, 69 (1), 1-11.

Beaudry, P. and Green, D. A. (2000). "Cohort patterns in Canadian earnings: Assessing the role of skill premia in inequality trends" *Canadian Journal of Economics/Revue Canadienne d`Economique*, 33(4), 907-936.

Biagi and Sebastian (2018). "New technologies and Routinization: How robust is the evidence for the EU??", (forthcoming).

Blinder, A. S. (2009). "How many US jobs might be offshorable?", *World Economics,* 10(2), 41.

Brunello, G., Fort, M. and Weber, G. (2009). "Changes in Compulsory Schooling, Education and the Distribution of Wages in Europe?", *The Economic Journal*, 119(536), 516-539.

Card, D. and Lemieux, T. (2001) "Education, Earnings, and the Canadian G.I. Bill". *Canadian Journal of Economics*, 34(2), 313-344.

Cortes, G. M., Jaimovich, N., Nekarda, C. J., Siu, H. E. (2014). "The Micro and Macro of Disappearing Routine Jobs: A Flows Approach", *NBER Working Paper No. 20307*

Eurofound (2014). *Drivers of Recent Job Polarization and upgrading in Europe: European Jobs Monitor 2014*, Eurofound, Dublin.

Fernandez, R. M. (2001). "Skill-Biased Technological Change and Wage Inequality: Evidence from a Plant Retooling", *American Journal of Sociology*, 107(2), 273-320.

Fernández-Macías, E. (2012). Job polarization in Europe? Changes in the employment structure and job quality, 1995-2007. Work and Occupations, 39(2):157-182.

Fernández-Macías, E. and Bisello, M. (2017). What do you do at work and how: a framework to measure tasks across occupations. Working paper.

Fernández-Macías, E. and Hurley, J. (2016). "Routine-biased technical change and job polarization in Europe", *Socio-Economic Review*, page mww016.

Fonseca, T., Lima, F., and Pereira, S. (2018). "Job polarisation, technological change and routinisation: evidence for Portugal", *Labour Economics*, 51, pp. 317-339.

Goldin, C., and Katz, L. F. (1996). "Technology, Skill, and the Wage Structure: Insights from the Past", *AEA Papers and Proceedings*, 86(2), 252-257.

Goldin, C., and Katz, L. F. (2007). "Long-Run Changes in the Wage Structure: Narrowing, Widening, Polarizing", *Brookings Papers on Economic Activity*, 2, 135-167.

Goos, M., Manning, A. (2007). "Lousy and Lovely Jobs: The Rising Polarization of Work in Britain", *Review of Economics and Statistics*, 89(1), 118-133.

Goos, M., Manning, A., and Salomons, A. (2009). "Job Polarization in Europe", *AEA Papers and Proceedings*, 99(2), 58-63

Goos, M., Manning, A. and Salomons, A. (2010). "Explaining job polarization in Europe: The roles of technology, globalization and institutions". CEP Discussion Paper No. 1026, *Centre for Economic Performance*, London School of Economics, London.

Goos, M., Manning, A. and Salomons, A. (2014). "Explaining job polarization: routine-biased technological change and offshoring", *American Economic Review*, 104(8): 2509-26.

Green, F. (2012). "Employee involvement, technology and evolution in job skills: A task-based analysis", *Industrial & Labor Relations Review*, 65(1): 35–66.

Handel, M. (2012). "Trends in Job Skills Demands in OECD Countries", OECD Social, Employment and Migration Working Papers, No 143, OECD Publishing.

ILO (2015) World Employment and Social Outlook: Trends 2015. International Labour Office , ILO, Geneva

Juhn, C., Murphy, K. M. and Pierce, B. (1993). "Wage inequality and the rise in returns to skills", *Journal of Political Economy,* 101, 410-442.

Kampelmann, S. and Rycx, F. (2011). "Task-biased changes of employment and remuneration: The case of occupations". *IZA Discussion Paper 5470*

Katz, L. F. and Murphy, K. M. (1992). "Changes in Relative Wages, 1963-1987: Supply and Demand Factors", *Quarterly Journal of Economics,* 107(1), 35-78.

MaCurdy, T. and Mroz, T. (1995). Estimating macro effects from repeated cross-sections. Technical report, University of Standford.

Manning, A. (2004). "We can work it out: The Impact of Technological Change on the Demand for Low-Skill Workers", *Scottish Journal of Political Economy*, 51(5), 581-60.

Marcolin L., Miroudot S. and Squicciarini M. (2016). "The routine content of occupations: new cross-country measures based on PIAAC", *OECD Science, Technology and Industry Working Papers*, 2016/02, OECD, Paris.

Matthes, B., Christoph, B., Janik, F., Ruland, M. (2014). "Collecting information on job tasks - an instrument to measure tasks required at the workplace in a multi-topic survey", *Journal for Labor Market Research*, 47(4), 273-297.

Mazzolari, F. and Ragusa, G. (2013). "Spillovers from High-Skill Consumption to Low-Skill Labor Markets", *The Review of Economics and Statistics*, 95(1), 74-86.

Michaels, G., Natraj, A., and Van Reenen, J. (2014) "Has ICT polarized skill demand? Evidence from eleven countries over 25 years", *Review of Economics and Statistics*, 96 (1), 60-77. 14

Naticchioni, P, Ragusa, G., and Massari, R. (2014) "Uncondicional and Conditional Wage Polarization in Europe", IZA Discussion Papers 8465, Institute for the Study of Labor (IZA).

OECD (2017). OECD employment Outlook 2017, OECD Publishing, Paris.

Sebastian, R. (2018). "Explaining Job Polarisation in Spain from a Task Perspective". *SERIEs,* Vol.9 Issue 2, pp215-248, Springer (DOI: 10.1007/s13209-018-0177-1)

Spitz-Oener, A. (2006). "Technical Change, Job tasks, and Rising Educational Demands: Looking Outside the Wage Structure", *Journal of Labor Economics*, 24(2), 235-270.

Tinbergen, J. (1974). "Substitution of Graduate by Other Labor.' *Kyklos* 27, 217-226.

Tinbergen, J. (1975). "*Income Differences. Recent Research"*, Amsterdam: North Holland

Wright, E. O. and Dwyer, R. E. (2003) "The Patterns of Job Expansions in the USA: A Comparison of the 1960s and 1990s", *Socio Economic Review*, 1, p. 289-325.

List of tables

The European Commission's science and knowledge service

Joint Research Centre

JRC Mission

As the science and knowledge service of the European Commission, the Joint Research Centre's mission is to support EU policies with independent evidence throughout the whole policy cycle.

EU Science Hub
ec.europa.eu/jrc

@EU_ScienceHub

EU Science Hub - Joint Research Centre

Joint Research Centre

EU Science Hub

Publications Office