European Commission

JRC TECHNICAL REPORTS

JRC Digital Economy Working Paper 2018-08

Will this time be different?

A review of the literature on the Impact of Artificial Intelligence on Employment, Incomes and Growth

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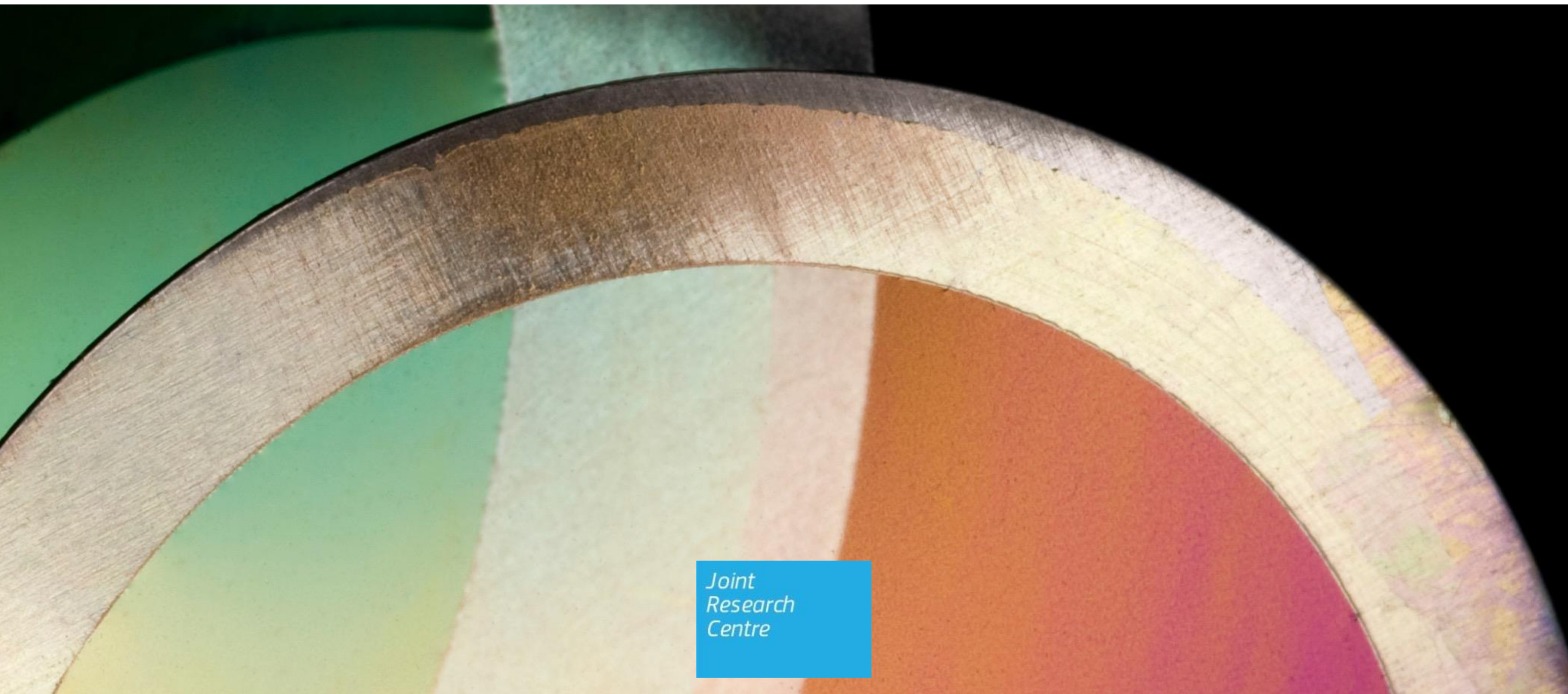
November 2018



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JRC Science Hub
https://ec.europa.eu/jrc

JRC114182

ISSN 1831-9408 (online)

Seville, Spain: European Commission, 2018

How to cite: Bertin Martens and Songül Tolan, Will this time be different? A review of the literature on the Impact of Artificial Intelligence on Employment, Incomes and Growth, Digital Economy Working Paper 2018-08; JRC Technical Reports.

Table of Contents

ABSTRACT 4
1. INTRODUCTION 5
2. THE TRADITIONAL MODEL: SUBSTITUTION AND COMPLEMENTARITY 7
3. THE TASK-BASED APPROACH 9
4. JOBS AT RISK FROM AI 12
5. WHAT WOULD MAKE AI/ML DIFFERENT? 13
6. THE IMPACT OF AI ON ECONOMIC GROWTH 15
7. AI AND INCOME DISTRIBUTION 17
8. CONCLUSIONS 21
BIBLIOGRAPHY 24

Abstract

There is a long-standing economic research literature on the impact of technological innovation and automation in general on employment and economic growth. Traditional economic models trade off a negative displacement or substitution effect against a positive complementarity effect on employment. Economic history since the industrial revolution as strongly supports the view that the net effect on employment and incomes is positive though recent evidence points to a declining labour share in total income. There are concerns that with artificial intelligence (AI) "this time may be different". The state-of-the-art task-based model creates an environment where humans and machines compete for the completion of tasks. It emphasizes the labour substitution effects of automation. This has been tested on robots data, with mixed results. However, the economic characteristics of rival robots are not comparable with non-rival and scalable AI algorithms that may constitute a general purpose technology and may accelerate the pace of innovation in itself. These characteristics give a hint that this time might indeed be different. However, there is as yet very little empirical evidence that relates AI or Machine Learning (ML) to employment and incomes. General growth models can only present a wide range of highly diverging and hypothetical scenarios, from growth implosion to an optimistic future with growth acceleration. Even extreme scenarios of displacement of men by machines offer hope for an overall wealthier economic future. The literature is clearer on the negative implications that automation may have for income equality. Redistributive policies to counteract this trend will have to incorporate behavioural responses to such policies. We conclude that that there are some elements that suggest that the nature of AI/ML is different from previous technological change but there is no empirical evidence yet to underpin this view.

JEL codes: J620, 0330

1. Introduction

Contemporary concerns about the impact of AI are triggered by a rapid rise in successful applications of machine learning (ML), a branch of AI.[1] Prior to ML, tasks could only be automated by giving a computer precisely defined instructions to perform a task. This expensive process is increasingly being replaced by a more automated process of running an existing ML algorithm on task-related training data of inputs and outputs without explicitly programming the mechanisms of the task. The algorithm takes the role of a datacomputer-driven black-box that transforms inputs into outputs. Current ML technology performs well in stable environments where large and accurate input-output datasets are available to automate tasks with clearly defined goals and metrics, no long chains of reasoning and no requirements of prior knowledge or detailed explanations (Brynjolfsson, Mitchell, and Rock 2018; Brynjolfsson & Mitchell, 2017). The performance of ML erodes very rapidly in situations that divert from these settings. Most computer scientists would agree that we are still far away from General AI that could completely replace human intelligence in all its aspects. The AI discussion in this paper should thus be seen in the context of the still somewhat limited capabilities of ML.

AI/ML is a recent technologynot a recent technology that is only graduall but it is only recently is ity finding its way into industrial and services applications. There is a lot of investment in AI/ML development but applications are still relatively limited across a wide range of sectors. It may be too early to detect that impact. According to Brynjolfsson et al. (2017) we are facing a "Solow Paradox: we see transformative new technologies everywhere but in the productivity statistics". This may be due to lags in implementation of the new technology and the restructuring of firms to adapt to the technology. That explains the paucity of empirical evidence in this paper about the impact of AI. Empirical evidence is, by definition, about the past. AI has as yet very little "past". Most of this literature review is therefore limited to more theoretical debates or speculative forecasts about potential impacts of AI. The only robust empirical evidence available is about general technological change, not AI, or is confined to the impact of robots in industry applications, arguably a limited subset of AI applications.

Societal concerns about automation, mechanisation and substitution between men and machines go back at least to the industrial revolution and probably much further. The current debate on AI fits well into that long-term trend. The past offers reassuring evidence for human employment: despite relentless waves of mechanisation since the industrial revolution and across all industries, human employment and incomes have kept growing. However the "this time is different"-syndrome keeps stirring concerns. True, past mechanisation did not replace human cognitive functions at the pace at which AI/ML seems to go about it. Of course, forecasts that half of all jobs could disappear in the next two decades (Frey & Osborne, 2017) fuel these concerns. How credible are these forecasts and what other considerations can be brought into the picture to balance these alarmist predictions, if any?

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[1] We use the term ML representatively for all of its subfields and fields that include applications of ML, such as Deep Learning, Reinforcement Learning or Natural Language Processing etc

Economic thinking on automation revolves around two opposite poles. Models that focus on the complementarity between men and machines predict that the labour-saving impact of technological progress is counterbalanced by higher wages, economic growth and more employment in other sectors. By contrast, substitution models assert that technology causes job displacement and leads to polarisation, de-skilling and possibly a jobless economy (Autor, 2015; Agrawal, Gans, and Goldfarb 2018a). Historical evidence on technological progress since the industrial revolution lends credence to compensation theory. Despite massive technological progress and substitution of human labour by machines across nearly all sectors, employment and incomes have substantially increased over the last two centuries though there are indications that the labour share of income is declining (Karabarbounis and Neiman, 2014). Still, the balance between substitution and complementarity keeps coming back in Why then do we keep looking at substitution models? This is partly a theoretical debates between economists comparing the features of these models and partly anin the empirical evidencedebate. While employment may generally rise, this is not necessarily always the case. Further, if this long-run gain was preceded by short-run pain, we need to understand the mechanisms to exploit the benefits of technological transitions. And of course, this time may be different.

In this review paper we present both perspectives and the related empirical evidence. We start with a discussion of the traditional capital-labour (machine-labour) substitution model where technology is assumed to be factor-augmenting, meaning that technological progress acts as if it increases the effective units of one of the factors of production. In other words, it leaves the possibility for increasing employment with capital deepening as long as the machine-labour substitution elasticity is lower than -1, i.e. a 1 per cent increase in the use of machines will displace less than 1 per cent of the work force. That model dominates most of the economic literature on technology and automation. We contrast this model with athe more recent task-based model (Acemoglu and Restrepo, (2016, 2017, 2018) that has emerged as a strong contender in the debate on the impact of AI on employment. Their model replaces factor augmentation with direct substitution between human and (automated) machine-executed tasks. Although it leaves the possibility of increasing labour demand through productivity and capital accumulation effects, automation will not lead to a proportional expansion of the demand for labour due to a powerful displacement effect. We review the empirical evidence on the relationship between AI proliferation and employment in the context of both models. While evidence that is based on the traditional model yields positive employment effects, evidence for the task-based approach shows rather negative mixed effects of automation on employment. These negative results stem from are not surprising given the emphasis of the task-based model on the displacement effect and the focus of this empirical literature on robotisation robotics in the manufacturing sectors which are prone to routinisation and automation. A broader application of the task-based model on routine-replacing technological change in the German context shows positive effects. Thus, the empirical literature is scarce and not decisive.

We discuss some other models that try to combine the two approaches and allow for both labour augmenting and depleting effects depending on the assumptions made on the elasticity of substitution between capital and labour in total production. Part of the debate has moved beyond the narrow focus on employment substitution effects and towards a more comprehensive perspective that takes into account the productivity effects of AI on economic growth. Even these growth models offer no robust insights and can only suggest a wide range of possible scenarios, mainly because there is as yet not sufficient empirical evidence in favour of any of these scenarios. We also review some papers on the impactthe distributional implications of AI on income distribution.. Again, that impact is not clear and depends on assumptions about AI as a complement or substitute for human labour. Finally, we discuss theories and empirical evidence that supports the view of AI/ML as a General Purpose Technology (GPT)that the impact of AI/ML on labour markets may be different from previous technological advancements.

2. The traditional model: substitution and complementarity

Autor (2015) summarizes very well the mechanisms of substitution and complementarity between men and machines: "Focusing only on [jobs] lost misses a central economic mechanism by which automation affects the demand for labour: raising the value of the tasks that workers uniquely supply". Many, perhaps most, workplace technologies are designed to save labour. When automation or computerization makes some steps in a work process more reliable, cheaper, or faster, this increases the value of the remaining human links in the production chain. Workers are more likely to benefit directly from automation if they supply tasks that are complemented by automation, but not if they primarily (or exclusively) supply tasks that are substituted. However,, the elasticity of labour supply and can mitigate these wage gains. dDemand side factors also play an important role in these wage dynamics. The output elasticity of demand for labour, combined with income elasticity of demand for the output, can either dampen or amplify the gains from automation. Over the very long run, gains in productivity have not led to a shortfall of demand for goods and services: instead, household consumption has largely kept pace with household incomes. In line with Baumol's (1967) "cost disease" [2] hypothesis, rising productivity in technologically leading sectors may boost employment nevertheless in lagging activities where humans exhibit a comparative advantage in comparison to robots".

However the speed of advances in machine capabilities may curtail aggregate labour demand as technology rapidly encroaches on human jobs - the “robocalypse” scenario. Autor (2017) examines if there is empirical evidence for this scenario by analysing the relationship between productivity growth and employment using country- and industry-level data for 19 countries over 35+ years. Consistent with both the popular (‘robocalypse’) narrative and the Baumol hypothesis he finds that industry-level employment falls as industry productivity rises, implying that technically progressive sectors tend to shrink. Simultaneously, he shows that country-level employment generally grows as aggregate productivity rises. Because sectoral productivity growth raises incomes, consumption, and hence aggregate employment, a plausible reconciliation of these results is that the negative own-

[2] Baumol (1967) observed that wages in slow productivity growth sectors will follow those in fast growth sectors and impose a cost that drives up the share of wages and keeps down the capital share. As a consequence, total productivity growth is limited by inputs that are hard to improve upon.)

industry employment effect of rising productivity is more than offset by positive spill-overs to the rest of the economy. This empirical evidence thus supports the complementarity hypothesis.

Karabarbounis and Neiman (2014) find some evidence that undermines the complementarity hypothesis. They show how the share of labour in value-added has declined since the 1980s and attribute this to a relative decline in the price of capital goods, induced mainly by ICT technology. This motivates firms to replace more human labour with machines. Still, it did not prevent Brynjolfsson & McAffee (2011, 2014) from debatingdebate arguments for and against the complementarityis hypothesis. Because automation increases the demand for capital and the rental rate, it encourages capital accumulation. It is thus possible to have periods of fast automation during which the labour share declines and capital accumulation accelerates even if the elasticity of substitution between capital and labour is less than one. This implies that rather than being the cause of the decline in the labour share (as argued by Piketty (2014)), capital accumulation may be a response to automation and lessen its negative impact on the labour share (when the elasticity of substitution is less than one).

Further evidence for the complementarity hypothesis is given by the literature on skill-biased technological change, although the complementarity here is between different types of skills. For instance, Autor et al. (2003) find evidence for computerization-driven routine-biased change in labour demand for US periods 1960-1998. Starting from the hypothesis that computers substitute workers in routine tasks and complement them in non-routine tasks, they show an overall increase of labour-input in non-routine tasks that is more pronounced in rapidly computerizing industries.

Deming (2017) revisits the ideaanalyses of skill-biased technological change in a model where workers can trade tasks according to comparative advantages in their productivity. In this model social skills reduce the costs of trading tasks. . In this model better social skills reduce trade costs. As technological change increases worker productivity, the value of complementary social skills also increases. The validity of the model predictions (demand shifts towards social skills due to technological change) are tested on US data, including the National Longitudinal Survey of Youth (NLSY) 1979, 1997 and occupational classification data (O*NET), against several alternative explanations. The empirical analysis shows the growing importance of social skills for employment, wages, and wage gains in the US economy between 1980 and 2012: Social skill-intensive occupations grew by 11.8 percentage points along with rapid wage increases in these occupations. While employment and wage growth has been strong in occupations with high math and social skill requirements, employment declined in occupations with high math but low social skill requirements. Comparing the NLSY1997 with the NLSY1979The analysis further shows the strength of social skills athat social skills are a strongs a predictor for full-time employment, wages and wage gains.

Note that the empirical evidence for all these studies goes back several decades into the past, long before AI became a source of concern. Therefore these studies more accurately investigate the general effect of "technological progress" on labour markets. Some of it provides reassurance about the beneficial impact of computers on employment but says nothing specific about the impact of AI.

Before we conclude this section we should point out that the traditional model can also be put to work in reverse mode: insufficient technological progress can be a source of unemployment and anaemic growth. Gordon (2012) argued that despite all technological progress over the last decade there is a slow-down in productivity growth in the US. Going down from sectors to occupations within sectors, Aum, Lee and Shin (2018) find that the driving force of the aggregate productivity slowdown is complementarity across occupations and industries. Occupations and industries with above-average productivity growth shrink in terms of value-added and employment shares, and their contribution toward aggregate productivity growth becomes smaller even when their productivity continues to grow fast. They ascribe this to “Baumol’s disease,” i.e., that aggregate productivity growth can slow down because sectors with high productivity growth may decline in importance (e.g., manufacturing). Their results show that it is the shrinkage of occupations with fast occupation-specific productivity growth, not sectors, that accounts for most of the downward trend in aggregate productivity growth.

3. The Task-Based Approach

Despite all the reassuring empirical evidence in favour of the complementarity hypothesis, concerns about AI displacing human employment have increased. This has tempted some economists to propose radically different economic models that put a heavier emphasis onallow for and emphasize the substitution effect (Acemoglu and Restrepo, (Acemoglu and Restrepo 2016, 2017, 2018a, 2018b, 2018c)2016, 2017, 2018). Acemoglu and Restrepo (2016) point out that robotics and AI have already spread in many industries and automated several parts of the production process. They argue that the traditional model, discussed above, misses a distinctive feature of automation: the use of machines to substitute for human labour in a widening range of tasks. To quote the authors: "At the heart of our framework is the idea that automation and thus AI and robotics replace workers in tasks that they previously performed, and via this channel, create a powerful displacement effect. In contrast to prevailing presumptions in much of macroeconomics and labour economics, which maintain that productivity-enhancing technologies always increase overall labour demand, the displacement effect can reduce the demand for labour, wages and employment. Moreover, the displacement effect implies that increases in output per worker arising from automation will not result in a proportional expansion of the demand for labour. The displacement effect causes a decoupling of wages and output per worker, and a decline in the share of labour in national income". The authors argue that traditional factor augmenting approaches rely on the elasticity of substitution to relate the impact of technology on employment. However that elasticity is meant to say something about how the relative price of machines and labour affect their use, but not how changes in technology affect it.

Acemoglu and Restrepo (2018b) split the production process into human and automated tasks. Automation expands the set of tasks that can be carried out by machines and replaces human labour. It inevitably reduces the wage share of value-added for that task and increases the share of capital or profits in value-added (Karabarbounis and Neiman, 2014). However, technological innovation may also lead to the creation of new human tasks that did not exist previously and cannot be done (yet) by machines. This reinstatement effect increases human employment. The combination of displacement and re-instatement effects reallocates tasks between workers and machines. They come on top of substitution and complementarity effects in the traditional model. The crucial difference with the traditional substitution effect is that the latter changes the demand for workers and machines without a re-allocation of to specific tasks. They add the complementarity effects to the model in two ways. First, machines may increase the productivity of workers for their remaining tasks and thereby push up wages and/or decrease product prices. Second, changes in relative prices across products will affect demand for products from different sectors and change the composition of the product basket in the economy. Acemoglu and Restrepo (2018c) provide empirical evidence for this comprehensive version of the task-based model using US data. The authors show that the negative substitution and positive productivity (complementarity) effects are too weak to explain the declining share of wages in manufacturing. The main drivers of the decline have been the change in task content and, to a lesser extent, the sector composition effect. They decompose the task content effect in a displacement and a re-instatement effect. In the US at least, displacement due to automation of existing tasks has been stronger than growth in new tasks. It reduces the labour share, labour demand and the equilibrium wage unless the productivity gains from automation are sufficiently large. Automation can reduce wages even though it increases productivity. The productivity effect, which results from the increase in aggregate output from automation, is positive. The displacement effect is always negative. In contrast to some popular discussions the authors argue that automation technologies that are more likely to reduce employment are not those that are "brilliant" and highly productive, but those that are "so-so" – just productive enough to be adopted but not much more productive or cost-saving than the production techniques that they are replacing.

Gregory et al (2018) apply a comparable task-based framework to EU data for the period 1999-2010. They confirm the existence of a strong employment-reducing substitution effect but also find that complementary demand and spill-over effects more than compensate for this, so that the net employment effect of technology is positive. However, this finding depends on capital income gains from technological progress feeding back into product demand. If only wage income gains feed back into demand, the total labour effect is only half as large. This underlines the importance of income redistribution policies (see section on inequality).

A critique of the task-based model is that it lacks a robust definition of the very object that it focuses on: tasks. Besides the productivity effect, another way how machine progress can generate positive employment effects is through the emergence of new tasks that cannot be done by machines. Balanced growth with a constant labour share requires the simultaneous expansion of automated and new tasks. But the model has no definition of what constitutes a new task. In line with Lin (2011), Acemoglu and Restrepo (2016) argue that half of the 17.5% US growth in total employment (1980-2007) is explained by employment growth in occupations with new job titles. They consider this sufficient evidence that new tasks are indeed emerging. However, an occupation may consist of many tasks. Sticking new occupational labels on a modified bundle of tasks does not necessarily imply that the underlying tasks are new. For example, the rapid rise in demand for data analysists does not imply that this occupation consists of new tasks. On the contrary, it could be considered as a re-bundling of statistical, mathematical and computer programming tasks that already existed before this new occupational label became fashionable. Going down to a fine-grained level of elementary tasks one may wonder if new tasks exist at all. All tasks can be perceived as a bundle of perception, physical manipulation, symbolic communication, social interaction and computation tasks. The model seems to hinge on coarse-grained bundling of tasks at a level where tasks can be confounded with occupations and jobs (see e.g. Fernández-Macías et al. 2018) in order to sustain the view that there is a supply of new tasks and jobs.

Note that the historical period covered by this empirical evidence dates back long before AI emerged as an automation technology. As such, it offers only a general view on the impact of technological innovation on employment, not a specific AI perspective on that question. A

nother line of empirical testing of Tthe task-based model that brings it closer to artificial intelligence and ML and uses more recent data has been tested empirically with revolves around data on the use of robots in industries. According to the International Federation of Robotics (2016) an industrial robot is "an automatically controlled, reprogrammable, multipurpose manipulator programmable in three or more axes, which can be either fixed in place or mobile for use in industrial automation applications"[3], whereas "an algorithm is an unambiguously defined process or set of rules to be followed in calculations or other problem-solving operations, especially by a computer"[4]. Every robot has an underlying algorithm that drives its physical activities but not every algorithm drives a physical machine (though its output will ultimately have to connect to some physical interface in order to be interpretable for humans). Robots could thus be considered as a sub-set of AI, the physical embodiment of ML algorithms in machines.

The advantage of robots is that there are statistics on the number in use. There are no statistics on ML algorithms that are not embodied in a physical device or application. Graetz and Michaels (2015) find positive employment effects, and no wage effects, of the use of robots in industries, using panel data for 17 countries. Acemoglu and Restrepo (2017) find large and robust negative effects of robots on employment and wages across US commuting zones. This impact is specific to robots and different from impact associated with offshoring, decline in routine jobs, or capital measures. Robotisation is only weakly correlated with any of these measures. Chiacchio, Petropoulos and Pichler (2018) repeat this study using 1995-2007 data for six EU countries. They find that the displacement effect dominates: one additional robot per thousand workers in industry reduces the overall employment rate in the economy by 0.16-0.20 percentage points. The displacement effect is particularly evident for medium-skilled and young workers. They do not find a significant impact of robots on wages or on employment in services sectors. Interestingly, while the impact of computers (or ICT capital) is positive in their study, the impact of robots is negative. Another EU study on the impact of robots showed no effect at all on employment at firm level (Fraunhofer Institute, 2015). Dauth et al. (2018) find no evidence that robot use in German manufacturing causes overall job losses. Every robot destroys two manufacturing jobs but this is offset by additional jobs in services. Robot exposed workers are more likely to remain employed in their original workplace. They find a negative impact of robots on wages for medium skilled workers but high-skilled managers gain. Overall, robots raise labour productivity but not wages; that contributes to a decline in the labour share of income.
To the best of our knowledge there are no empirical tests yet of the task-based model beyond robots.

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[3] See International Federation of Robotics (https://ifr.org/industrial-robots). The IFR refers to ISO 8373:2012 for this definition (https://www.iso.org/obp/ui/#iso:std:iso:8373:ed-2:v1:en).

[4] See https://en.wikipedia.org/wiki/Algorithm

Testing the task-based model of AI-driven automation with data on robots is likely to produce a biased picture of the impact of AI. While robots incorporate algorithms there is a fundamental economic difference between the two. Robots are rival products. They can only be used for one task in one place at the time. Doubling the output of robots requires twice the number of robots, and twice the investment cost in robots. By contrast, algorithms are non-rival. Once the algorithm is designed and trained it can be used to carry out many tasks in many places at the same time, without any change in design or training costs. For example, the Google Search algorithm works worldwide and responds to many search requests at the same time.

4. Jobs at risk from AI

Some authors go even further than the task-based model. They seek to circumvent the lack of past empirical evidence and move directly to predictions of the future impact of AI on employment, without any considerations about complementary employment or wage effects.

One of the earliest papers that kicked off the debate on the impact of AI on employment is Frey and Osborne (2017). Starting from US O*NET data that describe skills requirements for 702 occupations they assess the risk of automation for three categories of skills (perception and manipulation tasks, creative tasks and social intelligence). The risk of future automation of these occupations was assessed by asking ML experts “Can the tasks of this job be sufficiently specified, conditional on the availability of big data, to be performed by state of the art computer-controlled equipment?” They conclude that 47% of all US jobs are at high risk of being automated. This alarmist study triggered waves of concern about the future of work: If half of all existing jobs will disappear as a result of automation, will there be sufficient replacement jobs and where will they come from?

There are several methodological limitations with the Frey and Osborne (2017) study. First, as the authors admit, their approach only looks at the most negative aspect of automation, substitution between machines and human labour, and does not consider complementarity and other potentially more positive economic effects that such substitution would trigger. Second, they look at tasks at a fairly high level of occupational aggregation. For example, office clerks may spend part of their time doing well-defined tasks that can be automated but also require creative, social and physical manipulation skills that are much harder to automate. Still, the entire occupational category of office administration tasks is assumed to be at high risk of automation.

Complementarity between human and automated tasks will re-emerge as only some parts of a human tasks bundle are automated. Tasks still need to be combined and bundled at a more aggregate level in order to reproduce an underlying production process. For example, a face recognition algorithm may recognise and automatically register a person who comes to a complaints desk with a question. But solving the complaint requires knowledge of the subject area as well as social and emotional intelligence that may not easily be automated. Automating the registration process will increase the productivity of these human tasks and complementarity comes back into the picture. This is well-reflected by Hanson (2001) who combines the traditional model with an approach similar to the task-based model in a multifactor model in which machines can both substitute and complement human labour in a continuum of tasks in the economy. Each task complements all others in this model. Due to the distinction between human labour complementing and substituting machines, the model predicts the historical observation of rising human wages as machine intensity increases and subsequently falling wages as improved machines start to substitute human labour.

Autor and Handel (2013) present evidence that job tasks differ among workers within an occupation and that this variation is an important determinant of earnings. They argue that the O*Net data are not suitable for analysis of within-occupation heterogeneity in tasks between workers. Instead, they use a Princeton survey dataset. Arntz et al. (2016) estimate the risk of automation at the sub-occupational task level. Using OECD PIAAC survey data that contain a more detailed task description for each worker and occupation, they find that only 9% of all US jobs are at risk of automation. Using the same data Nedelkoska and Quintini (2018) make a cross-country comparison of 32 different countries and look at the distribution of risk among different population groups and the role of training in the transition of labour markets to structures that adjusted to the new technology. They found that across all countries almost 50% of all jobs are at risk of being significantly changed due to automation, a figure that comes close to Frey & Osborne (2017). For 14% the risk is above 70% while for 32% the risk is between 50% and 70%. Jobs in manufacturing and agriculture are more affected. Moreover, occupations most at risk only require basic to low level of education, supporting the job-polariszation hypothesis.

The high degree of variability in these findings shows once more that occupational or even sub-occupational level approaches to skills are too coarse-grained to be reliable. Coarse-grained occupational approaches will overestimate substitution. That begs the question how fine-grained the data should be in order to have a more robust estimate. In other words, what is the level of detail at which a task should be defined in order to assess the potential to replace human execution by automated execution? This requires definition of a task-framework that optimizes the trade-off between comprehensiveness and detail to accurately capture the impact of automation on the workplace (Fernández-Macías et al. 2018and Bisello 2017).

5. What would make AI/ML different?

So far we argued that the task-based model and empirical estimates of the number of disappearing occupations offer no satisfactory explanations why AI would be different from previous technological change and change the historically observed pattern that automation contributes to more employment creation, not less. In this section we examine two other candidate explanations why this time could be different: AI as a General Purpose Technology (GPT) and the non-rivalry of algorithms. In the next section we discuss a third factor: the automation of the production of ideas.

A frequently cited argument, starting with Brynjolfsson and McAffee (2014), is that AI is a GPT. GPTs are especially important for economic growth because they spread rapidly throughout the economy and create spill-over effects everywhere. Brynjolfsson et al. (2017) argue in favour of AI/ML as a GPT as defined by Bresnahan and Trajtenberg (1995). The core capabilities of ML systems of perception and cognition currently are pervasive, widely applicable and can be improved over time. Pervasiveness refers to widespread applicability across many sectors and domains. ML systems are actually programmed to improve themselves when new data become available. Note that the initial ML algorithm can be considered as a GPT because it can be trained to be used in a wide range of applications across practically all sectors. However, once an ML algorithm is trained on a particular dataset it can only be used for applications related to that dataset. That may still cover a wide range of sectors. For example face recognition or automatic driving algorithms may be widely applicable. Cockburn et al. (2018) explore the growth and spread in research on three types of AI, robots, symbolic systems and (deep) learning, using data on AI research papers and patents. They argue that robots are relatively confined to a limited number of specific manufacturing tasks and need to be re-programmed to adapt to other tasks. Robots exhibit relatively weak GPT characteristics, although some robotic applications such as automated cars could have a widespread impact across many sectors. Research on symbolic AI systems has somewhat stalled and does not seem to produce many applications. By contrast, research on ML systems has made a great leap since 2009 and the strongest growth is recorded in applications of deep learning systems across a wide variety of sectors – demonstrating the GPT nature of ML systems.

Brynjolfsson and McAffee (2014) contrast the technology-pessimist and -optimist scenarios on employment and growth. Pessimists like Cowen (2011) and Gordon (2012) suggests that unemployment is rising because growth is anaemic in the absence of major technological change and boosts to productivity growth. By contrast, optimists like Brynjolfsson and McAffee (2014) argue that unemployment is caused by very rapid technological change that is outpacing growth in demand. Labour productivity exceeds economic growth. That is where AI as a GPT fits in: AI/ML could accelerate the speed and rapid spread of technological change up to the point where it may outpace economic growth. Note that the contrasting pessimist and optimist perspectives emerged in the aftermath of the 2007-2008 financial crisis when unemployment was indeed a major concern. By 2018 most of these gloomy thoughts seem to be well behind us as economic growth has accelerated and unemployment has been substantially reduced. However, apart from the cyclical nature of these thoughts, the possibility that technological progress can expand rapidly and exceed economic growth is a structural concern. Brynjolfsson et al (2018) find some evidence that the uptake of a general purpose technology like AI follows a J-curve effect. The initial impact may be negative because heavy intangible investments in re-organisation and re-training drag down growth that only rebounds in later years. Historical evidence suggests that earlier general purpose technologies followed a similar pattern. The fact that AI is a general purpose technology would not be a reason to expect this time to be different.

Another economic characteristic that distinguishes AI from many other technological innovations is non-rivalry of AI algorithms. Non-rivalry is not a new argument. Romer (1990) already demonstrated how economic growth could accelerate when driven by non-rival knowledge because the production function is no longer homogenous in the first degree and the elasticity of outputs with respect to inputs would be higher than 1. This would be because many agents can use the same knowledge at the same time. With AI algorithms however, non-rivalry would be taken a step further. It would be sufficient for one scalable algorithm to have acquired the knowledge or skills for a specific task in order for it to be used in any production process anytime anywhere. Contrary to robots, there is no need to replicate or embody that skill or knowledge in another object. A single algorithm can, in principle, displace all workers that were performing that particular task for which the algorithm is trained. As a result, the use of knowledge becomes much more centralised in a world of non-rival AI algorithms, compared to a world where knowledge or skills are embodied in rival machines or human agents.

6. The impact of AI on economic growth

So far we have been looking at the impact of AI on employment mainly through the lens of displacement of human tasks by machines. However, the impact of AI on the economic situation of citizens depends not only on employment but also on income orfurther affect the total value of goods and services produced in an economy (= GDP). That requires a look at the impact of AI on economic growth, or productivity increases induced by AI. Just like the long-term empirical evidence on technological innovation suggests that unemployment remains relatively stable, the so-called Kaldor (1961)(1961) Facts or long-run evidence on economic growth suggests that growth rates and the share of capital in overall income remains relatively stable. More recent research however suggests that this is not necessarily the case. Karabarbounis and& Neiman (2014)(2014) show how the share of labour in value-added has declined since the 1980s. They attribute this to a relative decline in the price of capital goods, induced mainly by ICT technology. This has motivated firms to replace more human labour with machines. That research provided a first hint that "this time may be different", though not directly related to AI. Here we ask the question if AI could reinforce that "difference"? Will it have a structural impact on economic growth rates and will it increase the share of capital in incomes at the expense of wages?

Aghion et al. (2017) start from a simple model of automation of the production of goods and services, similar to Acemoglu & Restrepo (2016). Acemoglu & Restrepo (2016) compensate the loss in tasks that areIn their task-based model, the loss in tasks for human labour, as they are taken over by automation, can be compensated by means of growth in new tasks that come with innovation. This can be turned into a growth model that matches the empirically observed Kaldor Facts when Baumol's "cost disease" is introduced in the growth model, i.e. fast-growing sectors that are automated experience a declining share in GDP because the relative price of their outputs declines compared to the price of outputs of slow growing sectors that are less subject to automation. Aghion et al (2017) show that in these conditions, and with a constant growth rate of GDP, rapidly advancing automation can still keep the capital and wage shares in GDP constant over the longer run, even if automation replaces most jobs. Automation puts upward pressure on the capital share in GDP but this is pushed back by declining prices for the output of automated sectors. The value of the "last" human task will be so high that it compensates the value of all tasks lost to machines. The authors acknowledge that this may seem like an unlikely "knife edge" model of economic growth. They explore a saw-tooth model with periodic switches between pure substitution or automation-driven innovation and factor- or capital-augmenting innovation. They suggest that such patterns are more in line with the empirically observed facts in the US in the last decades of rapidly rising capital shares combined with slower economic growth. Capital shares have been rising in some industries like chemicals, automotive, computers and oil extraction; but they have been going down in many services industries. There may also be intra-industry shifts in the composition of firms, with a trend towards superstar firms with high capital shares.

In these models the growth consequences of automation and AI may ultimately be constrained by Baumol's cost disease (Baumol 1967) (the argument that wages in slow productivity growth sectors will follow those in fast growth sectors and impose a cost that drives up the share of wages and keeps down the capital share). The question is whether the balancing between capital shares and substitution of labour for capital is a natural constant (as the stability of the capital share seems to suggest) or whether this is the result of many other underlying forces. Under the condition that the elasticity of substitution between capital and labour is smaller than 1, the automated share of GDP will be bounded from above as a consequence of Baumol's disease such that the labour share will remain at an elevated level. Since technological change is also capital augmenting, a balanced growth path could be achieved if capital augmenting (technological advancement) and depleting (more tasks being automated) is forced to move at the same speed. In this case automation is purely labour-augmenting.

Aghion et al. (2017) then move from using AI for the automation of production of goods & services towards the use of AI for the automation of innovation itself, i.e. the production of new ideas by machines instead of human researchers. The production process of research or new ideas can also be described as a series of tasks, some of which can be automated by means of AI. Similar to the above arguments for automation of production, the share of AI in total research will be bound and stabilize at some level. Human researchers become the bottleneck. It increases but also stabilises the long-term growth rate. If we allow the elasticity of substitution between human and AI research to be greater than one, the model produces explosive growth: the long run growth rate will continue to increase as human researchers are no longer a necessary input for the production of research. That raises the question whether AI could produce an economic growth "singularity", a situation where the growth rate explodes and becomes infinite in finite time. Aghion et al. (2017) point out that there will again be Baumol-type cost factors that put constraints on this unbounded growth. Even though AI could take over human cognitive functions and create an intelligence explosion, turning this explosion into physical tasksThat is, any form of economic growth will run into physical and natural law constraints, for instance due to limits to the efficiency of energy use. In the end, economic growth will be determined not by what we are good at but by what is essential and hard to improve.

Cockburn et al. (2018) also suggest that AI systems may be the beginning of the automation of innovation. The automation of learning facilitates generating new ideas and insights in automated processes, provided the required data input is available. Agarwal et al (2018b) explore this argument in more detail. They consider the explosion of data and knowledge (Bornmann and Mutz 2015) that generates more potential combinations from which viable innovations have to be selected. As it becomes more difficult for individual researchers to access the growing amount of knowledge, algorithms can look for relevant combinations of knowledge. They apply this to the Romer-Jones model of endogenous growth and show how it can accelerate growth rates.

Cockburn et al. (2018) caution against overrating the possibilities of AI as an engine of perpetual innovation: "Many fields of science and engineering are driven by a mode of inquiry that focuses on identifying a relatively small number of causal drivers of underlying phenomena built upon an underlying theory. However, deep learning offers an alternative paradigm based on the ability to predict complex multi-causal phenomena using a “black box” approach that abstracts away from underlying causes but that does allow for a singular prediction index that can yield sharp insight. De-emphasizing the understanding of causal mechanisms and abstract relationships may come at a cost: many major steps forward in science involve the ability to leverage an understanding" that would still require human judgement.

Cockburn et al. (2018) conclude that these changes in the innovation process have policy implications in terms of ensuring access to data and keeping competition open. "If there are increasing returns to scale or scope in data acquisition (there is more learning to be had from the “larger” dataset), it is possible that early or aggressive entrants into a particular application area may be able to create a substantial and long-lasting competitive advantage over potential rivals merely through the control over data rather than through formal intellectual property or demand side network effects". They draw attention to the need to look again at the laws of data ownership and access.

Bessen (2017) looks at the role of demand in the relationship between technological innovations and employment. Sometimes productivity-enhancing technology increases industry employment. In manufacturing, jobs grew along with productivity for a century or more. Only later did productivity gains bring declining employment. He attributes these changes to output demand saturation in markets. While the literature on structural change provides reasons for the decline in the manufacturing share of employment, few papers can explain both the rise and subsequent fall. Using two centuries of data, a simple model of demand accurately explains the inverse U-shaped curve of rise and fall in employment in the US textile, steel, and automotive industries. He speculates that there may be hierarchical consumer preferences for different products as income rises and prices fall. He estimates a model of demand for outputs as a function of labour productivity. It fits well with textiles and automotive output patterns. The model also predicts that computer technology should generate relatively greater job growth in non-manufacturing industries today. Estimates show computer use is associated with declining employment in manufacturing industries, but not in other sectors. Bessen (2018) suggests that his (2017) model can be applied to AI as well. Apart from the question whether AI complements or substitutes human labour, the price effect of AI on services, and related price and income-driven demand effects, will have to be investigated.

7. AI and Income Distribution

The literature on labour market job-polariszation and skill-biased demand shifts away from lower skilled work due to automation and technological progress has raised concerns about negative effects of AI on the distribution of income. In this section we review identified channels through which technological progress and AI may affect the distribution of income and policy recommendations to mitigate technology-related increases in inequality. Here, too we will argue why the effect of AI may differ from previous technological advancements. However, as mentioned before, the empirical evidence on AI in this context is limited. Predictions on potential outcomes rely on assumptions about the feasibility of AI as a GPT to learn non-codifiable tasks, and the applicability of AI in the work place. We present some work on the general impact of innovation on the distribution of income, then discuss the impact of automation and ML driven AI subsequently.

The majority of the literature on this predicts a negative impact of AI on income equality. For instance, in a dynamic general equilibrium model with robots representing a separate form of capital that is complement to traditional capital, Berg et al. (2017) simulate different degrees of advancements in automation on the distribution of income. All scenarios eventually lead to an increase in inequality with the worst outcome when robots only substitute for unskilled labour. The most widely debated source of technology-driven income inequality is the increase in labour income inequality. Evidence suggests that labour market polarisation plays an important role in this. We observe polarising labour markets because tasks that are not easily performed by AI tend to be found on opposite ends of the skills spectrum while AI tends to replace humans in tasks that correspond to the 'mid-skill' category (Autor et al., 2003). Acemoglu and Autor (2011) and Autor and Salomons (2017) show suggestive evidence from the US on how job polarisation translates into wage polarisation or even a polarisation in working conditions. This highlights the need for appropriate policy responses to prevent income inequality due to AI proliferation.

There is evidence for Europe too, that labour market polarisation leads to a widening of wage gaps. Goos et al. (2014) find that improved technology has led to increased demand in well-paid high skill as well as low-paid low skill jobs while the demand for middle-income jobs decreased, thus supporting the hypothesis that technological progress can lead to income inequality. Yet, there are substantially differing trends of labour market polarisation between European countries (Goos et al., 2014; Darvas and Wolff, 2016), which can be explained by country-specific institutions and policies (Fernández-Macías, 2012; Fernández-Macías and Hurley, 2016).

A report by the OECD (2018) shows a different type of polarisation that is regional and occurs within countries. For instance, the share of jobs at high risk of automation varies by 12% between regions in Spain but only by 1% between regions in Canada. Technological progress tends to perpetuate the developmental divide within countries as regions that are expected to be more negatively affected by technological progress also exhibit low productivity growth and high unemployment rates.

Despite similar positive trends in labour demand for both high- and low-paying jobs, we observe diverging trends in respective job quality. On the one hand, technological progress leads to increasing wages in high-paying jobs that require skills which complement AI (Deming, 2017). In contrast, technological progress causes even further reductions in wages at the lower end of the wage distribution down to a level that does not support a reasonable standard of living (Autor and Salomons, 2017). The accompanying digitalisation of the economy and the emergence of platforms causes an increase in precarious forms of self-employment that are characterised by a limited duration, such as seasonal or on-call work, as well as the absence of social security coverage (OECD, 2018). This contributes to technology-driven increases increases in inequality.

Transitional unemployment, which occurs when AI makes workers redundant at a faster pace than they can move on to new jobs (Korinek and Stiglitz, 2017) can also be a cause for inequality enhancing effects. Differences in the pace of AI adoption across different regions and sectors, as well as differences between workers in their ability and speed to adjust to occupational changes may further increase inequality. For instance, historical data suggests that low-skill workers are slower than high-skill ones in adjusting to sudden structural labour market changes and transitioning to new sectors and occupations. This results in longer periods of transitional unemployment for low-skill workers (Goolsbee, 2018). Yet, new evidence from the impact of robots on the manufacturing sector in Germany suggests that transitional unemployment effects may not be that strong as a large part of the workers manage the transition within their firms and across occupations. Nevertheless, this job security comes at the cost of reduced wage growth for adjusting workers (Dauth et al., 2018).

There are additional channels through which the overall distribution of income may change. First, AI increases the share of capital income relative to that of human labour (Korinek and Stiglitz, 2017, Sachs, 2017). Together with the high degree of concentration of AI industries, it may lead to an increase in the inequality of capital income and also total income. Second, the extra wealth created by AI is likely be shared unequally across countries. Winner countries will have higher income levels, and they will also have more room for domestic redistributive policies (Lee, 2017).

It is commonly agreed upon that policy measures are needed to counteract the negative effects of technological progress on equality. Besides increasing access to high-paying jobs by increasing the overall skill level through increased education expenditures, policies should further ensure a reasonable standard of living. The literature discusses several types of policies to achieve this goal, such as universal basic income or guaranteed employment (Furman and Seamans, 2018), policies that aim at a redistribution from 'winners' to 'losers' and policies that shift the taxation of human labour towards the taxation of capital (Korinek and Stiglitz, 2017). In any case, the within-country regional variation of the impact of technological progress suggests that policies should be adjustable to local needs, where local offices can help in the design of targeted policies. It is important to be aware that such policies may lead to inefficiencies (equity-efficiency trade-off), decreasing the size of the pie to be distributed. Korinek and Stiglitz (2017) discuss market imperfections that make first-best public policy solutions to rising inequality due to labour-replacing innovations non-feasible. In reality there are many obstructions to achieving Pareto improvements due to technological progress, such as market failures or the missing of markets that would enable distributions across "winners" and "losers" of technological innovations. If ex-post distribution were costly, promises of redistributions would be non-credible and technological progress would not be unanimously supported. Other issues involve information problems, wage rigidities, aggregate demand problems or monopolies of innovators.

In fact, the authors identify two channels through which technological proliferation affects the distribution of resources: (1) through surplus earned by innovators and (2) through spill-overs to other agents of the economy, not involved in the process of innovations. The surplus of innovators occurs due to the nature of technology as an information and thus non-rival but excludable good. In this case, the first best solution would be a public fund of innovation. In reality private agents, who expect returns, are more successful in providing innovation. Once market returns concentrate, innovators could misuse their incumbent monopoly to drive out other market entrants and earn rents that go beyond their innovation contribution. This exacerbates if the individual returns to innovators do not correspond to social returns. Other agents not involved in the innovation process could be affected through pecuniary spill-overs, such as price and wage changes as a response to the structural labour market changes of AI and through non-pecuniary spill-overs such as changes in labour demand.

The authors recommend two types of policies: (1) policies that aim at sharing the surplus of innovators, such as targeted expenditure programs financed by high rent taxes, publically available research and the inclusion of workers as share-holders in the respective firms, and (2) policies that shift the taxation of human labour towards the taxation of capital, such as wage subsidies, earned income tax credits, a minimum wage or higher public expenditures which could be financed through taxes on carbon emissions or the elimination of tax deductions on interest rates. These policies including two additional alternative policies, namely universal basic income and guaranteed employment are also discussed by Furman and Seamans (2018).

However, unlike wage subsidies in the form of earned income tax credit (Hotz and Scholz 2006), the effects of these policies on employment and income inequality lack empirical evidence. Their feasibility to counteract negative effects of AI progress on labour markets depends on the respective behavioural responses of firms, innovators, workers and credit lenders.

Despite these negative prospects of technological progress on equality, there might be some benefits from the peculiar features of AI. As a general-purpose technology AI could yield equality enhancing effects. For instance, empirical evidence from the UK suggests that working in R&D intensive firms compared to other firms benefits lower-skilled workers more than higher skilled workers (Aghion, Bergeaud, Blundell, Griffith, et al. 2017). One reason for this could be that low-skill workers tend to remain longer at an innovative firm than workers in high-skill occupations as these are more prone to fluctuations. Thus, the low-skill workers in these firms will have higher firm-specific capital which also yields higher wages. In addition, according to (Acemoglu and Restrepo, 2016) AI can create new tasks which can be performed by high-skill workers in the short run. Yet, as these tasks become standardized in the long run, low-skill workers can benefit from it. In addition, AI shows potential to disrupt the spiral of labour market polarisation. It may be able to perform high-skill tasks that were previously beyond the abilities of technology, such as the classification of case documents for lawyers or the reading of medical images. Even creative and social tasks are not out of the realms of AI abilities (Brynjolfsson and Mitchell, 2017). In the end, AI may produce un-polarising effects.

In Acemoglu and Restrepo (2016) both the automation of old tasks and the creation of new tasks increases inequality because automation leads to displacement of low-skill workers and newly created tasks benefit high-skill workers. Overall, the empirical literature confirms the inequality enhancing effects of automation that the theoretical literature predicts. Yet, the authors also show how income equality can be improved through the creation of new tasks. If in the long run newly created tasks become standardized, low-skill workers can benefit from it. As mentioned before, the process of the creation of new tasks is exogenous in the model and it remains unclear how and even if truly new tasks can be created. Nevertheless, if the creation of new tasks could be attributed to AI as a GPT (because of its ability to spawn complementary innovations) rather than automation, then this shows a potential channel for positive distributional outcomes from AI advancement.

Aghion et al. (2017) investigate the relationship between innovativeness of a firm and worker wages using matched employer-employee data from the UK and data on expenditure on R&D. Since firms with higher R&D expenditure might also be more inclined to invest in AI (driven by ML), this could give an indication on potential implications of ML on distribution. They find that lower-skilled workers benefit more than higher skilled workers from working in R&D intensive firms which they attribute to the higher complementarity between high- and low-skill workers in more innovative firms. Low-skill workers tend to remain longer at an innovative firm as workers in high-skill occupations which are more prone to fluctuations. Thus, the low-skill workers in these firms will have higher firm-specific capital which also yields higher wages. Moreover, Aghion et al. (2017) suggest that the introduction of AI in a firm will lead to a decentralization of authority as AI reduces coordination costs between upstream and downstream workers as well as the loss of control involved in delegating authority, thus giving lower skilled workers more responsibility and consequently higher wages.

8. Conclusions

To date, the literature is ambiguous on the employment and wage effects of AI proliferation: It can be negative, if machines only substitute human labour, but positive if machines instead complement human workers and increase overall productivity. The latter effect can increase labour productivity and reduce output prices which can cause within- and between-sector increases in demand. Increased productivity also yields wage effects which can lead to a reallocation of workers across sectors.
There are concerns about the displacement of human workers with AI machines. Historic evidence shows that previous waves of innovation that replaced workers with machines ended up generating more jobs (re-instatement) and higher incomes, though transitions can be painful. There are some indications that the displacement effect has been stronger than the re-instatement effect over the past decades and that the labour share in incomes has declined, especially in manufacturing industries and long before the arrival of AI. We have no reliable forecasts for the future. Some studies predict that the share of human jobs at risk of automation ranges from 47% to 9% depending on the level of detail at which work tasks are defined. These alarming predictions focus on potential displacement effects only and ignore employment creation. They may indicate the magnitude of the challenge ahead but do not constitute a credible forecast.

AI is likely to increase productivity in many industries and services sectors and thereby boost economic growth, incomes and overall welfare. Increased growth will however run into the constraints imposed by factors that are essential to production but cannot be automated. Macroeconomic outcomes of AI are also shaped by firm behaviour and there is clear evidence for massive reallocation implications of AI. Generalising from the experience of globalisation and digitization in the past decades, this process is likely to be imperfect and slow, with high and unevenly distributed costs. Ensuring competitive markets, flexible organizations and facilitating sectoral reallocation are particularly relevant to realize the potential benefits of AI.

Yet, the nature of AI may be very different from previous technological progress as core capabilities of ML exhibit features of a general purpose technology that can rapidly spread to similar tasks across many jobs and industry sectors. These technologies : they are pervasive, widely applicable and can be improved over time. To the extent that machine learning generates new insights from data, it may contribute to the automation of the production of new ideas and innovation itself – so far a unique property of human labour. That would accelerate the pace of innovation. Finally, while human labour has rival properties, AI algorithms are non-rival and can be replicated widely at very low marginal cost. That facilitates their spreading. The task-based model opens a wider debate on the nature of machine learning as a general purpose technology that can rapidly spread to similar tasks across many jobs and industry sectors. To the extent that machine learning generates new insights from data, it may contribute to the automation of the production of new ideas and innovation itself. Economic growth models are starting to explore various scenarios but there is no empirical evidence yet that favours specific scenarios. The "productivity paradox" becomes once more apparent as the rapid growth in machine learning applications does not seem to be reflected yet in the productivity growth statistics.

The impact of technological progress on employment polarisation has raised concerns of increased inequality due to AI proliferation. Some empirical literature seems to confirm these concerns. Policies that create incentives for innovators to share their surplus or that shift taxes from human labour to capital may help to counteract the distortionary effects that automation may have for income equality but policy reforms change the structure of incentives that underlies individual decision making. Whether or not policy will be effective in mitigating the potential distortionary effects of automation is an empirical question.
The expected turbulence and potential mismatches between declining employment and increasing productivity and incomes call for appropriate social and redistributive policies. Such policies should avoid inefficiencies that decrease the size of the pie to be distributed. Beyond “sufficient income for living” wider social policies should look at meaningful ways of spending our time and living our lives through broader educational, cultural and community enhancing policies.

Studies that focus on the substitution effect by design find negative effects on employment. The share of jobs in the US at risk of being replaced by automation ranges from 47% to 9% depending on the level of detail at which work tasks are defined. Task-based models assume direct substitution of human tasks by machines. Some limited empirical evidence available to date, both for the US and the EU, shows that robots replace humans and reduce wages and employment rather than complementing it; but other evidence contests this. Job loss will be overestimated if we assign tasks to machines that are not fully machine executable. Thus, for the evaluation of the substitution effect researchers will have to find a scale for the definition of tasks that clearly differentiates the machine from human input in work production.

From a general equilibrium perspective, automation can increase labour productivity and wages, and at the same time generate additional employment rather than reduce employment. Technological improvements may favour specific types of skills, hence the notion of skills-biased technological change that may affect the income distribution. The long-term historical evidence massively favours this model: despite many waves of very substantial technological change, labour productivity, employment and wages have steadily increased.

This could yield effects that counteract negative effects on income equality. For instance, through a GPT's ability to innovate and create new tasks that can be performed by workers with lower skills. Reduced coordination costs can support the decentralization of authority which would give more responsibility to downstream employees.

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