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How firms will affect the Future of Work

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Abstract

In the current debate over the Future of Work, there is little discussion about how firms anticipate the evolution of their demand for labor and the related mix of skills as they adopt Artificial Intelligence (AI) tools. This article contributes to this debate by leveraging a global survey of 3000 firms in 10 countries, covering the main sectors of the economy. Descriptive statistics from the survey are complemented by econometric analyses of corporate labor demand decisions. The findings are four-fold. First, those are still early days in the absorption of AI technologies, with less than 10% of companies investing in a majority of AI technologies and for multiple purposes. Second, if an aggregate portion of firms anticipates reducing employment as a result of adopting AI technologies, as many other companies anticipate labor growth or reorganizing employment. Third, this reallocation picture holds true when we examine further demand by labor functions and skills, with talent shifting toward more analytic, creative, and interaction skills, and away from administrative and routine-based functions, in line with past trends of skill- and routine-biased technological change. Fourth, a novel to the literature on Future of Work, econometric results on employment change highlight that employment dynamics are driven by related spillover effects to product markets. Higher competition, larger expectations of market (share) deployment may counterbalance negative automation effect on employment dynamics.

Keywords : Artificial intelligence, Derived labor demand, Product market competition

1. Introduction

Recent advances in the field of artificial intelligence (henceforth, AI) have led to public fears that these technologies will substitute a large part of job occupations (Brynjolfsson and McAfee 2014, or Nubler 2016). This fear is being fueled by companies announcing their intention to replace groups of workers by smart algorithms and/or robots.

At the same time, a recent stream of academic work has strengthened the vision of a "workless future." In their seminal work, Frey and Osborne (2013) calculated that 47% of all US jobs are at risk of being automated by the rise of AI technologies. Another recent study by Acemoglu and Resterpo (2017) claims that every robot makes as many as eight jobs obsolete. Follow-up research by same authors (Acemoglu and Restrepo 2018) suggests that new technologies may fuel more automation than new jobs, creating inequality risks between workers, and likely pressure on total jobs.

Susskind (2020, forthcoming, develops a theoretical model of smart capital augmentation which is fully substitutable to jobs at high-wages, leading to an extreme scenario in which "wages can only decline to zero" to secure workers employability. Empirically, a recent study linking labor productivity and employment in a sample of large OECD countries by Autor and Salomons (2017) also suggests that higher productivity at sectorial level (often driven by technology innovations) is associated with *decline* in employment in the same sector.

Such fears are not new. Already at the time of the first Industrial Revolution, renowned thinkers such as John Stuart Mill and David Ricardo conceded the possibility of unemployment. Given the rise of manufacturing and its need for workers, however, the concern shifted quickly to issues around wages, which stagnated for 50 years until the middle of the nineteenth century—a "pause" noted by Engels.
The Great Depression brought a revival of concerns. John Maynard Keynes (1931) wrote his famous essay *Economic Possibilities of our*

Grandchildren, predicting that by 2030, the “most pressing problem in developed economies would be how to fill our leisure time.” Today, the top ten US firms by market cap employ 30% fewer people than the top ten firms in the 1960s.[1] Featuring among those top ten are the so-called GAFAs—Google, Amazon, Facebook, and Apple—which are able to generate every $1 of value with five times fewer employees than the largest US firms 50 years ago.

Some research brings however more nuance to a scenario of large unemployment, such as Gregory et al (2014). Atkinson (2013) concludes that, at least looking backwards, there is no single decade in the United States, from 1850 through 2010, in which the adoption of technology did not destroy employment *more* than it was responsible for creating new jobs. A McKinsey Global Institute (2017a)’s research across 46 countries has attempted to match *technical* capabilities of AI with those of humans —for example a virtual assistant system answering questions versus the task being done by a call-center agent.

Recognizing that typically jobs are composed by many tasks, it is found that automation technology would likely more affect the mix of activities *within a job* than it will threaten to replace an entire occupation. On average, in developed countries, the study finds that 25%–30% of existing jobs runs the risk of 70% of their tasks being automated. Further, the shift in tasks will be felt in more routine-based ones than in tasks requiring social and creative skills.[2] Those findings have been corroborated by parallel research at OECD (2017).

Likewise, absorption of technology takes time. Looking at a wide set of technologies in the last century, the median time of complete diffusion has been close to 40 years, even if diffusion speed has accelerated lately for digital technologies (Comin and Hobijn 2010). Our survey of large companies (see Table 1) confirms that AI adoption is in its early day. There are also large bottlenecks in digital assets and skills needed within the majority of incumbent firms that may lead to a somewhat slow diffusion of AI technologies (Bughin and van Zeebroeck 2018).

Table 1

Adoption stage of AI technologies by large firms, 2017, %

	AI technologies:					
Adoption status	**Machine learning (%)**	**Computer vision (%)**	**Language processing (%)**	**Robotics (%)**	**Virtual agents (%)**	**Robotics process automation (%)**
Not aware	29	24	5	12	42	90
Not yet invested	29	39	43	12	29	2
Piloting	15	14	18	14	11	2
Adopted one use case	13	12	18	28	10	2
Adopted many use cases	13	11	14	33	10	2

This paper contributes to the debate on a "jobless future" through the *demand side of the labor market*, as currently corporations account for about 90% of the jobs in developed countries. Through this lens, we hope to discover micro-findings on the dynamics of employment in relation to the corporate diffusion of AI technologies that are both consistent and new.

In effect, we bring together multiple streams of literature, on top of labor economics literature. Regarding the IT/IS literature, it is already clear that employment will follow gains of productivity arising from absorption of technologies (see Brynjolfsson and Hitt 2003), while technology adoption dynamics should mostly affect the mix of skills rather than total level of employment (Machin 2001). One reason for this is also that corporate returns to technology investment are often only attractive to the extent that companies invest in the complementary human skills that make technologies operate effectively at scale. As a case in point, Bughin (2016) shows that returns to big data investments are higher than the corporate cost of capital for firms which have also invested in the right pool of big data analysts. In fact, relying on work by the McKinsey Global Institute (2017a, b, 2018a, b), Pissarides and Bughin (2018) conjecture that the most important challenges will be the skill uplift associated with the diffusion of smart technologies, and frictions around this transition is likely one key driver of how labor markets behavior in years to come. Second, regarding the Strategic Management and Industrial Organization literatures, companies invest in technology for a variety of reasons, including greater labor efficiency but also because they wish to *create better or* new products/business models and expand their sales, in relation to product market competition and conduct. Hence, labor demand may increase (pending on how strong and fast competition reacts), as documented during the early diffusion of PC-based technologies (Spiezia and Vivarelli 2000), or in subsequent research by Garcia et al. (2002) and Peters (2004).[3]

This article looks at three hypotheses. The first one relates to the previously-noted fear that *AI will significantly reduce number of jobs*. This fear may be overblown, but has some truth as well. As we will see hereafter, our survey results suggest that, in aggregate, more than half of firms anticipate changes in employment *but if a sizable share of companies is considering reductions in employment—it may be only for some categories and a reallocation of skills*.

The second hypothesis is the skills- and routine-biased technological change hypothesis of a shift to more complex skills and less *routine-based jobs* [see Autor et al. (2015) or Goos et al. (2015)]. If one takes the first wave of IT technology deployment—that is, mainframe and PC—Handel (2016) suggested that IT accelerated the ongoing shift towards jobs requiring higher education by roughly 50%. When General Motors started to adopt the first generation of automation technologies in the car manufacturing industry in the 1980s, problem-solving capabilities for skilled workers rose by 40% (and fell by 10% for unskilled, blue collar workers), as did tasks with higher memory, accuracy and concentration skills (Milkman and Pullman 1991). As detailed hereafter, *we find support for the skill-bias hypothesis in our survey. In particular, we find evidence for employment increases in big data analytics and for occupations requiring interpersonal skills for corporations already well vested in AI. Increase in AI investment is also positively correlated to better odds ratios in categories such as leadership and creative design.*

The third hypothesis is that the effect of AI automation on employment will ultimately depend on product market overspill. These include new products and its interaction with a company's profitability, in line with the oligopoly theory of firm-induced labor demand. Our econometric *results are the first, to the best of our knowledge, to demonstrate that the effect of AI technology on labor demand must take into account those spill-over effects on product markets.*

This article is structured as follows: Sect. 2 describes our survey, as well as our definition of AI and the hypotheses we test. Section 3 presents the descriptive results, while Sect. 4 is concerned with the econometric analysis of labor demand by type of firms and firm pace of adoption of AI technologies. Section 5 concludes.

2. Background

2.1. AI Definition

Our definition of AI in the article (and in the survey questionnaire) is one of technologies being technically able to *mimic cognitive human functions.*[4] Consider Amazon's Kiva robots. Today, they are already able to handle parcels faster than humans and in a space that is half the size of traditional human–heavy logistics centers, leading to significant efficiency gains, and with return of investments easily a multiple of cost of capital (see McKinsey Global Institute 2018b). Likewise, virtual assistants such as IPSoft's Amelia are able to handle customer care much faster, and with more consistent positive responses, than humans, reducing cost of care by more than 50%, and improving quality of interactions with users.

The ability of AI to perform and self-learn obviously depends on big data, and on the use of powerful algorithms such as deep learning. Alphabet's DeepMind reported that it improved the overall power usage efficiency of Google's data centers by 15% after placing an AI program similar to a program taught to play Atari games in charge of managing a data center's control system.[5]

Based on actual evidence of technologically readiness, we have surveyed the use of five types of technologies (computer vision, language processing, robotics, robotic process automation, and virtual agents) in the market place. We add to the list deep-learning techniques (and their derivatives), as most of the above technologies usually rely on deep machine-learning algorithms to deliver their results.

2.2. Survey Collection and Highlights

2.2.1. *Sample*

We leverage a C-suite executive survey conducted in the spring of 2017, covering 10 countries and 14 sectors. The survey was commissioned externally to a major research firm, covering topics such as awareness and use of a set of AI technologies, returns to AI investment, as well as impact on strategy and labor resources allocation by skills and company functions. In total, there were about 25 questions to answer, for an average time to fill of less than 20 min, in order to maximize take-up rates and adequate responses. The survey was administered online. The survey questionnaire is accessible in the appendix of other research report by Bughin et al. (2017).

We received 3073 fully completed and validated set of responses out of a original sample of 20,000 firms stratified to reflect both firm size distribution (small, medium, large) as well as sectorial contribution in added value to each country's GDP. The answer rate is a relatively good answer rate (more than 15%) from a total random sample of companies.

The ten countries we focused on were the United States, Canada, the five largest European countries and Sweden, China, Japan and South Korea. We picked those countries as they are the largest contributors to world GDP, are the most digitally-advanced, and have recently scaled their investments in AI recently.[6] The largest portion of answers came from the United Kingdom (12%) followed by the United States. The country with the fewest answers was Sweden (5%). 27% of firms were very small firms, i.e. with fewer than 10 employees, while 7% of the sample includes firms with more than 10,000 employees. The sample covers service, agriculture, and industrial sectors, from professional services (14% of our final sample) and high tech (10%) or retail (8%), to travel and tourism (4%), automotive/assembly (4%), or the education sector (5%).

The responses we received were tested for absence of bias by industry—specifically we tested whether they were any difference in our sample of answers with the original target of firms, in terms of mean difference in key financial metrics of respondents and non-respondents (revenue, revenue growth, profit and profit growth). We used simple one-way test per financial metric, as well as a multivariate logit model of having answered or not, linked to all the financial metrics (see Whitehead et al. 1993). We could not find statistical difference in answer rates. Finally, we tested for some self-reported biases. This was originally minimized by randomizing questions order in ten subs-samples; those sub samples were then checked for any, and did not find, bias in responses. We nevertheless checked for systematic responding (either extreme, or only middle answers).

We spotted 122 answers, or 4% of answers regarding companies whose difference in answers by category of the questionnaire (AI awareness, AI impact on profit, AI impact on employment, and on employment mix) were found to be very low (in the bottom 5% in difference in answers across all categories). However, the econometric results are not sensitive to including or not those responses, so we keep our full sample as basis of our results here-after.

2.2.2. *Data Highlights*

Our survey confirms that like any other technology (Comin and Hobijn 2010), AI adoption may take time to spread. By 2017, diffusion is still in its early days (see Table 1). Only one out of 8 companies report using AI at scale (for multiple use-cases), and a very large set of companies (90%) are not even aware of RPA.

Further, among firms adopting and piloting AI, the variety of absorption is rather narrow. A large portion (48%) has only adopted one of the six technologies surveyed, and only 4% which have already deployed close to the whole set of technologies at scale (see Table 2).

Table 2

Technology variety absorption, 2017, % of firms adopting AI

Degree of penetration of AI technologies among AI-adopting firms	
Adoption of one technology	48%
Adoption of two technologies	24%
Adoption of three technologies	16%
Adoption of four technologies	7%
Adoption of at least five technologies	4%

While not reproduced here for sake of space, the sample shows that US and Chinese firms are more advanced in adoption and breadth of diffusion, in line with other research that most buoyant markets in AI investment are in those two geographies (see Bughin et al. 2017). Likewise, sectors that are more advanced in digitization, such as telecom, high tech, and media are already more advanced in AI adoption than other sectors such as construction. Patterns of adoption by technology type is also industry specific; for instance, RPA is twice more often adopted in automotive and assembly than average, while virtual agent technology is most advanced in B2C services such as consumer high tech and telecom (22% versus 12% on average).

Table 3 further provides a picture of the economic motivation for AI adoption, where all sources of motivations are rescaled to 100%. This includes only firms piloting or adopting AI.

Table 3

Rationale for decision to adopt any AI technology, 2017, % of firms piloting and adopting AI

Industry	**Output growth**			**Efficiency gains**			
	Market share (%)	**Market size (%)**	**Total (%)**	**Capital (%)**	**Labor (%)**	**Non-labor (%)**	**Total (%)**
High tech	14	21	35	27	24	14	65
Automotive	16	12	28	25	21	26	72
Construction	8	8	17	30	27	27	83
CPG	26	19	45	19	26	10	50
Retail	20	20	40	24	20	16	60

Table 3

Rationale for decision to adopt any AI technology, 2017, % of firms piloting and adopting AI

Industry	Output growth			Efficiency gains			
	Market share (%)	Market size (%)	Total (%)	Capital (%)	Labor (%)	Non-labor (%)	Total (%)
Media	17	29	46	14	17	22	54
Telecom	23	28	52	20	20	8	48
Travel	10	24	34	17	21	27	66
Transport/logistics	24	7	31	24	30	15	69
Financial services	23	23	46	16	30	9	54
Professional services	21	16	38	21	21	20	62
Education	17	20	37	27	16	20	63
Health	20	15	35	24	32	9	65
Energy	21	12	33	24	24	18	67

Table 3 provides two critical insights.

The first is that, when planning to invest in AI, companies report multiple rationales (3 rationales out the 5 surveyed). Otherwise stated, companies do not generally invest in AI for only a *single* purpose, and usually it is for a mix of efficiency *as well as to facilitate* top line growth. This link to product market is not explicitly discussed in the labor market literature. Looking further at use cases of companies investing in automation of labor, most of those cases have also an augmentation component- e.g. using in-silico AI simulation to support management decisions on market entry; or using algorithms and virtual assistants in marketing to target more appropriate customer segments.

Second, the current debate on the future of work implicitly relies on the issue of labor automation, leading to the question of how, to what degree, smarter capital can replicate human tasks. However, our data demonstrate that *labor* efficiency is only used as motivation for adoption by firms in *only 24% of* cases. Remarkably too, market expansion and market share gains are almost as frequently quoted as labor efficiency (and at higher rates than labor efficiency in four sectors—retail, media and telecom, travel, and education). This clearly suggests that the narrative of labor substitution is possibly too restrictive. In general, firms seem to expand productivity as result of AI adoption by other means than labor, as well as leverage AI to expand their influence on the product market.

3. Employment Dynamics :Descriptive Statistics

Our survey also explicitly has asked on how AI-related technologies has affected or, will impact employment and employment skill mix in the future.[7]

3.1. AI and the Dynamics of Employment

Regarding expectations, survey responses are summarized in Table 4 for companies adopting or piloting AI. 44% of companies do not see an impact, while the portion of companies reporting a decline in total employment is about 19%, compared with only 10% that report an increase in demand for labor. Interestingly, 27% of companies say that there will be a labor reduction in some occupations, but with a similar employment *increase* in other occupations. In other words, companies tell us that *there is more job re-allocation than total job shrinkage*, in line with our first hypothesis that the effect of AI on employment may be more balanced than feared.

Table 4

Expected employment dynamics, 2017, % of firms piloting or adopting AI

Industry	**It will reduce our need for employees with total employment levels down (%)**	**It will reduce employees in some areas, but overall employment may go up (%)**	**It will not change our need for employees significantly (%)**	**It will increase our need for employees (%)**
High tech	19	32	32	18
Automotive and assembly	23	34	33	10
Construction	25	24	40	11
Consumer packaged goods	19	33	36	12
Retail	16	26	49	9
Media and entertainment	24	25	43	8
Telecommunication	24	32	25	18
Travel and tourism	17	30	41	12
Transport and logistics	22	26	38	14
Financial services	18	32	41	10
Professional services	13	14	66	7
Education	20	20	54	6

Table 4

Expected employment dynamics, 2017, % of firms piloting or adopting AI

Industry	**It will reduce our need for employees with total employment levels down (%)**	**It will reduce employees in some areas, but overall employment may go up (%)**	**It will not change our need for employees significantly (%)**	**It will increase our need for employees (%)**
Healthcare systems and services	14	28	53	5
Energy and resources	19	33	41	7
Average	19	27	44	10

The same conclusion is also drawn if we compared employment changes of AI adopters versus non-AI adopters- in general, those who do not adopt tend to anticipate that AI may reduce more often employment level than those already adopting.

Finally, the pattern of employment dynamics expectations is not necessarily influenced by some sectors. The pattern remains the same at industry level, with the exception of construction, where the dynamics is more on employment reduction. Noteworthy is that sectors that are more advanced in AI are those in which the larger portion of companies expects to both increase and reallocate their labor demand. About half of telecom and high-tech companies surveyed will be ramping or reallocating labor as a consequence of adopting AI- related technologies.

3.2. AI and Employment Mix Change

The picture of employment evolution is even clearer if one disaggregates labor demand by occupations and by skills type (see Table 5).[8] The portion of surveyed executives who report a reduction in employment is about 25% for almost every function. The highest frequency of decline is visible in functions with *more routine-based* activities such as operations and back-office, while the lowest frequency of decline lies in senior management roles. Further, there are as many companies reporting an increase in the level of employment by function as those reporting a decline. The net balance is less favorable for more routine-based jobs, while functions in data and analytics and IT/Design are more likely to increase than decrease, as already hypothesized in simulations presented in the McKinsey Global Institute (2018a) research on probable skill shits.

Table 5

Expected employment dynamics by skill type, 2017, % of firms piloting or adopting AI

	AI impact on employment:				
By functions	**Less**	**More**	**By skills**	**Less**	**More**
Back office	28	30	Basic literacy skills	25	33
Front line employees	30	31	Basic numerical skills	27	34
Operations	30	30	Basic IT skills	26	43
Sales and marketing	22	32	Advanced IT skills	21	51
Data and analytics	23	37	Advanced data skills	23	49
Engineers, IT, design	22	41	Critical thinking	24	43
Finance, HR	25	33	Social skills	21	39

Table 5

Expected employment dynamics by skill type, 2017, % of firms piloting or adopting AI

	AI impact on employment:				
By functions	**Less**	**More**	**By skills**	**Less**	**More**
Middle management	22	30	Communication skills	20	39
Senior management	19	29	Creative design	23	41
Average	25	33	Craft/technical skills	21	34
			Engineering skills	22	41
			R&D skills	24	47
			Leadership skills	20	33
Average	25	33		23	41

The largest portion of firms reporting a decline is for basic literacy and basic numerical skills. 40% of companies will increase any skill, and the largest portion of companies is willing to raise labor demand once again for advanced data and IT skills. This is clearly consistent with our second hypothesis that AI may lead to a skill-biased technological change in employment mix, as happened in the recent past (Autor and Handel 2013).[9]

4. Employment Choice: The Econometric Analysis

The above data suggest that the dynamics on employment may be more complex than the narrative that AI will reduce jobs. We formally test this in this section. In the first subsection, we start by specifying a simple derived labor demand that serves as the backbone of our econometric specification laid out in a second sub-section. Then results are reported and discussed.[10]

4.1. The Short-Term Derived Labor Demand as a Function of AI Automation

4.1.1. *Product Market Spillover*

One important element of this article is to emphasize the link between labor and product markets and how it may affect how AI diffusion influence labor demand.

We consider a firm r which maximizes profit, π, while being in competition with other firms, and supplying a product Q_r, with iso-price elasticity of product demand, κ, ($\kappa < 0$).[11] Given competitive interactions, this firm's equilibrium market share is given by, $MS_r = Q_r/Q$ (where Q is total market supply) and product price over marginal costs, $P/MC = \mu_r$ ($= > 1$) is:

$$\mu_r=\kappa MS_r/(MS_r\kappa+1+COMP),\mu_r=\kappa MS_r/(MS_r\kappa+1+COMP) \qquad (1)$$

COMP is a conjectural variation parameter, and lies between $[-1,1]$, and $COMP = -1$ means perfect competition ($\mu = 1$), while $COMP = 0$ means that all firms behave as Cournot.
Based on the above, it is easy to show that the growth in μ,($=\phi$), is a positive function of the growth in MS, ΔMS, as well as a negative function of growth in competitive intensity, COMP, $\Delta COMP$. We note:

$$\delta\log(\mu)=\phi=\phi(\Delta MS,\Delta COMP)\delta\log(\mu)=\phi=\phi(\Delta MS,\Delta COMP) \qquad (2)$$

ϕ in Eq. (2) will turn to be important as it reflects the extent of how AI automation effect on production efficiency is passed-through into profitability of the firm, see infra.

4.1.2. Derived Labor Demand

Now assume that the firm also decides to invest in AI technologies for multiple purposes, in consistency with Table 3. We denote, AIL > 0 if the goal of leveraging AI is labor automation. Likewise, AIE > 0, if AI leads to any other complementary labor productivity gain and AIM(S) > 0, when it concerns the use of AI for enlarging market (share).

The firm produces its output, Q, via a Leontieff function of labor and capital, which is dependent of each of the n AI technologies used. Here we follow Martinez (2018), by stating that there is a one-to-one capital stock that embodies each AI-based technology AIL_j (j = 1,…n). This implies that, if it takes workers one unit of time to complete all tasks of the use case in [0, t_j], a worker-AI machine pair would produce $1/(t_j - AIL_j)$ goods in one unit of time, and thus the higher AIL_j, the less the need for hiring workers as result of automation arbitrage.

The productivity of a worker-AI pair for attribute j is given by, (with γ >1 implies returns to specialization):

$$z(AIL_j)=(t_j/t_j\text{-}AIL_j)^{\gamma} z(AILj)=(tj/tj\text{-}AILj)\gamma \qquad (3)$$

If the distribution of AI_j, is represented by a beta distribution, with upper bound (AILH) of diffusion, then the firm aggregate supply converges to a CES function:

$$Q=T((1-\alpha)K^{(\sigma-1/\sigma)}+(\alpha)(L)^{(\sigma-1/\sigma)})^{(\sigma/\sigma-1)}Q=T((1-\alpha)K(\sigma-1/\sigma)+(\alpha)(L)(\sigma-1/\sigma))(\sigma/\sigma-1) \qquad (4)$$

where K, L are aggregate capital and labor at firm level; ρ = σ/1 − σ where σ is the typical (constant) elasticity of substitution between capital and labor, while the total factor productivity term T and the weight α are endogenized as:

$$T=z(AILH)^{1-\sigma}T=z(AILH)1-\sigma \qquad (5)$$

$$\alpha=z(AILH)^{\sigma-1}\alpha=z(AILH)\sigma-1 \qquad (6)$$

6

If one notates that $\gamma = \rho + \varepsilon$ ($\varepsilon > 1$).

Equations (4)–(6) illustrate how AIL affects factor intensity and in particular, how automation may put pressure of labor. To see that more simply, take the log of (6), that is $\ln(\alpha) = \varepsilon.\ \ln(1\text{-}AILH)$, as well as the special case $\varepsilon = 1$. Then, we find roughly that the labor share is directly linked to increased automation AILH:

$$\alpha=(1-AILH)\alpha=(1-AILH) \qquad (7)$$

This is in line with the idea in the literature that efficient automation exerts a direct decline in labor share (Autor and Salomons 2018),

4.1.3. *Employment Dynamics in Function of AI*

As said earlier, the derived labor demand must take into account all channels and namely the indirect impact on full supply through the change in μ. In fact, using (2)–(4)–(5)–(7), the first order condition for profit maximization leads to the following short-term employment elasticity that is[12]:

$$\tau=(\partial \log L/\partial AILH)=-\kappa\phi(\Delta MS,\Delta COMP)\theta+(1-\sigma)\varepsilon\tau$$
$$=(\partial \log L/\partial AILH)=-\kappa\phi(\Delta MS,\Delta COMP)\theta+(1-\sigma)\varepsilon \qquad (8)$$

Where the first term can be broken down as the opposite of the product of three terms: (a) the product elasticity; (b) the elasticity of mark-up as described by Eq. (2) and (c) θ, the elasticity on marginal cost of automation intensity change.

Taking all those terms together, their product tends to be *negative*, so that an increase in automation AILH boosts employment. The sign of second term is not known a priori—it depends on how large capital and labor are substitutes to each other; in an aggregate Cobb-Douglas specification, the term collapses to zero; if capital and labor are strategic complements, $\sigma < 1$[13]; if there are gross substitutes the term is negative. Nevertheless, the second term increases in labor specialization ε, and declines in σ.

From the different tables, and equations above, we can further assume that κ is a decreasing function of AIM, while ϕ is a positive function of AIMS. Further, if labor is strategic complements/substitutes with other inputs, θ may be a positive/negative function of AIE. Hence, we thus clearly see that the effect of investing in automation (AILH) on employment depends on the nature of the technology, the indirect effect on product supply (and the latter is being affected by the additional mix of objectives in investing in AI).

One extreme case is when capital and labor are gross substitutes, and that the firm only uses AI for automation (AIQ = AIE = 0), and has monopoly power- in this case, labor is the only adjustment variable, leading to a decline. On another extreme, a firm invests in AI with its labor being more complement to capital and where AI leads to higher market (share) expansion, may rather lead to a net positive effect on employment. The latter is likely to be more relevant when it concerns crucial employment skills that must be bundled with new type of smart capital, as early mentioned in Brynjolfsson and Hitt (2003).

4.2. The Econometric Specification

We now turn to an empirical specification for τ, using Eq. (8), as backbone of drivers that determine the level of τ.

Table 6 in particular demonstrates that, among firms already adopting AI, the largest segment is from companies investing both in automation and other forms of product market shifting, while the segment using AI for product market shifting is actually larger than the one doing it only for labor automation. This type of overspill to the product market is sufficiently frequent that it must controlled for in the discussion on the effect of automation on employment.

Table 6

How firms leverage AI, % of firms

												Split sample
												Among aware AI
							Yes	19%				28%
				Yes	29%	AIM(S) > 0						
							No	10%				14%
	Yes	68%	AIL> 0									
Aware of AI							Yes	17%				24%
				No	39%	AIM(S) > 0				No	3%	4%
	No	32%					No	25%	Pilot only			
										Yes	22%	32%

Our survey collects only data on the *direction* of employment change as a result of investing in automation. We thus consider a model of the form, I(I) where I = 1 if planned employment is on the decrease, 0 otherwise. As we do not have a view on output, I(I).

Using a log-linear approximation at firm level we aim to estimate a typical logistic model of the form (9):

$$I(l)=1/1+\exp\{a+b(AILS)+c(AILG)+d(\pi)+e(\pi g)+f(AIMS)+g(AIM)+h(S)+cross-effects+fixed\ effects+u I(l)=1/1+\exp\{a+b(AILS)+c(AILG)+d(\pi)+e(\pi g)+f(AIMS)+g(AIM)+h(S)+cross-effects+fixed\ effects+u \qquad (9)$$

where the coefficients “a to h” are parameters to be estimated; u captures all unmeasured effects, fixed effects are industries/countries (capturing among others the common unobserved industry technical production parameters).

Remember that in our theoretical model, AILH reflects the level of maturity of investing in the variety of use cases and of AI technologies for automation. We thus build a variable as the share of AI technologies adopted by each firm for multi-use cases and for automation. This variable takes a value between 0 and 100%, as a stock effect, e.g. the amount of technologies of AI already adopted to date (denoted by *AILS*). Note as well that the equation reflects the expectations on employment changes; we thus include a flow effect, that this, the intent of a firm to invest in the future into new AI (denoted by AI*LG*).[14]

Consistent with Eq. (8), we are to control for product market variables. We control for profit *(π*) as well as its expected change due to AI adoption, *(πg*). The first measure positively correlates with μ, while the second is more a summary of how firms envisage the AI diffusion pass-through into profits, as a mix of ability to expand, and/or to reap more margins.

We include the fact as well that firms may choose to invest in AI to affect its product market, either via output expansion (which we denote by AIM), or via market share (AIMS).[15] All those product market effects should in fact play as interaction terms to AILS/AILG.

We include them both as cross-effects and shift variables, and we let data speak. We finally control for company size (S), as it is well known that technology shape may be different by size (Dupuy and de Grip 2003).

In practice the model (9) is being estimated as a multi-logit model given three categories (increase, decrease, or no impact) of employment changes, and in difference versus industry average, so we control for trends in industry dynamics. The variables πm, πmg as well as AI*LG* are all categorical variables. Given our coding, one delta in πm is 5 points extra of current margin, one delta in πg is 3 extra points of expected margin in next 3 years, while one delta in AI*LG* amounts to 20% growth in investment in AI technologies in next 3 years. The size variable (s) is categorical with eight categories of employment, from 0 to 10 employees (small firms) to very large firms (more than 10,000 employees). The largest firm size category is the default variable.[16]

4.3. Results

4.3.1. Employment level effects

Our results for *total* employment are presented in Tables 7 and 8. For readability, we only reproduce statistically significant coefficients at 10% in both tables. The model always controls for industry and country effects (not reproduced). Employment increase is the reference categories, so that a negative estimated sign found in our model will be equivalent to a larger probability to increase (versus decrease or freeze) employment. Table 7 estimates a simple model linking employment choice to AI and profit, without the interaction terms.

Table 7

How firm's employment is linked to AI, direct effects

Category		**Value**	**Sig.**
Reduce needs for employment	Intercept	0.51	
	AILH	−0.023	0.101
	AlG	−0.074	0.01
	Πg	−0.093	0.007
No change need for employment	Intercept	0.41	
	AILH	−0.082	0.919
	AIG	−0.031	0.001
	s (10–50 employees)	0.096	0.008
Notes: Marginal probability, default category is employment increase as a result of AIL			

Table 8

How firm's employment is linked to AI, direct and indirect effects

Category		**Value**	**Sig.**
Reduce needs for employment	Intercept	0.31	
	AILH	0.24	0.05
	AIM∗AILH	−0.14	0.01
	AIMS∗AILH	−0.10	0.08
	πg∗AILH	−0.06	0.10

Table 7

How firm’s employment is linked to AI, direct effects

Category		**Value**	**Sig.**
No change need for employment	Intercept	0.37	
	AIG	−0.04	0.01
	πg∗AILH	−0.09	0.02
	AIM∗AILH	−0.07	0.06
	AIMS∗AILH	−0.11	0.01
	Employment_10_50	0.06	0.03
	Employment_5000_10000	0.0.3	0.06
Notes: Marginal probability effect; default category is employment increase as a result of AIL			

In such a specification, AIM(S) do not appear significant- but we know from Table 6 that AIM positively correlates with AILH. The most significant variable is AIG (AI investment growth), then profit growth expectations, while AILH is barely significant at the margin. Nevertheless, results suggest that the more companies are vested in AILH and especially, will commit to further spend to adopt AI, the more likely they will be to increase employment, rather than reduce or not affect level of employment.

The effect of AI growth is *not small*; using estimated probabilities, a firm which will scale its investment budget by 20% in next 3 years, will be 65% more likely to increasing employment (18%) than the current average of 12% in the sample.

All things being equal, AI therefore *seems more employment accreditive than substitutive* for companies boosting their commitment to AI technologies. Table 8 reports results of a more appropriate specification, as variables other that AILH enter as interaction with AILH on employment changes, as per Eq. (8). Interestingly, AILH comes as a significant driver for decline in employment evolution. This effect is however counter-balanced by any plan to expand output in the form of market and market share extensins.

Likewise profit growth expectations as well as plans for further AI investment remain associated with higher employment plans.

Using the estimates, we can provide some sensitivities of AI linked to employment. Consider first a case where a firm only invested for automation-and is no longer planning to increase level of AI, while its profit growth out of AI investment is limited. In such as case, the probability to reduce (some forms of) employment is dominant (it goes to 55%) and the likelihood to increase employment collapses to zero.

The opposite, and optimistic case is a firm that d continues aggressively to invest in AI (more than 20% a year), increases its profit by 3 points of margins, and further uses AI not only for automation, but for market (share) deployments.

In such as case, the probability of increasing employment becomes dominant (51%), while the probability of decline decreases to 25%, from an average in our sample of 45%. Clearly, the product market overspills are changing the distribution probabilities of employment as result of AI decision.[17]

4.3.2. Employment skill mix effects

We finally zoom by skills type in Table 9. The first column of the table uses the gross statistics shown in Table 2 to compute an indicator of net employment expectations (versus all skills' average). This indicator becomes more negative the higher the portion of firms planning to reduce, or the lower the share of companies willing to increase employment, for this skill type. Basic listening and numerical skills have 7.5 points fewer employment opportunities than the average, in relative contrast to advanced data or IT skills, for example, which have respectively a 6.5%/11.5% higher employability.

Table 9

How firm's employment is linked to AI, difference by skills

		Increase in employment linked to:		
Skills	**Relative employment change (%)** AQ8	**AILH (%)**	**AIX∗AILH (%)**	**Total (%)**
Basic listening skills	−7.50			
Basic numerical skills	−7.50			
Leadership skills	−6.50		14.4	14.4
Craft / technical skills	−5.50		16.1	16.1
Communication skills	−2.50		7.2	7.2
General management skills	−2.50		12.3	12.3
Basic IT skills	−1.50		7.30	7.3
Engineering skills	−1.50		7.6	7.6
Interpersonal skills	0.50	4.5	9.90	14.4
Optimisation and planning	0.50		10.10	10.1

Table 9

How firm's employment is linked to AI, difference by skills

		Increase in employment linked to:		
Skills	**Relative employment change (%)** AQ8	**AILH (%)**	**AIX∗AILH (%)**	**Total (%)**
Creative design skills	1.50		9.80	9.8
Project management skills	2.50		6.70	6.7
Critical thinking / problem solving	3.50	10.3	26.6	36.9
Advanced data skills	6.50	11.2	27.8	39.0
R&D skills	8.50	14.4	6.2	20.6
Advanced IT skills	11.50		9.0	9.0

The other columns of Table 9 show the marginal probability from the multi-logit equation to *increasing* employment versus other categories (no change of employment or decrease). Only statistically significant coefficients at 10% are presented in Table 9.

As expected, we find only rare cases where AILH is statistically associated with higher employment. However, it is remarkable that when it is, it is visible in skills with higher than average employability in the future, e.g. advanced data skills, interpersonal skills, among others. Further, an increase in AI investment growth that is aiming at increasing output boosts employment across *all* categories, except notably for skill categories with the least employability potential, e.g. *basic listening and numerical skills*. The largest potential in employment growth lies in advanced data skills, or critical thinking/problem-solving, and to a lesser extent, R&D skills, all of which are skills with relatively more employability than average.

Those results are consistent with the idea that there is a tendency of skill redistribution

5. Conclusions

The research above is rather new and may be extended in many ways. First, the sample can be extended and updated; second, it would be great if employment changes emerge directly for observed from data, rather than from qualitative survey. Finally, our results should be checked for robustness in terms of sample selection, in terms of omitted variables (e.g. wages as determinant of employment changes), among others.

Nevertheless, this article has put the narrative of a “workless future” to a first and new test, looking from *the derived demand side of labor by companies*. We have argued that this lens complements the recent stream of research focusing on technical automation and skills from the supply side, as corporations are primary influencers, both deciding on timing and extent of technology adoption as well as on the arbitrage to make between capital and labor, and pass-through to higher output (thus employment) or not.

Our results confirm that the narrative should indeed be more nuanced. Rather than an inevitable era of depletion of all type of jobs, our data suggest that the ultimate balance will depend on product market spillovers as well as type of skills. The product market spillover is itself dependent on how AI is used by firms- and the good news is that many firms report using AI, not (only) for pure labor automation, but for other aims, among others, expanding their product and services and competitiveness. Those are critical elements to assess how AI will be linked to employment, even if our current estimates still show an asymmetry towards lower than higher hours employment out of automation.

Regarding reallocation, our data analysis confirms a tendency towards skill-bias change. The demand for certain new skills will certainly rise, including skills linked to social, new analytics, and interfacing skills (see Deming 2017). Basic skills (including basic IT ones) exhibit lower employability and are subject to further arbitrage when companies increase their plan to invest in AI. Hence, on top of some fear of employment reduction due to automation, one may also want to ensure enough supply of skills in demand. In general, there are often frictions in the short term for new skills, e.g. STEM talents (Holtgrewe 2014 or Walvei 2016).

Hence, companies in need of those new skills will have to poach the best talent in their onboarding strategy. Likewise, those companies will need to nurture their workforce via all possibilities of on-the-job and lifelong training. Perhaps this is why most of the most innovative HR practices are now coming from digital companies, from Zappos to Netflix.[18] In a world of up-skills, those companies with the right skill mix and adequate expansive business models will be those to thrive in both labor and product markets.

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End-notes

[1] Discussion with Mark Purdy from Accenture research at the G-20Y in Evian, Sept.

[2] See *A future that works: Automation, employment, and productivity*, McKinsey Global Institute, January 2017.

[3] As a case in point, let us consider the Associated Press news agency, which used to deliver reports on large corporations using 65 journalists in its newsroom. With AI technologies, the company quickly managed to automate the production of simple stories of quarterly earnings for 10 times as many small companies in the long-tail. This output gain was not done at the expenses of reporters; the in-house reporters did not lose their jobs, but were instead redirected to write longer research article on business trends as a major latent demand spotted by the company. See Ramaswamy, S (2017) at https://hbr.org/2017/04/how-companies-are-already-using-ai

[4] Substitution may arise when, furthermore, the economics are attractive to replace human capital for example.

[5] https://www.infoq.com/news/2016/07/deepmind-cooling-pue

[6] For statistics, see https://www.thetechedvocate.org/six-countries-leading-the-ai-race/ and https://qz.com/1264673/ai-is-the-new-space-race-heres-what-the-biggest-countries-are-doing/

[7] We are rather keen to understand the expectations of firms as the current level of AI diffusion across all technologies is still relatively low.

[8] Here we show results in aggregate, but the same picture is also visible by industry.

[9] The same skill-biased tendency is also noticeable in the econometric analysis conducted by Arntz et al. (2016) linking occupations and tasks to the OECD PIACC skill database.

[10] Note that the sample used will concern only firms which are aware of, but not necessarily adopting, AI technologies. We sub-select those firms, and survey responses on the impact on AI are likely not to be largely noisy for those respondents with limited understanding of AI technologies

[11] With no loss of generality, we drop the suffix r hereafter.

[12] See also Ugur et al. (2016).

[13] The preponderance of empirical estimates on the substitution between labor and capital point to $\sigma < 1$,

[14] We do not have any mean to split this variable in terms of investment objectives, however.

[15] We do not include AILE as otherwise, we have perfect multicollinearity.

[16] There is a case for a selection bias in the sense that we only concentrate on firms aware of AI. However, firms not aware of AI have not given data, and if yes, noisy ones, so we can not control for them. We tried a Heckman correction where we try to predict awareness or not of AI in a first step. But it is rather difficult to have specific regressor for this first step.

[17] See however the asymmetry- in this present case, employment decline has still a positive probability; while employment increase in the previous case was nil. Everything being equal, it still suggests that employment pressure may be happening along automation.

[18] See https://hbr.org/2014/01/how-netflix-reinvented-hr

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