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How the risk of job automation in the UK has changed over time

Matthew James Darke*

Abstract

Developments in Artificial Intelligence and Machine Learning technologies have had massive implications for labour automation. This paper builds on the task-based methodology first adopted by Frey and Osborne (2013) to predict how the risk of automation evolved in the UK labour between 2012 and 2017 using data from the UK Skills and Employment Survey. The analysis accounts for technological progress, making use of two sets of experts' assessments for 70 occupations. The probability of automation is predicted for each individual using a set of self-reported job skills. It finds that the proportion of jobs at high-risk from automation has risen from 10.6% to 23.4%, and that this is largely due to better technology rather than changing job skill requirements. It also identifies sectors experiencing the greatest increase in automation risk between the two periods and, in contrast, those which appear complementary to technology, drawing on occupational case studies as evidence.

Keywords: Employment, Skills Demand, Technology

JEL Classifications: J01, J21, J24, J62, O33

I. Introduction

I would like to thank Natalia Zinovyeva for her support throughout this research project. Her diligence and guidance were extremely helpful, and she always provided an interesting discussion on the topic.

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Technological improvement is an ever-present aspect of the modern age. In 1965, Gordon Moore observed that the number of transistors in an integrated circuit doubled every two years. This high rate of technological improvement has been labelled 'Moore's Law' and has become the standard for modelling the pace of technological progress. Such progress has brought increased scope for computers to carry out job tasks. For instance, the introduction of the ATM in the 1960s carried huge implications for bank tellers at the time. Or, more recently, we have seen a large proportion of retail checkout occupations being replaced by self-checkout machines.

Many Economists have attempted to model how these technologies have impacted Labour demand across different occupations. Initially, the literature found evidence of the existence of a skill bias related to new technology (Acemoglu, 1998; Krusell et al, 2000). Autor et al (2003) contend that the routine nature of occupations determines substitution from technology. Further to this, more recent literature has cited routine middle-skilled occupations as being most susceptible to automation, contributing to job polarisation (Goos and Manning, 2007; Acemoglu and Autor, 2011; Goos et al 2014). Recently, Acemoglu and Restrepo (2020) find evidence of a negative impact of robot penetration on employment and wages within industries.

However, recent developments in Artificial Intelligence, Machine Learning techniques and Mobile Robotics have rendered this simple routine vs non-routine framework outdated. For example, AI data analytics processor IMB Watson, launched in 2013, uses speech recognition and vast data stores to answer questions across a huge variety of business industries to help companies worldwide solve problems.

Inspired by these fascinating developments, Frey and Osborne (2013) use a novel methodology with 70 expert-labelled occupations to predict the probability of automation for US occupations. This methodology has been adopted and improved by several studies since and forms the basis of my analysis. I draw on their expert's assessment and make use of a more recent 2019 assessment to apply the methodology to two time periods, predicting the evolution of probability of automation for UK occupations.

My data source is the UK Skills & Employment survey (SES) from 2012 and 2017, distinguishing my research from other studies that use OECD data. The datasets contain information on individual's job characteristics and skill requirements, which I will use to model the probability that each individual's work can be automated.

The main finding of this paper is that the predicted proportion of jobs at 'high-risk' of automation rose between 2012 and 2017 from 10.6% to 23.4%. This rise is largely attributable to technology improvements between the two time periods, arising from the change in expert's assessment of automatable jobs, rather than changing characteristics of job tasks. It may also be a symptom of changing occupational structure in the UK, although this is likely limited due to the small timeframe. I also find that certain jobs and job sectors are indeed complementary to new technologies and identify others which face growing risk of displacement.

Like existing studies, the focus of my paper is on feasibility of automation, rather than whether these occupations will be automated in practice. This is still extremely useful to policy makers as it identifies sectors facing growing risk and perhaps suggests what sectors and associated skills education should target in the long term.

II. Literature Review

As mentioned above, Autor et al (2003) argue the key issue relating to labour automation is whether work tasks are routine. By definition, routine tasks apply explicit rules to carry out a small set of well-defined activities. Using a task model, they conclude that computers are only substitutable for routine cognitive and manual labour tasks and are instead more complementary to labour in non-routine cognitive situations. However, these conclusions soon became outdated, as technological development in the fields of AI and Robotics allowed for the automation of non-routine tasks (Brynjolfsson and McAfee, 2011).

Frey and Osborne (2013) implement a novel methodology to predict the risk to labour from technology for US occupations from a feasibility perspective, arguing that technological development rendered previous studies less useful. Working together with Machine Learning researchers, they identify three "engineering bottlenecks" (Frey and Osborne 2013, p23) inhibiting task automation. Requirements for any of these abilities within job tasks limits the ability for computers to substitute for labour.

The authors follow an occupation-level approach, utilising O*NET 2010 data on US occupations including variables corresponding with the three bottlenecks. Using a training dataset, from manual diagnosis of 70 occupations by experts based on whether each occupation can be automated with existing technology (which I will refer to as FO training dataset from now), the authors construct a model based on relevance of 'engineering bottleneck' skills in the job tasks and use it to predict automation probability for the remaining 702 occupations. They find an alarming 47% of US employment is at high-risk to automation.

A key limitation of this high estimate is that heterogeneity of job tasks and characteristics within occupations isn't factored in, as well as the fact that a given individual may work on tasks spanning multiple occupations. Arntz et al (2016) build on the analysis and estimate automatability for 21 OECD countries. They employ an individual-level approach to account for heterogeneity, utilising Programme for the International Assessment of Adult Competencies (PIAAC) survey data. By matching automatability from Frey and Osborne to US observations and regressing on similar job characteristic variables, they find that only 9% are at high-risk. Applying the model to other OECD countries, they find significant cross-country variation in probabilities (hence why this paper is interested in the UK specifically) and estimate 10% of the UK are at high-risk.

This variation is further validated by Nedelkoska and Quintini (2018) who expand and improve the analysis to 32 OECD countries. Using the same two step approach, they find that 14% of OECD jobs and 12% of UK jobs are at high-risk of automation. In addition, like this paper, they also use UK SES 2012 data to predict automation risk using a similar methodology. However, this is only to check robustness of their main analysis and uses minimal variables.

A study by the ONS (Office for National Statistics, 2019) aims to estimate the probability of automation for the UK labour market specifically. They combine UK PIAAC data with Frey and Osborne probabilities to predict automation risk for given job characteristics. They map these outcomes to the Annual Population Survey using common characteristics to carry out demographics analysis. They estimate that, in 2017, 7.4% of the 20 million analysed jobs in England are at high-risk. Repeating the methodology for 2011 yields 8.1%. However, they fail to draw any conclusions for why automation risk in England appears to have reduced and, critically, don't account for technological change between the two periods.

PWC conduct a comprehensive study (PWC, 2021) on the potential impact of AI on employment. As part of the study, they run an AI expert workshop (held in 2019) to reassess the 70 occupations originally assessed in Frey and Osborne (2013), notably changing the assessment of 6 occupations to become feasibly automatable. The study finds 7%, 18% and 30% of UK jobs face high automation risk over the next 5, 10 and 20 years respectively, with the latter identified as the likely time horizon over which the FO assessments will occur in practice.

An optimistic view of the impact of automation on employment is presented by Vermeulen and co-authors (2018) that is ignored in the above literature. They argue that job losses in sectors where technology substitutes for labour is limited, whilst the potential for job creation in existing and new sectors involving 'making' of such technology is great. In addition, Hughes (2017) argues that until human creativity and social intelligence is matched by AI, the employment opportunities utilising these skills may expand in the medium term due to technology being complementary.

This paper contributes to the above literature in two key aspects. Firstly, benchmarking against existing studies that use PIACC data, I will use the UK SES to estimate UK automation risk. This dataset is only used by Nedelkoska and Quintini (2018), but this paper highlights weaknesses in their small set of variables.

Secondly, this paper also adds a dynamic aspect which the above studies lack, modelling automation risk between two periods and consolidating findings with complementary vs substitutionary views for different occupation groups. I apply the FO and updated PWC assessment to the 2012 and 2017 surveys respectively to examine how risk has evolved over time. Unlike the 2019 ONS study, my analysis controls for technology improvement over time, inevitable from 'Moore's Law'.

III. Methodology

My methodology continues to follow the assumptions from Frey and Osborne's paper that technology cannot yet rival human labour in tasks which involve significant requirement for any one of the so-called 'engineering bottlenecks': perception or manipulation, creative intelligence and social intelligence. This is a standard assumption for proceeding literature and moves discussion away from routine vs non-routine.

I follow a simple two-step analysis to predict the probability of automation for each of the individuals across the two datasets based on their job characteristics. Firstly, I match the occupations in the datasets as closely as possible to the 70 expert-labelled occupations, assigning a value of 0 to those not deemed automatable and a value of 1 to those which are based on current technological capabilities. The 2012 dataset is matched with the FO assessment and the 2017 dataset with the PWC assessment. I hence assume that the 2013 assessment of AI and robotic capability is applicable to 2012 and, similarly, the 2019 assessment to 2017.

These sets of observations form the training dataset for each period (table 1). I was able to match and identify individuals in 56 out of the 70 FO occupations within my survey data, with 6 occupations deemed automatable in 2017 but not 2012. These six occupations indicate increased ability of AI to carry out both managerial and consumer-facing roles, as identified in PWC's report (PWC 2021, p80). As is common for prediction analysis, I randomly split each training dataset into a 'train' and 'test' component in the ratio 7:3 to assess how well the model fits the expert's assessment in each period.

$$P(y=1 \mid f(x)) = \frac{1}{1+\exp(-f(x))}, \text{ where } f(x) = \sum_{j=1}^{J} \beta_j x_{ij} + \varepsilon_{ij}$$

I perform a likelihood estimation to construct a model with the outcome, y, being the binary expert assessment for that individual's occupation. The discriminant function (f) contains a set of variables (x) that describe the individual's use of perception/manipulation, creative intelligence and social intelligence skills in their occupation (equation above), with weights attached to each variable to maximise the likelihood from the training data.

Due to a large number of characteristics being insignificant in a simple regression, I use a lasso logit regression. Lasso stands for 'least absolute shrinkage and selection module'. It is used to prevent overfitting of the prediction model, 'penalising' coefficients and selecting the variables which are highly relevant to the training data (appendix A).

Secondly, I use this model to predict the probability of automation for the remaining individuals in each dataset. Those with a probability of automation of 70% or more are labelled 'high-risk', those with less than 30% are 'low-risk' and in-between are 'medium-risk'. This can be interpreted as a predicted timeframe for when these individual's occupations will be automated, with high-risk occupations facing threat of automation within 20 years. I analyse what sectors and demographics of the UK are at both highest and lowest risk, and how the risk they face has changed between the two periods. I also investigate specific occupations' automation risk in the two periods to validate the analysis and provide evidence for complementary or displacement theory.

I repeat this methodology for a second specification. This to predict the probability of automation for each period assuming the FO assessment holds in both periods. This is to see how the susceptibility to automation has evolved between the two periods based only on changing job skills requirements and UK occupational structure without modelling improvement in technology.

IV. Data

As mentioned, I use UK SES data from 2012 and 2017, contrasting with prior studies that use PIACC data. The surveys cover individuals in employment aged 20-65, with the 2012 and 2017 editions comprising of 3,200 and 3,306 individuals respectively. The sampling was stratified across UK postcode sub-regions and, within sub-regions, across standard Socio-economic classification to ensure a representative sample.

Our lasso logit model uses a set of 22 ordinal variables (table 2) which are similar to those used in prior studies and are linked to human-bias skills. For each individual, the interviewer asks: "In your job, how important is" followed by a job skill/characteristic. The individual can then respond with 1 – essential, 2 – very important, 3 – fairly important, 4 – not very important and

5 – not important at all. The self-reported nature of these variables leads to subjectivity. An individual may perceive an aspect of his/her job to be 'essential' which others may disagree with and vice versa, which may lead to attenuation bias in our lasso coefficient estimates.

The chosen set of variables depicting the requirements of the three 'engineering bottlenecks' is similar but unique compared to other studies. In particular, the inclusion of the 'caring' variable, a job characteristic that requires significant social intelligence, gives an advantage over PIACC studies that don't include such information, perhaps contributing to any differences in our risk predictions compared to prior studies.

Figure 1: change in mean ordinal index value between 2012 and 2017 for each variable

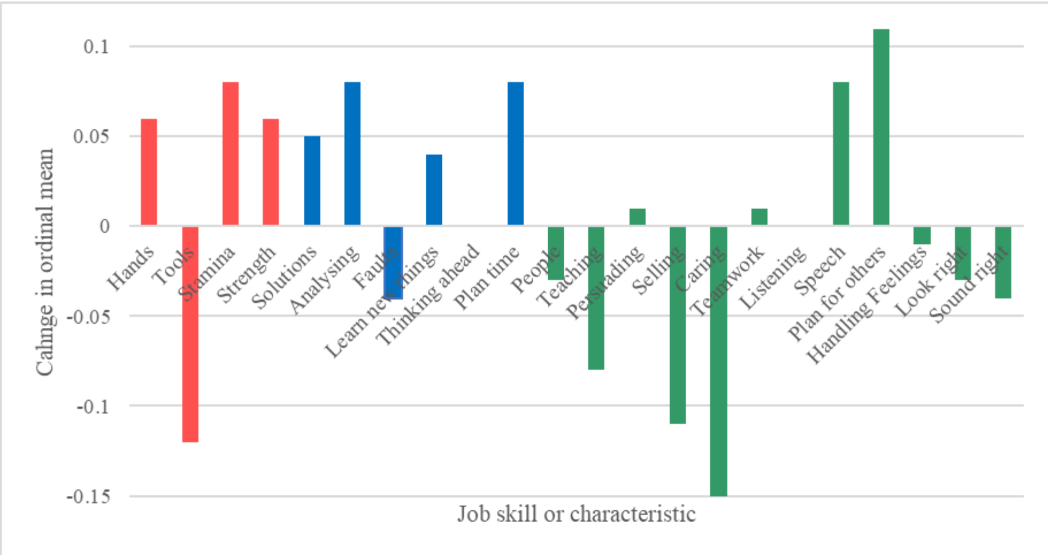


Figure 1 shows how the importance of each of the job characteristics/skills changes between the two datasets through the change its variable's mean index value. Here, the scale been reversed so that an increase in a variable's mean implies it is more important in 2017.

It appears that most skills related to perception/manipulation (red) and creative intelligence (blue) have become slightly more important over the 5-year period, with the exception of operating tools and spotting problems or faults. However, the evidence regarding social intelligence skills (green) is more mixed. Notably, interpersonal, teaching, selling and caring skills all appear to have declined in importance slightly. Considering the set of variables overall, no clear inference can be made on whether jobs will become more or less susceptible to automation between the periods.

Individuals in the training dataset make up 541 out of 3,200 observations for the 2012 dataset and 515 out of 3,306 observations for 2017 (table 3). Applying the FO assessment, 34.38% of the 2012 training dataset are deemed automatable, whilst 40.97% of the 2017 training dataset are automatable after applying the updated PWC assessment. Table 4 shows a comparison of the job characteristic variables between the two training datasets.

V. Empirical Evidence

Table 5: OLS regression results for two models: (1) includes only variables used by Nedelkoska & Quintini (2018) in their robustness check and (2) is the full 22 from this paper

	2012		*2017*	
	(1)	*(2)*	*(1)*	*(2)*
Hands	0.065***	0.039*	0.050***	0.036*
	(5.16)	(2.38)	(3.82)	(2.03)
Faults	-0.016	-0.022	-0.061**	-0.067**
	(-0.78)	(-0.94)	(-2.85)	(-2.72)
Analyse	0.014	-0.001	0.054**	-0.000
	(0.80)	(-0.04)	(2.91)	(-0.02)
Teach	0.066***	0.033	0.071***	0.033
	(4.11)	(1.76)	(4.25)	(1.67)
Persuade	0.077***	0.063**	0.054**	0.010
	(4.06)	(3.04)	(2.67)	(0.48)
Selling	-0.042***	-0.048***	-0.057***	-0.052***
	(-3.35)	(-3.66)	(-4.28)	(-4.00)
Caring	0.0271	-0.006	0.067***	0.068***
	(1.82)	(-0.34)	(4.64)	(4.35)
Tools		0.003		-0.002
		(0.18)		(-0.10)
Stamina		0.052*		0.028

		(2.55)		(1.38)
Strength		0.005		-0.026
		(0.26)		(-1.21)
Solution		0.010		0.052
		(0.38)		(1.83)
Ahead		0.021		0.058*
		(0.74)		(2.16)
Newthings		0.069*		0.157***
		(2.44)		(4.62)
People		0.056		-0.048
		(1.85)		(-1.63)
Speech		0.017		0.039*
		(0.92)		(2.12)
Teamwork		0.020		-0.020
		(0.83)		(-0.74)
Listen		-0.061*		-0.038
		(-2.44)		(-1.34)
Mytime		0.020		0.026
		(0.81)		(1.01)
Planothers		0.030		0.032
		(1.71)		(1.73)
Feelings		0.040		-0.001
		(1.72)		(-0.02)
Look		-0.003		0.029
		(-0.14)		(1.25)
Sound		-0.014		-0.049
		(-0.57)		(-1.82)
Constant	-0.142*	-0.397***	-0.032	-0.177
	(-2.27)	(-4.72)	(0.46)	(-1.88)
N	541	541	515	515
Adj R^2	0.208	0.254	0.232	0.308

Table 5 shows a simple regression of the binary FO expert assessment (1= feasibly automatable), on two sets of job characteristic variables. Model 1 is the limited set of variables used by Nedelkoska and Quinitini to predict automation risk as a robustness check. Model 2 is the full specification this paper uses. These models are run for both time periods.

The inclusion of the additional set of characteristics has a big impact on the coefficient estimates in model 1. For the 2012 regression, running model 2 shrinks all coefficients except on spotting faults and selling, and the teaching variable is no longer statistically significant even at the 10% level. Similarly, in the 2017 regressions, model 2 shrinks all coefficients apart from on spotting faults and caring. The characteristics analysing, teaching and persuading become insignificant. There is a significant increase in the adjusted r-squared value from model 1 to 2 for both periods. The lack of significance of many characteristics, highlights the requirement for lasso.

Table 6: lasso logit model coefficient selection and penalised coefficient values

Variable	*2012*	*2017*
Hands	0.205	0.199
Faults	-0.027	-0.274

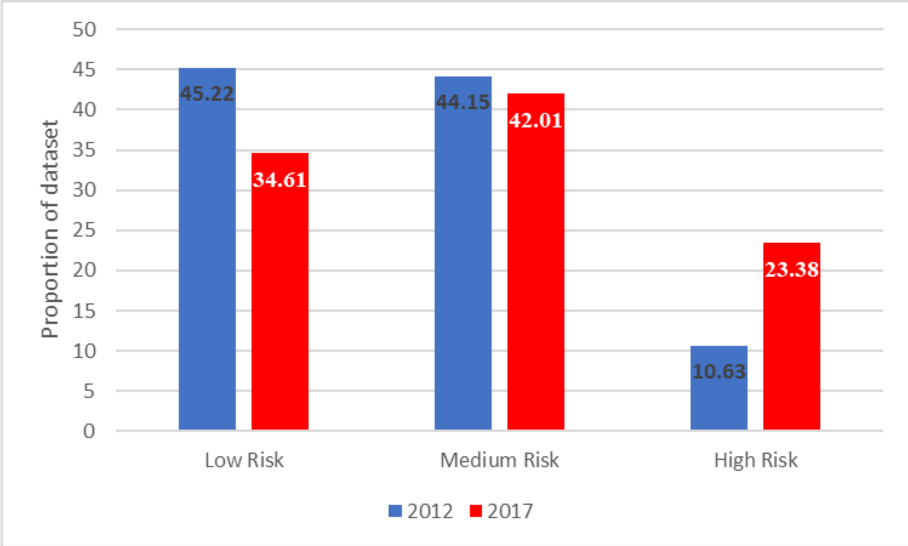
Analyse	x	x
Teach	0.168	0.188
Persuade	0.329	0.069
Selling	-0.26	-0.309
Caring	x	0.357
Tools	x	x
Stamina	0.296	0.108
Strength	0.017	-0.082
Solution	x	0.191
Ahead	0.078	0.338
Newthings	0.322	0.86
People	0.197	-0.263
Speech	0.073	0.202
Teamwork	0.021	-0.104
Listen	-0.193	-0.231
Mytime	0.079	0.213
Planothers	0.189	0.174
Feelings	0.162	x
Look	x	0.08
Sound	x	-0.17
Constant	-4.736	-3.773

(x=variable omitted by lasso)

Table 6 shows the variable selection from the lasso logit model and the 'penalised' coefficients for each period. Analysing complex problems and skills with tools are omitted by lasso in both periods, suggesting they don't impact automation risk. We expect the coefficient on each variable to be positive because a greater index value implies that job skill is less important and hence technology will be more substitutable. This is the case for most of the selected variables. However, the ability to spot faults, to sell and to listen are associated with greater probability of automation for both datasets. Our model for 2017 suggests the biggest limiting factor is continuously learning new things.

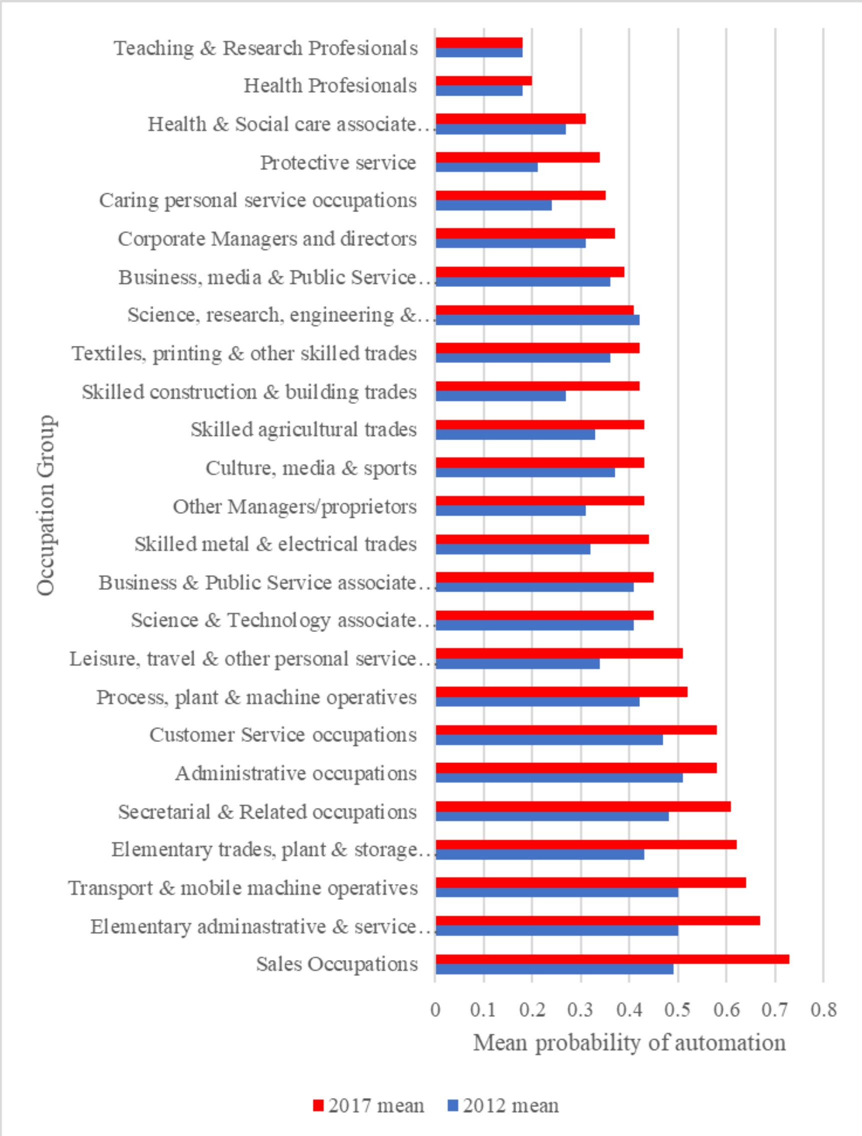
Using these two lasso logit models to predict the probability of automation for the remaining individuals yields our key results. Table 7 shows the statistics from the goodness-of-fit test for how well the model from the training data fit the test data. The results suggest the model fits the data much better for 2017 than 2012, suggesting the 'bottleneck' assumptions are more applicatable in the more recent time period.

Figure 2: proportion of individuals in each dataset at each risk level



The proportion of individuals predicted at high-risk of automation has risen from 10.63% to 23.38% between the periods. The proportion of individuals at medium and low-risk respectively has reduced from 44.15% to 42.01% and from 45.22% to 34.61% (figure 2). The evolution of the distribution of probabilities is demonstrated visually in the kernal density graphs in figure 3, highlighting the lower number of individuals falling in the low-risk band and a larger tail at the high-risk end. In 2017, the highest risk industry is wholesale and retail trade, with a mean probability of 64%. At the other end of the spectrum, only 7% of the Education industry were predicted high-risk (table 8).

Figure 4: mean probability of automation by SOC 2-code occupation groups



Sales occupations have the highest mean risk of automation for 2017 (figure 4). The mean risk for occupations in this group has grown by an alarming 24 percentage points. Occupations here include sales/retail assistants, checkout operatives, merchandisers and telephone salespersons. ‘Elementary trades, plant and storage’ occupations see an increase in mean probability of 19 percentage points, the second largest. This group incorporates a variety of manufacturing process operators (e.g. food, textile or chemical manufacturing), product assemblers, routine inspectors/testers and sewing machinists.

The analysis predicts that occupations in lower risk groups experienced lower rises in mean automation probabilities. We see very little change in probabilities for Health, social care, teaching, research, business, media and public service-related professionals or associate professionals, and for directors and managers. This is despite technology improvements between the periods, indicating these occupations increasingly rely on creative and social intelligence, with technology perhaps more complementary. The greatest indicator of this effect are occupations in science, engineering and technology (including lab, IT and engineering technicians), which have actually experienced slight reduced probability of automation. Overall, this suggests the presence of a skill bias even for modern AI.

I show how automation probabilities have changed by skill level in figures 5 and 6, distinguishing between low, medium and high skilled jobs (table 9) and further separating out the low and medium jobs into routine and non-routine. Despite AI improvement, the routine nature of occupations appears to still play a vital role in automation risk. Whilst probabilities for routine vs non-routine middle skilled jobs are very similar in 2012, routine middle skilled jobs become much more susceptible to automation in 2017 than their non-routine counterpart, and also, interestingly, than low-skilled non-routine jobs. The proportion of individuals in routine low and middle skilled jobs at high-risk has risen by 26 and 25 percentage points respectively. Testing the significance of the routine nature of an individuals' occupation on the binary experts assessment evidences that it still plays a role. However, the F-statistic is far greater for 2012 than 2017 (table 10).

We see a U-shaped relationship between age and job automation risk from figure 7 that is well documented in prior studies (ONS, 2019; Nedelkoska & Quintini, 2018). The model predicts young working individuals aged 20-24 as the most likely to be displaced by technology, followed by those aged 60+. Meanwhile those workers aged 35-44 face lowest risk and have been least affected by the improvements in technology between the two time periods.

It appears that existing high-risk age bands have experienced a greater increase in risk than the lower risk bands between the periods. The exception to this is the 30-34 band, who had the lowest proportion of individuals with high probability in 2012. The proportion of individuals at high-risk in this age band has risen from only 6% up to 22%.

Our second specification for 2017, where we hold constant technological feasibility by using the FO assessment to construct our training dataset, yields proportions of 13.88%, 37.84% and 48.28% of observations at high, medium and low-risk respectively. Although this prediction is a lot closer to that of 2012, the proportion at high-risk is still higher despite not modelling technology improvement. This implies that individuals in high-risk occupations are carrying out less tasks associated with engineering bottlenecks. However, the proportion of individuals at low-risk has increased between the two periods, suggesting jobs require more of these human-bias tasks and thus implying technology is complementary here.

Figure 8: change in mean automation between 2012 and 2017 by SOC 2-code occupation group using the Frey and Osborne 2013 expert's assessment for both time periods (ordered by original 2017 specification predicted automation risk)

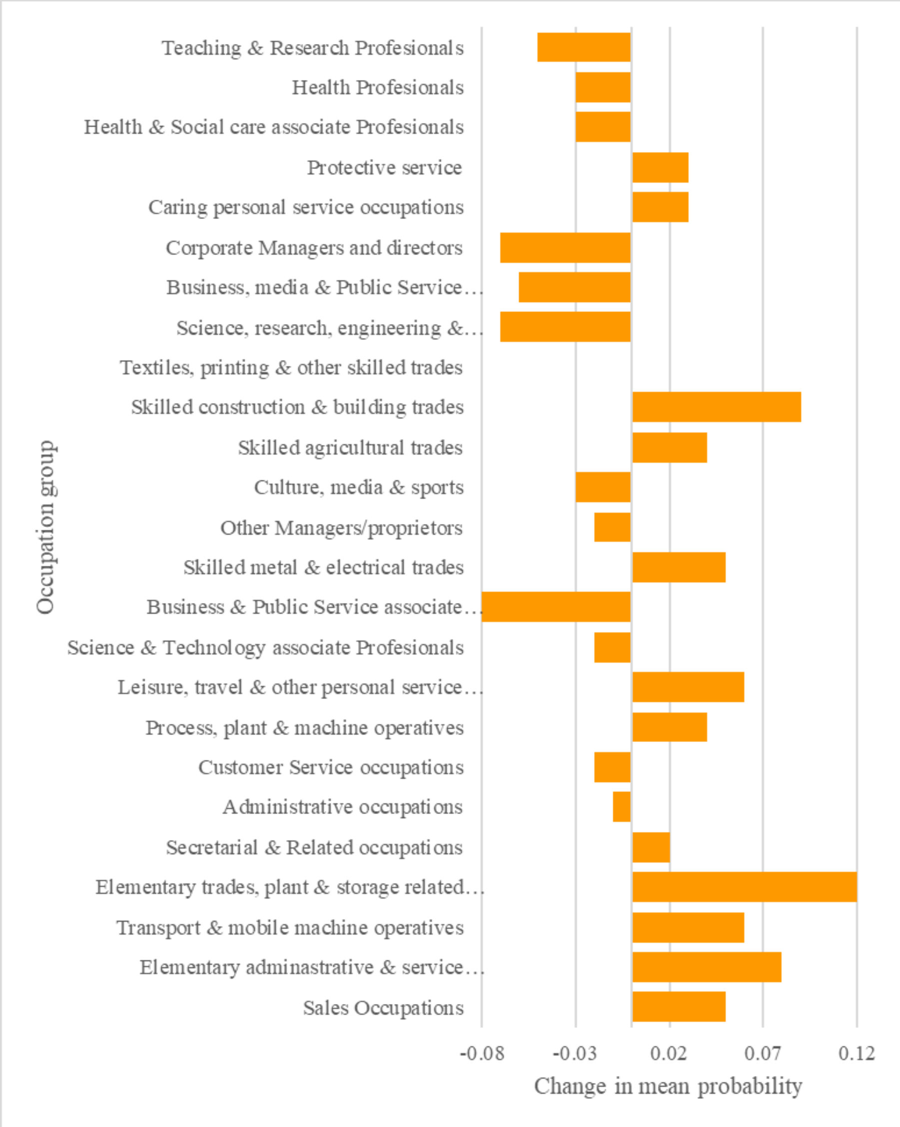


Figure 8 highlights the change in mean probability from this specification for each occupation group. This provides clear evidence for complementary effects in low-risk groups since changes in automation probability between the two periods is predominantly based on task structure for each individual. We see reduced automation risk and suggesting increased human-biased tasks for occupations related to business, media, public service, teaching and healthcare.

VI. Validation

This section seeks to somewhat validate the model through occupational case studies. Well-documented is the decline in secretarial related occupations, which can be at least partly explained by technologies such as automatic meeting scheduling or reminders, automatic redirecting of phone calls and, notably, automatic gathering and organising of consumer information. We find that company secretaries have a mean probability of 0.75 in our 2017 prediction, supporting this risk narrative.

There have been instances of bars incorporating mobile robotics to carry out bartending drink-making duties. Whilst this is not a widespread practice, we expect jobs in this field to be high-risk, especially since our 2017 expert assessment deems waitering automatable. In our 2017 prediction, bar staff have a mean probability of 0.72, with 10 of the 19 individuals falling into the high-risk band, reconciling well with reality. Note that some bar staff may have to use social intelligence regularly, hence contributing to heterogeneity in predicted probability.

Intuitively, teaching cannot yet be feasibly replaced with AI due to the rigorous demand for social intelligence and the transfer of not just knowledge, but also wisdom. This is validated in our 2017 analysis, which predicts very low mean probabilities for Primary, Secondary and Higher Education teachers of 0.16, 0.16 and 0.17 respectively.

For occupations that are technology compliments (Autor et al, 2003), we would expect a fall in automation risk and growing labour demand. This is because the use of technology in technology-biased tasks, which boosts productivity, allows an individual to focus more on 'human' skills. This changing task structure will thus reduce our risk prediction. For occupations that are more likely to experience a displacement effect in the future, we are unlikely to see any decline in probability.

On top of the extensive requirement for social and creative intelligence, Lawyers are required to carry out mundane tasks reviewing countless documents. Such tasks can now be more efficiently carried out by complex software, a trend that will likely grow in the future. We see evidence of this complementary effect in our prediction for the two time periods, as the mean probability of automation for solicitors in our sample has declined from 0.43 in 2012 (medium-risk) to 0.30 in 2017 (low-risk). This evidences an increased prevalence of human-bias skills and less time spent on (e.g.) document reviewing.

Programming and software development has also been aided by AI programs that can spot errors in code and automate tedious programming tasks (e.g. Deepcode or Software 2.0), allowing for such developers to focus on more complex problems requiring extensive creative intelligence. This complementary theory is also validated in our predictions, with mean probability declining from 0.52 to 0.44 despite technology improvement.

In contrast, we see no decrease in predicted automation risk for many occupations that can be feasibly replaced by technology, painting a more pessimistic picture for these individuals in the face of technology improvement. My analysis predicts a rise in probability of automation for receptionists from 0.44 to 0.64. Packers, bottlers, canners and fillers, representing manual occupations that can be robotised, see a rise in mean probability from 0.53 to 0.61. Finally, Individuals working as telephone salespeople now face an alarming mean probability of 0.89, up massively from 0.55, resulting from our model associating selling with greater risk.

VII. Conclusion

As quoted previously, the key finding from this paper is that the proportion of jobs at high-risk from being automated has increased from 10.6% in 2012 to 23.4% in 2017. From the second specification, where technology is constant between the datasets, the proportion at high-risk rose still, but only to 13.88%, whilst the proportion at low-risk actually reduced from 48.3% to 45.2%. This suggests that the task structure of low-risk jobs increasly require human-bias skills, meanwhile those at the high-risk end require less. It also indicates that the largest effect causing the rise in predicted risk comes from technology improving between the two periods. This explains why the 2019 ONS study, which did not account for changing technology, actually predicted a slight fall in the proportion of high-risk jobs between 2011 to 2017.

This paper also finds evidence that occupational groups at highest average risk of automation are also, in general, the ones which have seen the greatest rises in predicted automation risk, suggesting they are most threatened by the latest developments in AI and robotics. This suggests the skill-bias technology change observed in prior decades (Acemoglu, 1998) will continue despite AI's ability to perform more complex tasks.

We can compare our 2012 prediction with other studies that use Frey and Osborne's assessment. In line with other studies, our individual-level rather than standardised occupation approach has yielded a much lower high-risk prediction Frey and Osborne's US prediction of 47%. Our prediction is very similar to the PIACC prediction in both Arntz et al (2016) and Nedelkoska & Quintini (2018) of 10% and 12% for the UK respectively. Therefore, the new set of variables used in this paper to estimate automation risk validates the predictions from these studies for the UK.

No studies have yet used the PWC 2019 experts assessment apart from the publication itself (PWC, 2021). Given PWC's likely time frame of 20 years for the jobs to be replaced in practice, accounting for other factors such as labour vs technology costs, we can consolidate our result with PWC's prediction of UK jobs which will likely be automated by the 2030s to see a lower prediction (23.38% vs 30%).

From our 2017 model, the biggest limiting factors for whether a job is automatible appear to be skills in learning new things, caring for others, problem-solving and thinking ahead. Skills in learning new things are highly relevent also for the 2012 model, where persuasion, hand or finger dexterity and stamina were much greater limiting factors.

Contrary to what was expected, the ability to spot faults, to sell and to listen are associated with greater probability of automation for both datasets. This result can perhaps be rationalised. Firstly, with respect to spotting faults, modern AI is now capable of spotting errors in equipment and can also predict the probability of machinery breakdown in a given time period. Secondly, whilst selling to customer requires significant social intelligence, sales process automation is now common, for example through automatic emails or customer relationship tools (e.g. Salesforce). Thirdly, and perhaps most intuitively, voice recognition software now has the ability to receive and interpret dictation and is not far from rivalling human listening ability.

Another finding from this paper is that the routine nature of an individuals' occupation still massively impacts automation risk. Despite AI development, more routine occupations within skill levels are at far higher risk. The increase in proportion of high-risk individuals for both low and medium skilled routine occupations between 2012 and 2017 is much greater than for non-routine occupations. Greater risk for medium-skill routine jobs than ordinary low-skill jobs supports the job polarisation effect cited by Acemoglu and Autor (2011). I argue this is perhaps a symptom of technologies replacing routine tasks being simpler and thus much cheaper to implement. Meanwhile, more novel and complex AI is needed for non-routine settings.

As with prior studies that have followed the broad methodology of Frey and Osborne (2013), this paper focuses on technological feasibility rather than whether occupations will be automated in reality. To make such a prediction depends on many factors, such as the cost of relevant technologies vs wages, legal barriers and regulatory policy, and is thus not limited to a focus on skill use. Studies which observe the actual automation process of jobs would be able to account for these, a likely direction for future economic research. Job creation, from growing use of AI and robotic technologies, may be substantial in some industries (Vermeulen et al, 2018) and the prediction model also doesn't consider general equilibrium effects (Bessen, 2019) and increased consumer demand in some industries. In reality, these will likely play a role over the next 20 years and may mitigate displacement effects.

Due to data limitations, this paper also lacks evidence from wages to support the complementary vs displacement narrative (Autor et al, 2003). For example, Autor and Dorn (2013) highlight a reallocation of labour from routine tasks to low-skilled service occupations which are harder to automate and show that wages in routine occupations have subsequently declined. Such wage evidence would help to provide evidence to support displacement effects here, with rising wages also evidencing a complementary effect.

Finally, if history has taught us anything, the potential for shock developments within the field of technology is great. Future innovations in the realms of these areas may render the assumptions of this methodology outdated. If the scope for technologies to rival labour and carry out job tasks is no longer restrained by our so-called 'engineering bottlenecks', this will likely lead to much greater job displacement than predicted.

References

Acemoglu, D. (1998) ‘Why Do New Technologies Complement Skills? Directed Technical Change and Wage Inequality’. The Quarterly Journal of Economics, Volume 113, Issue 4, November 1998, Pages 1055–1089. Available at: https://doi.org/10.1162/003355398555838 (accessed 11th April 2022)

Acemoglu, D. and Autor, D (2011) ‘Skills, Tasks and Technologies: Implications for Employment and Earnings’. Handbook of Labour Economics, Volume 4, Part B, Pages 1043-1171. Available at: https://doi.org/10.1016/S0169-7218(11)02410-5 (accessed 11th April 2022)

Acemoglu, D. and Restrepo, P. (2020) ‘Robots and Jobs: Evidence from US Labor Markets’. Available at: https://www.journals.uchicago.edu/doi/abs/10.1086/705716 (accessed 18th November 2021)

Autor, D., and Dorn, D. (2013) ‘The Growth of Low-Skill Service Jobs and the Polarization of the US Labor Market.’ American Economic Review, 103 (5): 1553-97. Available at: https://www.aeaweb.org/articles?id=10.1257/aer.103.5.1553 (accessed 5th April 2022)

Autor, D., Levy, F. and Murnane, R. (2003) ‘The Skill Content of Recent Technological Change: An Empirical Exploration’. Available at: https://academic.oup.com/qje/article-abstract/118/4/1279/1925105 (accessed 27th October 2021)

Arntz, M., Gregory, T. and Zierahn, U. (2016) ‘The Risk of Automation for Jobs in OECD Countries: A Comparative Analysis’. Available at: https://www.oecd-ilibrary.org/social-issues-migration-health/the-risk-of-automation-for-jobs-in-oecd-countries_5jlz9h56dvq7-en (accessed 27th October 2021)

E, Brynjolfsson. and A, McAfee. (2011) ‘Race Against The Machine’. Digital Frontier Press Lexington (accessed 13th November 2021)

Bessen, J. (2019) ‘Automation and jobs: when technology boosts employment’. Economic Policy, Volume 34, Issue 100, Pages 589–626. Available at: https://doi.org/10.1093/epolic/eiaa001 (accessed 13th April)

Frey, C. and Osborne, M. (2013) ‘The future of employment: How susceptible are jobs to computerisation?’. Available at: https://www.oxfordmartin.ox.ac.uk/publications/the-future-of-employment/ (accessed 18th October 2021)

Goos, M. and Manning, A. ‘Lousy and Lovely Jobs: The Rising Polarization of Work in Britain’. The Review of Economics and Statistics 2007; 89 (1): 118–133. Available at: https://direct.mit.edu/rest/article-abstract/89/1/118/57634/Lousy-and-Lovely-Jobs-The-Rising-Polarization-of (accessed 19th April 2022)

Goos, M., Manning, A. and Salomons, A. (2014). ‘Explaining Job Polarization: Routine-Biased Technological Change and Offshoring." American Economic Review, 104 (8): 2509-26. Available at: https://www.aeaweb.org/articles?id=10.1257/aer.104.8.2509 (accessed 11th April 2022)

Hughes, J. (2017) ‘What is the Job Creation Potential of New Technologies?’. In: K, LaGrandeur. and J, Hughes. ‘Surviving the Machine Age’. Palgrave Macmillan, Cham. Available at: https://doi.org/10.1007/978-3-319-51165-8_9 (accessed 18th November 2021)

James, G., Witten, D., Hastie, T. and Tibshirani, R. (2021). ‘An Introduction to Statistical Learning’. Second Edition. Available at: https://hastie.su.domains/ISLR2/ISLRv2_website.pdf (accessed 19th April 2022)

Krusell, P., Ohanian, L.E., Ríos-Rull, J.-V. and Violante, G.L. (2000), ‘Capital-skill Complementarity and Inequality: A Macroeconomic Analysis’. Econometrica, 68: 1029-1053. Available at: https://doi.org/10.1111/1468-0262.00150 (accessed 11th April 2022)

Nedelkoska, L. and Quintini, G. (2018) ‘Automation, skills use and training’. Available at: https://www.oecd-ilibrary.org/content/paper/2e2f4eea-en (accessed 27th October 2021)

ONS. (2017) ‘The probability of automation in England: 2011 and 2017’. Available at: https://www.ons.gov.uk/employmentandlabourmarket/peopleinwork/employmentandemployeetypes/articles/theprobabilityofautomationinengland/2011and2017 (accessed 10th November 2021)

PWC. (2021) 'The Potential Impact of Artificial Intelligence on UK Employment and the Demand for Skills'. Available at: https://www.gov.uk/government/publications/the-potential-impact-of-ai-on-uk-employment-and-the-demand-for-skills (accessed 21st February 2022)

Vermeulen, B., Kesselhut, J., Pyka, A. and Saviotti, P. (2018) 'The Impact of Automation on Employment: Just the Usual Structural Change?'. Available at: https://www.mdpi.com/2071-1050/10/5/1661 (accessed 15th November 2021)

Data: UK Skills and Employment survey 2012 and 2017 releases accessed from the UK Data Service (https://beta.ukdataservice.ac.uk/datacatalogue/studies/study?id=7466 and https://beta.ukdataservice.ac.uk/datacatalogue/studies/study?id=8581)

Appendix A

Lasso regressions are used in a similar setting to ridge regressions to shrink coefficients towards zero by applying a penalty (James et al 2021, p241). This is particularly useful in settings with a large set of explanatory variables, many of which may be insignificant. Lasso helps improve the accuracy of prediction models and reduce bias, in particular when some of the control variables are highly correlated and the model could otherwise suffer from multi-collinearity. For p parameters over n observations, it solves the problem:

$$\min_{\beta} \sum_{i=1}^{n} (y_i - \beta_0 - \sum_{j=1}^{p} \beta_j x_{ij})^2 + \lambda \sum_{j=1}^{p} | \beta_j |$$

Where llamda is a tuning parameter chosen through cross-validation. Here, the first term is simply the residual sum of squares, and the second is the lasso penalty. The higher the value of this parameter for coefficient j, the greater the coefficient penalty. The key difference between ridge and lasso is that lasso will shrink coefficients to zero for a sufficiently large llamda (i.e., drops variable).

The use of this lasso selection in a logistic regression is important for this paper since many job characteristic variables appear insignificant in the first stage regression. It is important to identify which job characteristics don't explain variation in our training data binary assessment and remove them from our prediction. Lasso also helps to address concerns regarding high correlation of some of our job characteristics and the potential for multi-collinearity. For example, intuitively, the presence of both simple and complex problem solving in an occupation are likely to be highly correlated, as is the relevance of both teamwork and people skills.

Appendix B

Table 1: Occupations in the training dataset and their respective experts assessment

UK 2010 Standard Occupational Classification	*Can this job be feasibly automated?*
Medical practitioner	0
Dental practitioner	0
Social welfare manager*	0
Aged care services manager*	0
Primary and nursery education teaching	0
Clergy	0
Nurses	0
Counsellors	0
Chief executives and senior officials	0
Civil engineers	0
Product, clothing and related designers	0
Legal professionals	0
Solicitors	0
Conference & Exhibition Managers	0 (2012) and 1 (2017)
Other Health Professionals	0
Inspector of standards and regulation	0 (2012) and 1 (2017)
Childminders and related occupations	0
Chefs	0
Electrical engineers	0
Physical scientists	0
Hairdressers	0
Beauticians	0
Athletes and sports competitors	0
Biologists, Botanists, Zoologists and Related Professionals*	0
Plumbers and heating and ventilating engineers	0
Air travel assistant	0 (2012) and 1 (2017)
Quantity surveyors	1
Chartered surveyors	1
Barristers and judges	0
Estimators, valuers and assessors	1
Managers/directors in transport and distribution**	0 (2012) and 1 (2017)
Managers/directors in storage**	0 (2012) and 1 (2017)

Marketing associate professionals	1
Marine and waterways transport operative	1
Bus and coach drivers	1
Housekeeping and related occupations	0
Building and civil engineering technician	1
Fishery workers, hunters and trappers*	0
Assemblers of electrical and electronic products	1
Sheet metal workers	1
Medical secretaries	1
Sewing machinists	1
Taxi drivers and chauffeurs	1
Personnel clerks (HR assistant) *	1
Fork-lift truck drivers	1
Chartered and certified accountants	1
Waiters and waitresses	0 (2012) and 1 (2017)
Postal workers, mail sorters, messengers + couriers	1
Legal secretaries	1
Telephone switchboard operators*	1
Retail cashiers and checkout operatives	1
Records clerks and assistants	1
Credit controllers	1
Credit and loans officer*	1
Data entry clerk*	1
Insurance underwriters	1

*International Standard Classification of Occupations 2008 (ISCO) not SOC 2010
**One occupation in Frey and Osborne (2013)

Table 2: description of job characteristic variables which are used

Variable	*Description*	*Mean (s.d.) 2012*	*Mean (s.d.) 2017*
Hands	Skill/accuracy using hands/fingers	3.10 (1.53)	3.04 (1.52)
Faults	Spotting problems or faults	1.95 (1.08)	2.00 (1.07)
Analyse	Analysing complex problems in depth	2.64 (1.34)	2.57 (1.34)
Teach	Teaching individuals	2.41 (1.34)	2.49 (1.35)
Persuade	Persuading or influencing others	2.69 (1.27)	2.68 (1.30)
Selling	Selling a product or service	3.22 (1.59)	3.33 (1.57)
Caring	Advising, counselling or caring for customers or clients	2.37 (1.46)	2.52 (1.49)
Tools	Knowledge of operation of tools	2.81 (1.57)	2.93 (1.57)
Stamina	Physical stamina	3.09 (1.40)	3.01 (1.45)
Strength	Physical strength	3.31 (1.42)	3.25 (1.46)
Solution	Thinking of solutions to problems	2.08 (1.11)	2.03 (1.10)
Ahead	Thinking ahead	1.80 (0.92)	1.80 (0.93)
Newthings	Constantly learning new things	1.86 (0.77)	1.82 (0.76)
People	Dealing with people	1.43 (0.81)	1.47 (0.84)
Speech	Making speeches or presentations	3.54 (1.37)	3.46 (1.39)
Teamwork	Working with a team of people	1.90 (1.14)	1.89 (1.15)

Listen	Listening carefully to colleagues	1.89 (1.04)	1.89 (1.06)
Mytime	Organising own time	1.91 (1.08)	1.83 (1.01)
Planothers	Planning/organising for others	3.14 (1.37)	3.03 (1.38)
Feelings	Handling feelings of others	2.12 (1.07)	2.13 (1.04)
Look	Looking the part	2.48 (1.15)	2.52 (1.17)
Sound	Sounding the part	2.20 (1.11)	2.24 (1.11)

Table 3: structure of the training dataset for 2012 and 2017

Year	*Training observations*	*Automatable = 1*	*Automatable = 0*
2012	541	186	355
2017	515	211	304

Table 4: comparison of mean values for a selection of variables between the training dataset from each period

Variable	*2012*	*2017*	*t-statistic*
Sex (1=female)	0.593	0.590	0.10
Age	42.752	44.274	2.09*
Hands	2.982	3.037	0.97
Faults	1.962	2.043	1.19
Analyse	2.595	2.588	0.12
Teach	2.388	2.449	0.69
Persuade	2.745	2.691	0.63
Selling	3.312	3.512	2.12*
Caring	2.142	2.307	1.90
Tools	2.728	2.994	2.77*
Stamina	2.945	3.049	1.30
Strength	3.338	3.464	1.50
Solution	2.078	2.113	0.44
Ahead	1.739	1.697	0.71
Newthings	1.750	1.726	0.43
People	1.320	1.342	0.45
Speech	3.466	3.334	1.67
Teamwork	1.834	1.903	0.98

Listen	1.837	1.868	0.44
Mytime	1.837	1.711	2.08*
Planothers	3.092	2.983	1.32
Feelings	1.969	1.948	0.33
Look	2.266	2.313	0.60
Sound	2.111	2.093	0.31
Observations	541	515	

***reject null of two-sided t-test for equality of means at the 5% significance level**

Table 7: goodness-of-fit test results for the lasso logit model in both periods

	Datatype	*Deviance*	*Deviance ratio*	*Observations*
2012	*Train*	0.933	0.269	379
	Test	1.112	0.152	162
2017	*Train*	0.938	0.31	360
	Test	1.033	0.227	154

Figure 3: kernel density graph of the distribution of probabilities for each time period

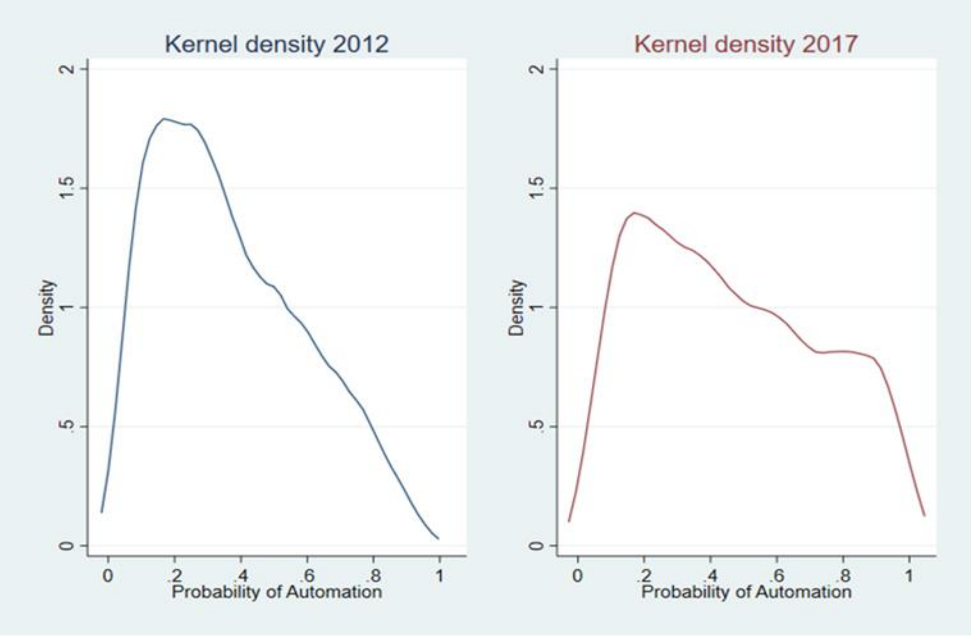


Table 8: probability of automation grouped by industry for 2017

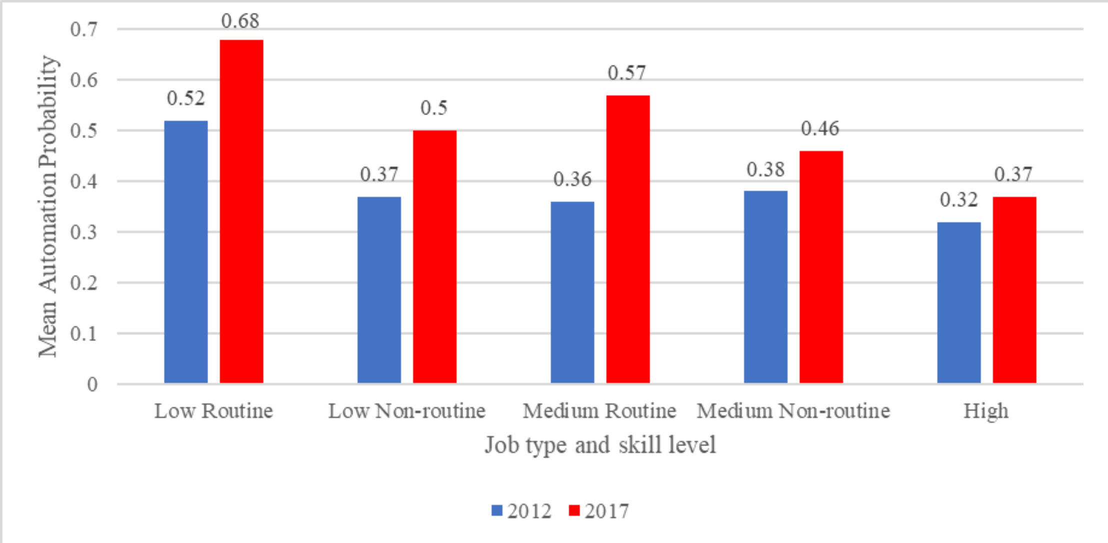
Industry	*Mean Probability*	*Proportion at High-Risk*
G: Wholesale and Retail Trade; Repair of Motor Vehicles	0.637	52%
N: Administrative and Support Service Activities	0.579	38%
H: Transportation and Storage	0.565	35%
I: Accommodation and Food Service Activities	0.560	36%
E: Water Supply; Sewerage and Waste Management	0.534	25%
C: Manufacturing	0.511	27%
A: Agriculture, Forestry and Fishing	0.502	25%
K: Financial and Insurance Activities	0.486	22%
L: Real Estate Activities	0.485	23%
F: Construction	0.467	20%
S: Other Service Activities	0.458	16%
D: Electricity, Gas, Steam and Air Conditioning Supply	0.449	13%
M: Professional, Scientific and Technical Activities	0.443	17%
B: Mining and Quarrying	0.440	24%
J: Information and Communication	0.438	17%
O: Public Administration, Defence and Social Security	0.419	18%
R: Arts, Entertainment and Recreation	0.349	12%
U Activities of Extraterritorial Organisations and Bodies	0.319	20%
P: Education	0.269	7%

(Industry variable not available in 2012 dataset)

Table 9: classification of low, medium and high skilled occupations

SOC-2010 1-digit Occupation group	*Skill Level*
Managers, Directors and Senior Officials	High
Professional Occupations	High
Associate Professional and Technical Occupations	High
Administrative and Secretarial Occupations	Medium
Skilled Trades Occupations	Medium
Caring, Leisure and other service Occupations	Medium
Sales and Customer Service Occupations	Medium
Process, Plant and Machine Operatives	Low
Elementary Occupations	Low

Figure 5: mean probability of automation by individuals' skill group (separating out routine and non-routine occupation*)



*Routine includes individuals in a semi-routine occupation whose task requirement contains a large routine component as described by the National Statistics Socio-economic classification

Figure 6: proportion predicted as high-risk by skill group

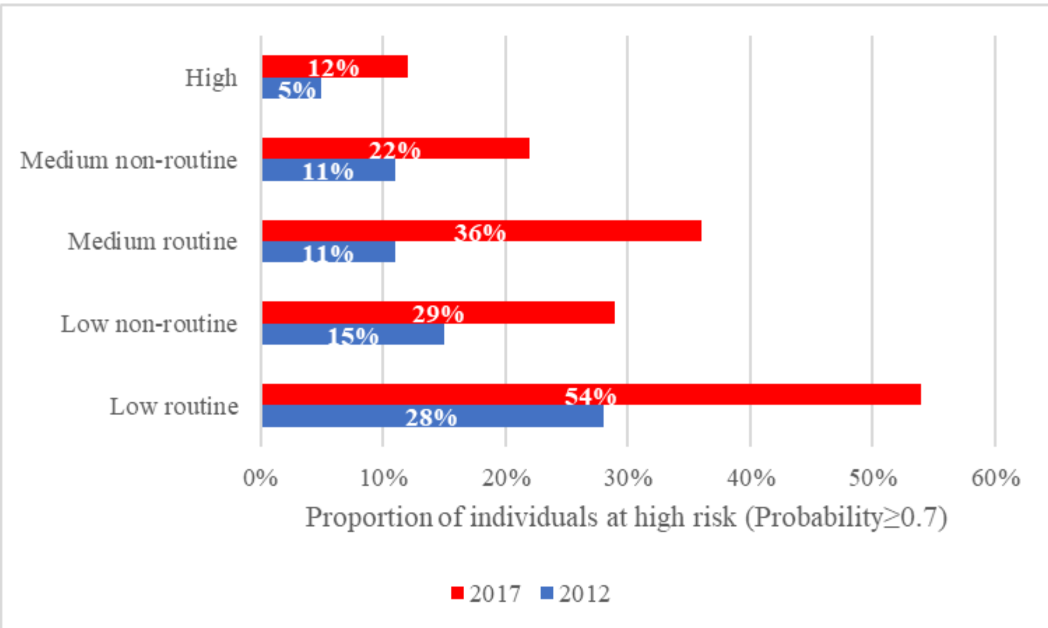


Table 10: results from F-test of the joint significance of the routine and semi-routine dummy variables when added to our OLS regression model (2) (table 3)

Year	*F statistic*	*P-value*	*Reject H0**
2012	26.31	0.000	Yes
2017	6.31	0.002	Yes

*at the 1% significance level

Figure 7: proportion of individuals predicted at high-risk by age group