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Back to the Future - Changing Job Profiles in the Digital Age*

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Abstract

The uniqueness of human labour is at question in times of smart technologies. The 250 years-old discussion on technological unemployment reawakens. Frey and Osborne (2013) estimate that half of US employment will be automated by algorithms within the next 20 years. Other follow-up studies conclude that only a small fraction of workers will be replaced by digital technologies. The main contribution of our work is to show that the diversity of previous findings regarding the degree of job automation is, to a large extent, driven by model selection and not by controlling for personal characteristics or tasks. For our case study, we consult Austrian experts in machine learning and industry professionals on the susceptibility to digital technologies in the Austrian labour market. Our results indicate that, while clerical computer-based routine jobs are likely to change in the next decade, professional activities, such as the processing of complex information, are less prone to digital change.

JEL classification: E 24, J 24, J 31, J 62, O 33.

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1 Introduction

The motivation behind our work is the discussion about technological unemployment, which has accompanied technological processes throughout the last 250 years. The debate about the susceptibility of human labour to digital technologies accelerated since a prominent study by Frey and Osborne (2013) concluded that half of US employment will be automated within the next 20 years, which would pose a sizeable thread to societal stability ¹. Their estimations are the basis for several follow-up studies, which infer that the share of jobs at risk is much smaller. Our work examines the reason for the stark diversity in previous findings about job automation. We propose that differences in the degree of susceptibility emerge mainly from model selection. In order to test this assumption, we conduct a case study similar to Frey and Osborne with a survey among Austrian research and industry experts. Our model testing confirms that differences in previous findings on the automation of jobs are mainly driven by the design of the model, rather than heterogeneity among tasks within occupations. Our results indicate that, while clerical computer-based routine jobs are likely to change in the next decade, professional activities, such as the processing of complex information, are less prone to digital change.

Machines have both complemented and competed with human labour in the past. Inventive ideas and creative destruction, as Schumpeter (1942) puts it, have competed with powerful social and economic interest over the technological status quo. Various movements, such as the *Luddites*, who destroyed new machinery in the 18th century textile industry, have tried to deter progress in times of rising unemployment. However, the *Luddite fallacy* has found its way into the literature, as employment has not been eradicated alongside fast technological development, but instead continued to expand. Rather than eliminating human labour as such, technological advancements have changed a number of work profiles and led to the creation of new professions.

Whenever modern society experiences technological advancement, concerns about technologically induced unemployment arise. In recent history, technological progress has often been linked to a displacement in specific professions (Bresnahan, 1999) or even entire industries (Charles et al., 2013; Jaimovich and Siu, 2012). However, to date, technological progress has not caused mass

¹In addition and interaction with other global dynamics, such as rising income inequalities (Stephany, 2017, 2019) or climate change and mass migration (Hoffmann et al., 2019).

unemployment. We have seen a shift in labour from the agricultural sector to manufacturing branches, and further into the service sector (Autor, 2015). Overall employment has been steadily increasing worldwide, despite (or perhaps because of) technological progress. Hence, new technologies display two opposite effects on employment (Aghion and Howitt, 1994). On the one hand, technologies substitute human labour in order to decrease production costs and increase productivity. This displacement effect lowers employment. On the other hand, reduced production costs increase real income and hence demand. The latter effect fosters production and demand for labour.

According to Goldin and Katz (1998), technological progress led to the simplification of work processes in the 19th century. A combination of machines and unskilled labour substituted skilled labour and decreased demand in terms of skills. However, as technologies improved, technological job displacement shifted away from skilled to unskilled labour. Acemoglu and Restrepo (2017) calculate that an increased use of robots in the US economy between 1990 and 2007 had a negative effect on the labour market. According to their calculations, an increase in the number of industrial robots by one, per 1,000 people employed, reduces the employment-to-population ratio by 0.18 to 0.34 percentage points.

Similar to signs of competition with routers for physical work, McAfee and Brynjolfsson (2014) emphasize that computerization has now started challenging human performance in cognitive tasks. Beaudry et al. (2016), in an empirical analysis, find evidence that the demand for skilled labour has been declining in recent years. This is an indication that skills under pressure of substitution are altering as technological progress persists. Autor and Dorn (2013) show that the implementation of computer-based technologies has put pressure on wages. As routine tasks are increasingly automated, displaced workers reallocate to the lower skilled service sector with deteriorating wages. According to Goos et al. (2009), this has resulted in the increased polarization of the labour market in a number of developed economies (see also Dustmann et al., 2009). Increasing demand for well-paid jobs in which non-routine cognitive tasks are performed, as well as non-routine manual work at the lower end of the income distribution, in combination with the automation of repetitive cognitive skills, is forcing employment away from the middle of the income distribution (see also Autor et al., 2003; Autor, 2013; Michaels et al., 2014).

Recent publications, such as Ford (2015), raise concerns that "this time it could be different" and there will be no room for creating new jobs. Frey and Osborne (2013) set the starting point for a series of papers that attempts to calculate the impact of digital technologies on the demand for human labour. Based on their original data, collected during a workshop involving machine learning experts, several papers about the susceptibility of jobs have been published.

Yet, transferring the data on susceptibility from the US labour market to European economies is challenging in many respects. Until now, there has been no piece of research that has analysed the impact of computer automation on the labour market by using newly collected data from European countries. This approach allows us to correct the shortcomings in transferring the original US data (O*NET) of Frey and Osborne (2013) to the International Standard Classification of Occupations (ISCO). It also adjusts for regional particularities in labour markets, for example, differences in regulation or cultural particularities. Even though technological innovations have become market-ready, customers may hesitate to substitute them for human interaction. In addition, we analyse the possibility of a non-linear relationship between education and future digitalization, since both low- and high-skilled jobs are assumed to be less affected by digital technologies than medium-skilled professions Dustmann et al. (2009).

Addressing previous limitations, we assume that the strong differences in the degree of susceptibility between Frey and Osborne (2013) and follow-up studies is due to model selection. As case study, our investigation examines the degree of future digitalization of job profiles in Austria. We link expert opinions with individual data from the OECD's PIAAC data, which in turn allow for heterogeneity among workers within the same occupation. Our results indicate that, models with a binary outcome, as applied by Frey and Osborne (2013) result in a much higher share of jobs at risk than models with a fractional dependent variable, as used by the OECD. In both settings, clerical computer-based routine jobs are likely to change in the next decade, professional activities with the processing of complex information are less prone to digital change. The following section 2 describes the methodology and data, followed by the 3 section, which summarizes the results, while the last section concludes the paper.

2 Data and Methods

Frey and Osborne (2013) were the first to attempt to quantify the potential of computer-based job displacement in the near future. Based on the estimates of robotic experts, the authors calculated the susceptibility to computerization of different jobs, according to the O*NET database in the US. They conclude that 47% of the jobs in the US are at a high risk (>70 % probability) of being replaced due to computerization. Bowles (2014) applies the same method and transfers the results to European economies using the differences in the sectoral structure of each country. He concludes that 54% of jobs in Austria have a high risk of being displaced by computers.

Arntz et al. (2016) emphasize that the method used by Frey and Osborne (2013) overstates the share of jobs susceptible to computerization. As Frey and Osborne (2013) do allow for heterogeneity in tasks between different jobs, they do not allow for alterations in the tasks within one occupation. According to Arntz et al. (2016), one profession may contain different sets of tasks, and thus the risk of computerization could vary within this profession. Using PIAAC survey data, they combine information about the composition of tasks within each job profile with information from robotic experts on the susceptibility of jobs for the US labour market. They further transfer the results to other OECD member countries, indicating that 9% of US workers and 12% of Austrian workers are at high risk due to computerization.² Among OECD countries, Austria, as well as Germany, displays the highest share of the workforce at a high risk of computerization.

For the German labour market, Dengler and Matthes (2015) relate the risk of job automation to the tasks that are characteristic of each profession. They compute the share of tasks that can be classified as routine based, according to the classification by Spitz-Oener (2006). According to their findings, 15% of German workers are employed in jobs with a high risk of automation. Likewise, for Austria, Peneder et al. (2016) find that 12% of Austrian workers primarily perform routine-based tasks.

²Bonin et al. (2015) use a similar approach for Germany, Pajarinen et al. (2014) for Finland, and Nagl et al. (2017) for the Austrian economy. According to Nagl et al. (2017), 9% of Austrian workers have a high risk of being automated.

Similar to the approach by Frey and Osborne (2013), we begin our analysis with expert opinions. Between 7th December 2017 and 7th January 2018, we consulted Austrian industry experts and machine learning professionals. The final data set contained 35 individual experts' opinions, with 14 individuals representatives of Austrian companies in the fields of construction, consulting, insurance, investment, media, real estate and retail, and 21 responses were from industry and academic experts in machine learning and AI. Experts from both groups were individually requested to participate in an online survey. In comparison, the expert workshop by Frey and Osborne (2013), which was held in 2013 at Oxford University's Engineering Sciences Department, included 70 machine learning experts (Brandes and Wattenhofer, 2016). Together with their team of experts, Frey and Osborne (2013) initially labelled 70 out of 703 US jobs. These binary labels were then used to predict risks of automation for all US professions. The resulting estimations formed the basis of the aforementioned studies in a European context. However, for the estimation of impacts of digital technologies on the Austria labour market, our expert opinions are better suited than the opinions stemming from the Oxford seminar. Machine learning experts are familiar with the scientific principles of the technologies disrupting the labour market, but they may not be fully aware of the social environments in which smart technologies could be implemented. For example, even when chatbots in the financial service sector become market-ready, from a technological point of view, some customers will still prefer interaction with a human. In addition, the gap between technological readiness and implementation varies to a sizeable extent between countries and cultural backgrounds. In order to address this aspect of the application of new technologies, we consulted Austrian experts from the field of machine learning/AI and professionals from various industry domains.

The participants in our survey were asked about their opinion on the 100 most common professions in Austria, as listed in Table 1. In contrast to the focus on the susceptibility to computerization (Frey and Osborne, 2013), we asked our experts: *"Do you think that the tasks, which are characteristic of this profession today, will be substituted, to a significant degree within the next 10 years, by algorithmic technologies (such as machine learning, computer vision and natural language processing) or mobile robotics?" (Yes=1/No=0)*. This question analyses the degree to which the

nature of certain professions is going to change due to technological advancement. Answers to this question do not necessarily reflect the risk of occupations being fully substituted by technologies.

Experts were allowed to avoid answering the question in relation to as many jobs as they wished. However, in the end, only a small minority of jobs remained unlabelled. In order to extract an indicator of future digitalization that is unique to each profession, we calculated three measures: the *mean* and *mode* of all expert opinions, as well as an indicator of the experts' *consensus* on each profession. The *consensus* is equivalent to the mode, but only for those professions to which at least 75% of all experts attributed the same label. With this definition of *consensus*, 45 professions remained and received a binary label, as shown in Table 1.

TABLE 1 ABOUT HERE

In the second step, the profession labels were matched with profession groups from the Austrian and German samples of the 2015 OECD survey of the PIAAC. The PIAAC survey supplied our analysis with individual characteristics, as well as job- and firm-level indicators. In addition, the survey contains information about the frequency of specific tasks performed by interviewed individuals during their average working routine. These tasks, as listed in Table 2, include human interaction, IT usage, physical work, problem-solving, reading or understanding, and writing or calculating. As the individuals provided answers about the frequency by which they undertake a given task, we normalized the answers according to the value of the working hours as follows: '*on a daily basis*' (value=1), '*less than daily, but more than once a week*' (value=1/2), '*less than once a week, but more than once a month*' (value=1/7), '*less than once a month*' (value=1/30), or '*never*' (value=0). This labelling is likewise applied by Arntz et al. (2016), since it reflects the differences in scale between days, weeks and months.

TABLES 2 ABOUT HERE

Thirdly, the expert opinions about the future change of professions are related with the PIAAC data. These opinions about professions are matched via the ISCO-08 classification for each individual's job³. The PIAAC survey is conducted in a way that it contains a representative sample of the population. However, not all observations within the survey contain answers to all questions.

³Only the German PIAAC sample contains the respective ISCO-08 Level 4 job classifications. Hence, the fitting of the inferential models is performed only with the labelled subset of the German employees.

Thus, the specification of the model leads to a loss in observations due to non-responses. There is no reason to assume that the loss in observation systematically changes the sample. We perform a mean imputation for the non-response values, which increases the model’s sample size by 55%, but does not lead to a significant difference in results. Compared to the 2012 labour force survey, our sample displays a slight shift towards younger age groups. Furthermore, the sample shows a higher share of female employees (for details, see Table 3). Nevertheless, the impact of technological change on job profiles stays unchanged.

In order to relate the above-mentioned characteristics to the given expert opinions about the individual’s job, we test three inferential models. The *consensus* indicator serves as the dependent variable, while various combinations of personal-, job- and firm-level controls, as well as task frequencies, are included in the model (Table 3). The correlation analysis in Table 6 across all characteristics only indicates a sizeable association between the three test score variables. All measures are considered at the individual level with a sample of 507. The extrapolated sample contains 4,438 individuals: 2,051 from Austria and 2,387 from Germany. In a first round, we apply a logit model. This stepwise procedure is illustrated in Columns (1)-(6) in Table 4. The Akaike information criterion indicates that Model (6), with all controls, yields the best model fit. In the second round of the model selection, we test a linear discriminant analysis (LDA) with a Bayesian estimation of the dependent variable (James et al., 2013, Chapter 4)⁴, which is similar to the approach chosen by Frey and Osborne (2013). In order to compare the logit and LDA models, we apply a cross-validation method (40% training sample). The comparison of the in-sample predictions shows that the logit model (area under the curve (AUC)⁵: 0.94) slightly outperforms the LDA model (AUC: 0.92). The estimations of the LDA model are very similar to the results of the logit model, as summarized in Table 5. Lastly, we compare the results of the logit model with a fractional response model (Papke and Wooldridge, 1993)⁶. In this model, the mean of the experts’ opinions is considered as the dependent variable. Accordingly, the fractional model refers

⁴The probability of belonging to class k , given characteristics X , is described by $P(Y = k|X = x) = \frac{f_k(x)\pi_k}{P(X=x)}$, while $f_k(x)$ describes the probability of $X = x$, given that $Y = k$, while π_k is the prior probability of observing $Y = k$.

⁵The AUC measures the area under the receiver operating characteristics (ROC) curve. The AUC is a measure of prediction accuracy, since the ROC curve plots the true positive rate against the false positive rate of a prediction model.

⁶ $E(y|X) = \frac{e^{(\beta'X)}}{1+e^{(\beta'X)}}$, while $\beta'X = \beta_0 + \beta_1x_1 + \dots + \beta_kx_k$

to a larger sample size. However, the results in Table 4, Columns (6) and (7), show that the logit model still yields a significantly better model fit.

TABLE 3 AND 4 ABOUT HERE

After identifying the appropriate model environment, the logit model (1) is used to predict the digitalization probabilities, $P(y=1|X)$, for all individuals in the sample, based on their set of characteristics ($\beta'X$). Here, individuals with professions, which have not been judged by our experts, also obtain a probability. The average estimated probabilities of future digitalization are shown in Figure 2, and are aggregated for ISCO-08-Level 1 (Figure 3) and ISCO-08 Level 2 (Figure 4) professions in Austria.

$$P(y = 1|X) = \frac{1}{1+e^{-(\beta'X)}}, \quad \beta'X = \beta_0 + \beta_1x_1 + \dots + \beta_kx_k \quad (1)$$

Based on the *consensus* of our experts, we are able to specify a degree of future digitalization for 47 occupations. More than 75% of our experts agreed that the characteristic tasks of these professions will change to a significant degree with the development of digital technologies and mobile robotics. With the use of the PIAAC data set, we are able to relate the degree of digitalization to personal characteristics and occupation-specific tasks. Based on this relationship, we estimate the degree of digitalization for all professions in the data set. In contrast to the work by Frey and Osborne (2013), we apply local experts' opinions and perform our estimations on the basis of individual characteristics.

3 Results

For some tasks we see a clear relationship with the *consensus* of our experts. In Figure 1, the frequencies of the 39 tasks are compared to the *consensus* of our experts. On average, some tasks, such as coding (*itusage_code*), are, on average, performed less than once a month, while others, such as sharing information with others (*human_share*), are carried out on an almost daily basis. For some activities, prevalence does not differ significantly between the two *consensus* job groups, for example, *itusage_code* or *human_share*. However, for most of the activities, a clear separation between the *consensus* groups is visible. Activity involving long physical work (*physical_long*) is

less commonly performed in professions that are expected to change during digitalization, according to our experts. Other activities show the exact opposite pattern. Calculating (*wricalc_calculator*) or the use of computer software *Excel* (*itusage_excel*), for example, is much more prevalent in professions that are expected to change. This observation, confirmed by the findings of the inferential model, is a first indication that professions with a high degree of computer-based office routines are more likely to change in light of digital technologies.

FIGURE 1 ABOUT HERE

In addition to the 39 tasks, individual-, job- and firm-specific characteristics can help explain the consensus opinions of our experts, as shown in Table 4. The final and full model (6) indicates that, apart from work activities, education, firm sector, job responsibility and training are related to the degree of future digitalization. Individuals with a high level of education, who work in a job that requires training or responsibility, are typically less likely to be employed in an occupation that is going to change significantly. Interestingly, our results indicate a non-linear relationship with education. Individuals with a medium level of schooling are employed in jobs with a higher level of future digitalization than workers with high or low levels of education.

Our model indicates that certain work activities are strongly related to the degree of digital change in the workplace. Tasks such as extracting complex information by reading books (*reading_book*) or writing non-routine content (*wricalc_report*) are related to professions with a low degree of technological change. On the other hand, activities such as calculations (*wricalc_calculator*) or extracting simple information (*wricalc_news*) are associated with a stronger change in the job profile in the near future. McAfee and Brynjolfsson (2014), for example, show that news stations have begun implementing algorithms that are able to write simple pieces in the context of sports or weather forecasts. Moreover, for professions that predominantly rely on physical labour, impacts of technological change are also low.

FIGURE 2 ABOUT HERE

Among occupations, there is a clear trend (Figures 3 and 4): clerical support workers, who perform simple computer-based office routines, are highly susceptible to technological changes. This is in line with previous findings. On the other hand, professionals, who work with complex

and unstructured information, and skilled workers in agricultural fields, who perform physical work, are less likely to experience major changes in their job profile. Professional occupations involving teaching and healthcare within legal, social or cultural environments (Figure 4) exhibit particularly low probabilities of digital transformation. This finding is consistent for individuals working in a job that requires an academic degree, as well as for those without such a qualification. On average, most occupations show a probability of change between 40% and 60%.

FIGURES 3 and 4 ABOUT HERE

When comparing our model findings, clear differences emerge with regard to the degree of susceptibility in employment to digital technologies. However, our model testing suggests that these difference are mainly driven by model selection, rather than heterogeneity among tasks within occupations. Table 5 compares the set-ups of our research and previous studies.

TABLE 5 ABOUT HERE

Two types of model settings are prevalent. Frey and Osborne (2013) start with binary opinions of experts and extrapolate them via a classification model for all occupations. Bowles (2014) directly transfers these estimations to European labour markets. Both studies conclude that a high share of workers (47% in the US and 54% in Austria) share a high risk of computerization. Arntz et al. (2016) and Nagl et al. (2017), on the other hand, begin with discrete probabilities and apply a fractional model in order to extrapolate. In comparison, they show that only about 12% and 9%, respectively, have an automation risk of more than 70%. In light of these contradictory findings, our model testing suggests that the different estimations are mainly due to the choice of model. Binary models yield a bimodal distribution of predicted probabilities with large high-risk groups. Fractional models lead to a bell-shaped distribution of probabilities with relatively low levels of high-risk individuals. Our own estimations for a fractional model (Figure 5) confirm this assumption. The ranking of occupational classes does not change significantly after the fractional model (Figure 6) has been used. However, predicted probabilities converge towards the mean.

FIGURES 5 AND 6 ABOUT HERE

When comparing the outcome of the binary and fractional model, the results of the latter contain a lower number of covariates, which are statistically relevant to the degree of digitalization.

The fractional model, however, does not show any statistical significance concerning the covariates that have not been relevant in the binary model. In the fractional model, education and job responsibility show no statistical significance. Likewise, the tasks of speaking in front of humans, reading books, using words, and coding are not significant in the case of the fractional model environment. This general observation is not surprising from a statistical point of view, since the formally strict binary outcome in a small sample has now been changed to a smooth continuous scale in a sample twice the original size. However, it becomes clear that some covariates, such as physical work, writing reports, performing calculations or firm characteristics, are still aligned with the distribution of the fractional model. The distribution of other covariates has been polarized by the truncation of the binary model. The unconditional distributions of the binary and fractional models are shown in Figures 7 and 8.

FIGURES 7 AND 8 ABOUT HERE

Similarly, when moving the threshold of consensus from our final value towards 0.5, the outcome of the binary model starts to slightly approach the results of the fractional model. However, no significant changes appear, except for a deterioration in statistical significance.

4 Conclusion

Our model explicitly diverges from the approach taken in previous contributions to this field. We assume that the diversity of previous estimations of job susceptibility stems from model specification. In order to test this assumption we conducted a case study with local expert opinions about near-term changes in occupations in Austria. This is a significant conceptual improvement in contrast to prior investigations (Arntz et al., 2016; Bowles, 2014), which studies rely on the judgement of machine learning experts concerning the US labour market, stemming from the workshop organized by Frey and Osborne (2013). However, the authors do not allow for heterogeneity within the same profession. This limitation is ruled out by our model approach. Past findings are, in part, contradictory. 47% of jobs in the US (54% in Austria) share a high risk of automation, according to Frey and Osborne (2013) and Bowles (2014), while Arntz et al. (2016) and Nagl et al. (2017) estimate this share to be 12% and 9%, respectively, for Austria. Our findings show that these

differences are mainly driven by the selection of the model, and not so much by controlling for personal characteristics or tasks.

Our findings show that the tasks that humans perform during their typical working day are of significant importance when determining the impact of digital technologies on the future workspace. Activities such as extracting complex information by reading books or writing non-routine content reduce the impact of technologies. On the other hand, tasks such as calculations or extracting simple information will lead to a stronger change in job profiles in the next decade. Furthermore, as the current generation of technological progress has a stronger impact on cognitive and routine tasks than on physical labour, the extent of physical work within a job profile reduces the effect of digital change. Although the future of work will most likely be a complementary partnership between humans and computers, workers performing computer-related routine activities, such as spreadsheet calculations or Internet usage (Stephany and Braesemann, 2017; Stephany et al., 2019), are under stronger pressure to adapt. Our findings about the "inverse U-shaped" relationship between education and digitalization support previous hypotheses about the skill-based polarization of the labour market (Goos et al., 2009). This suggests further polarization in the near future.

Our results indicate that some jobs can expect to change more than others during the current phase of digital progress. This is surely not the first time in history that this has happened. During the Industrial Revolution, technological advancements made manufacturing jobs less intensive in terms of monotonous physical labour. In contrast to the age of the steam engine, today's technologies, such as algorithms, unfold their potential in disciplines that require routine cognitive effort. Typical computer-backed office tasks, such as in the clerical professions, are more exposed to digital transformation than occupations marked by physical labour. Likewise, jobs in which complex information is processed and that require a high level of education and training are less prone to digital change in the near future. Teaching and health-care professionals working within in legal, social or cultural environments belong to occupations with the lowest level of technological pressure. In the near future, these disciplines can be regarded as a sustainable choice for future generations seeking job security in unsteady times.

In addition, while most research focuses on human labour that can be replaced by technology, little attention has been given to the effect that digital technologies have on job creation. As our findings improve the understanding of the displacement effect of technologies, more research should be conducted in order to incorporate the effect of job creation, and in turn appreciate the full impact of the technological change on the labour market.

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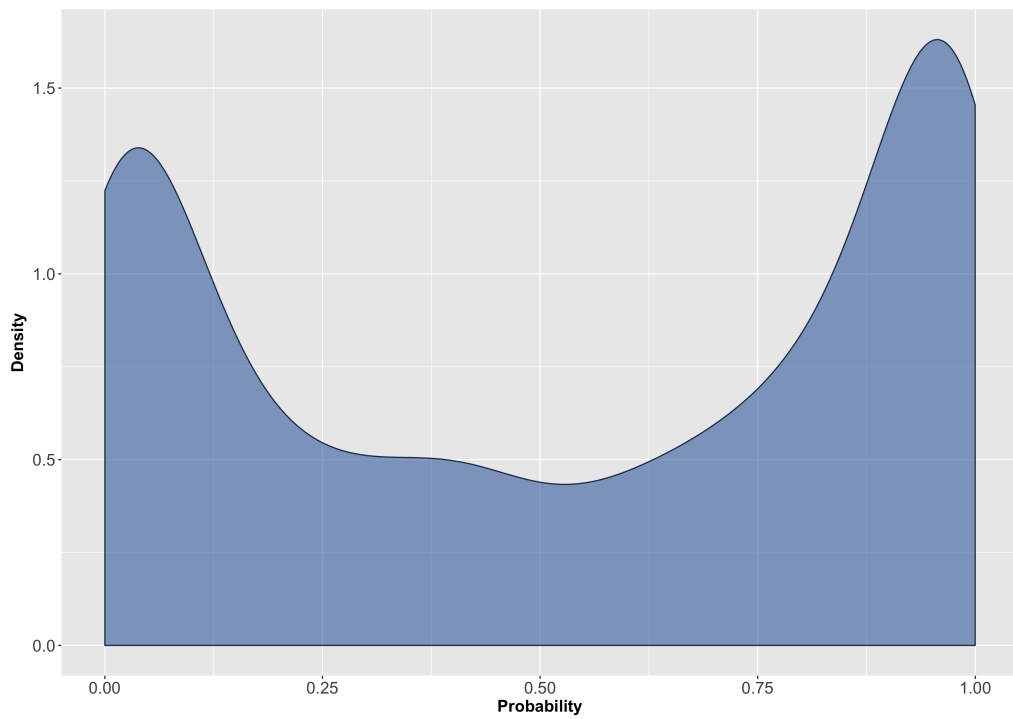


Figure 2: *Future digitalization*: Jobs in Austria are polarized between high and low levels of future digitalization. The distribution of individual levels of future digitalization mirrors the initial estimation of our experts.

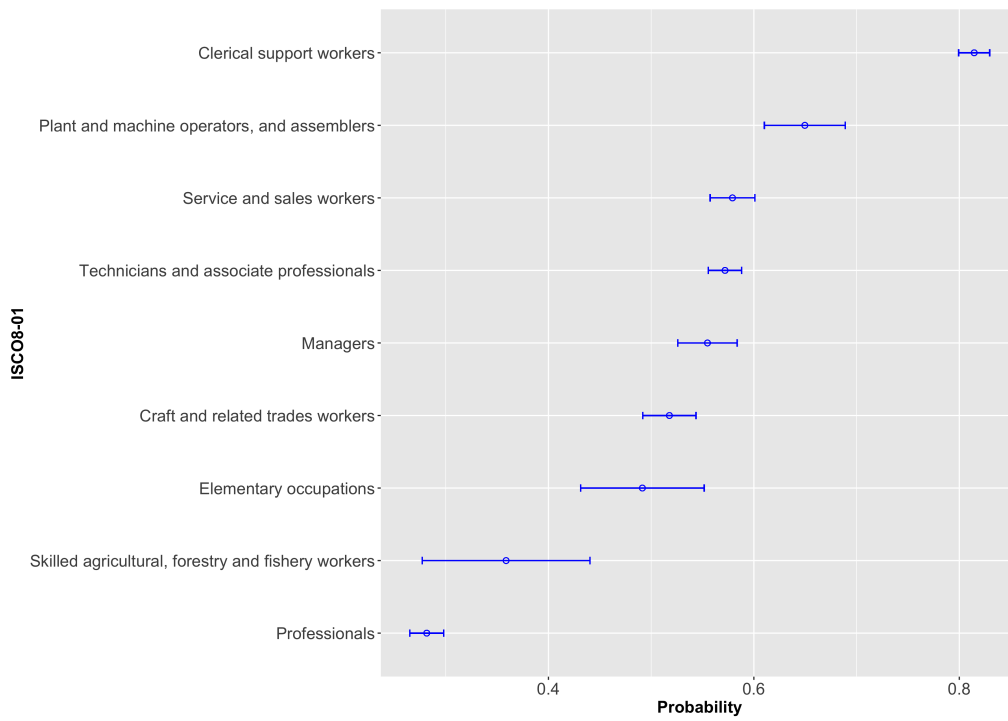


Figure 3: *ISCO Level 1*: For the top level of occupations, clerical professions have, by far, the highest risk of future digitalization. Professionals are at the lower end of the scale.

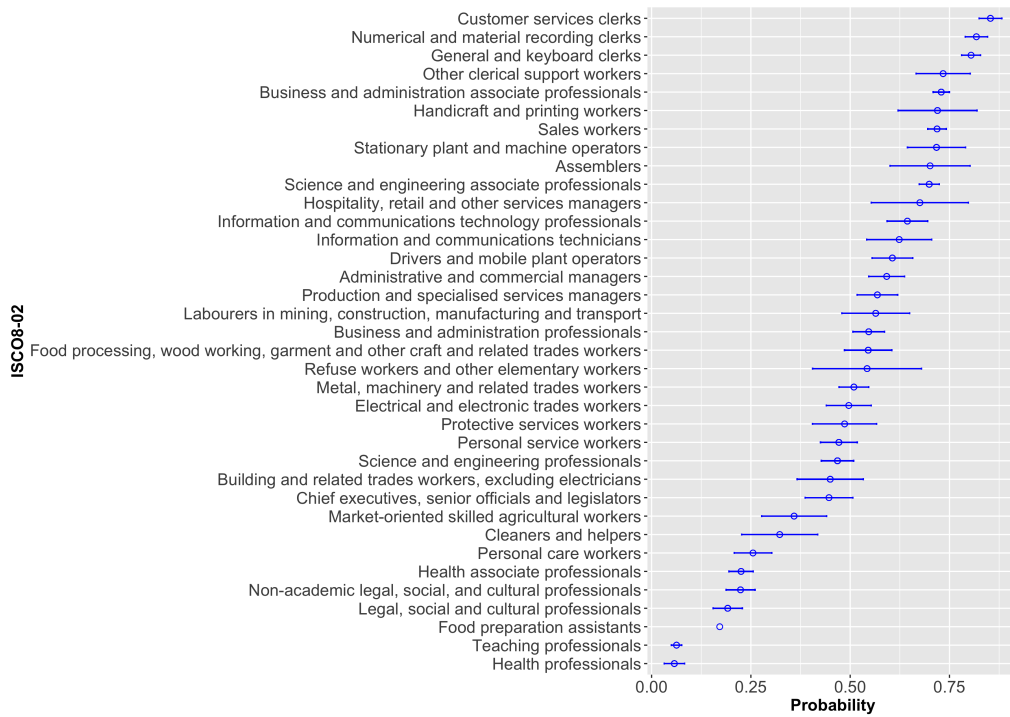


Figure 4: *ISCO Level 2*: Professional occupations involving teaching and healthcare, within legal, social or cultural environments, exhibit particularly low probabilities of digital transformation.

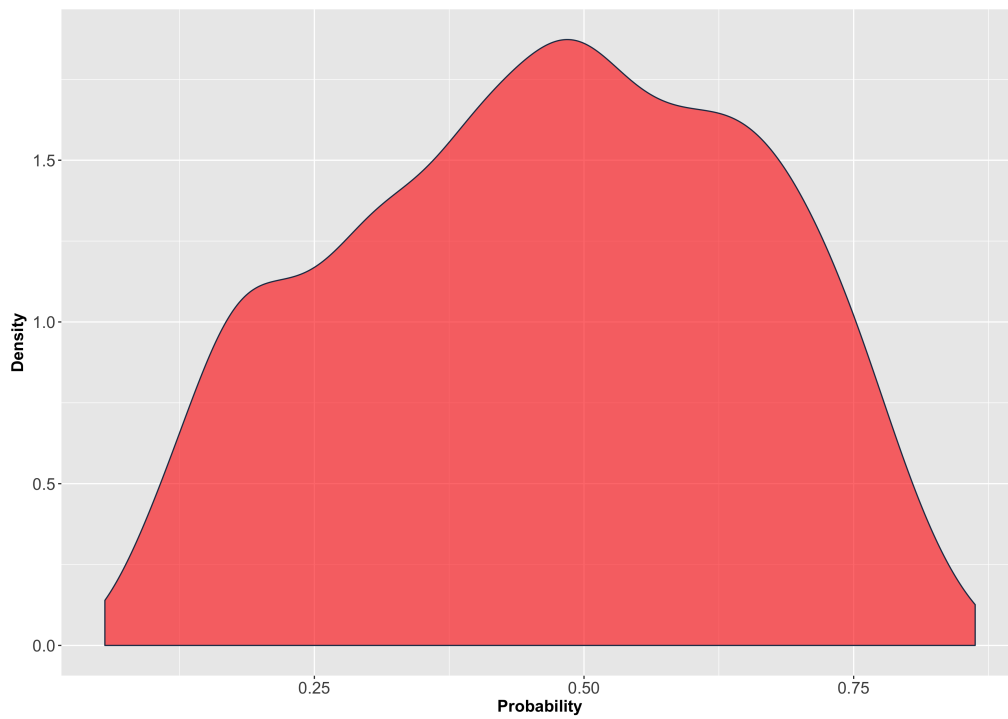


Figure 5: *Fractional model*: Similar to the work by Arntz et al. (2016) and Nagl et al. (2017), the application of a fractional model (Papke and Wooldridge, 1993) yields a bell-shaped distribution of predicted probabilities.

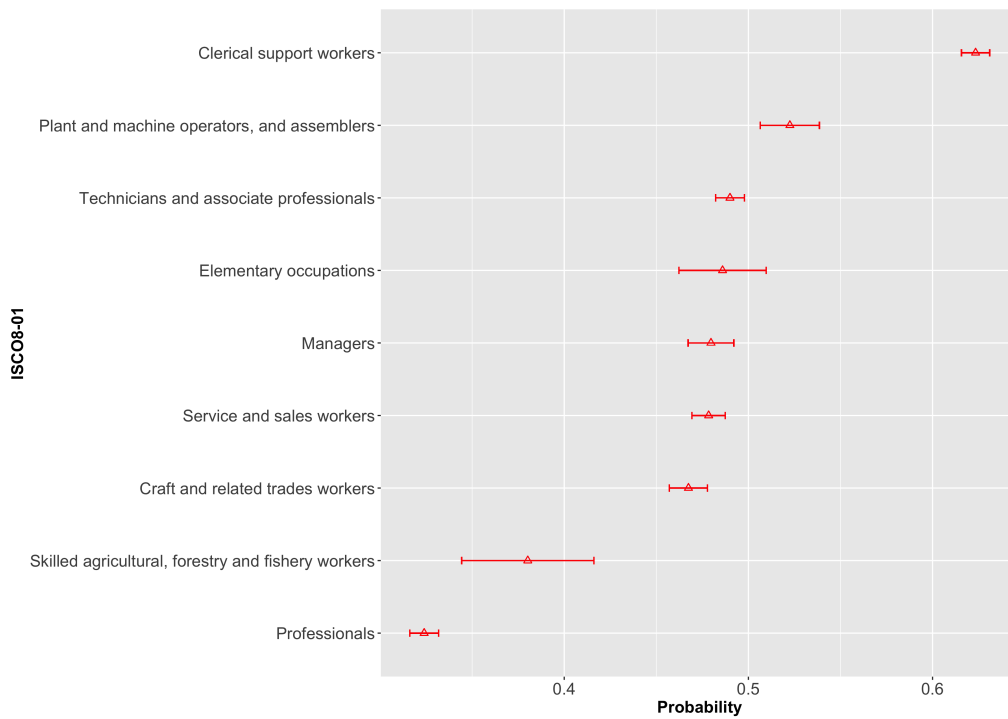


Figure 6: *ISCO Level 1*: The ranking of occupational classes does not change for the fractional model. However, predicted probabilities converge to the mean.

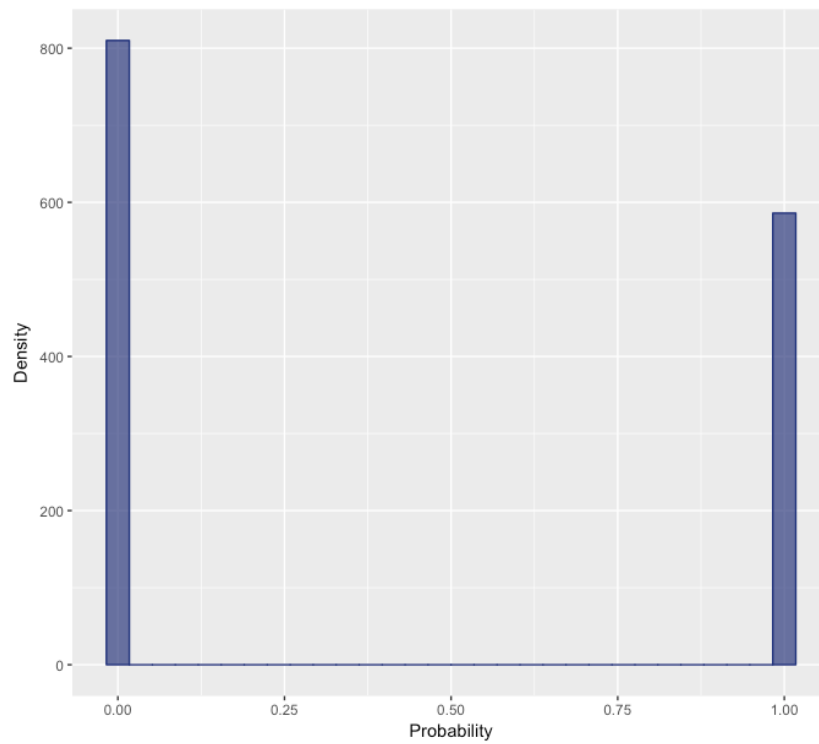


Figure 7: *Initial binary distribution*: Initially, in the logit model, slightly more individuals are labelled with a *consensus* outcome of 0.

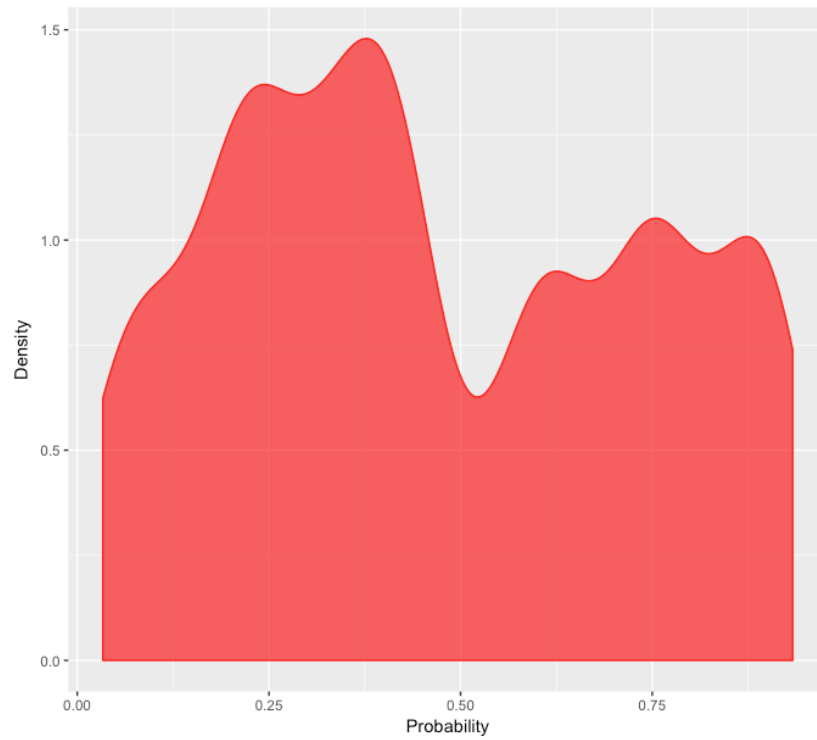


Figure 8: *Initial fractional distribution*: The initial distribution of the dependent variable in the fractional model is slightly skewed towards the lower values.

Table 1: Our experts gave their yes/no responses in relation to the 100 most common professions in Austria. The *mean*, *mode* and *consensus* (at least 75% responded with yes or no) were calculated for each profession.

ISCO-08-4 Code	ISCO-08-4 Name	Mean	Mode	Consensus
5311	Childcare workers	0.033	0	0
5120	Cooks	0.034	0	0
3255	Physiotherapy technicians and assistants	0.038	0	0
2652	Musicians, singers and composers	0.067	0	0
5141	Hairdressers	0.067	0	0
3412	Social work associate professionals	0.071	0	0
5412	Police officers	0.071	0	0
2341	Primary school teachers	0.074	0	0
2635	Social work and counselling professionals	0.103	0	0
3355	Police inspectors and detectives	0.103	0	0
5321	Healthcare assistants	0.103	0	0
6113	Gardeners, horticultural and nursery growers	0.111	0	0
2161	Building architects	0.148	0	0
6130	Mixed crop and animal producers	0.148	0	0
7421	Electronics mechanics and servicers	0.160	0	0
2212	Specialist medical practitioners	0.172	0	0
2310	University and higher education teachers	0.172	0	0
5131	Waiters	0.179	0	0
7126	Plumbers and pipe fitters	0.179	0	0
7512	Bakers, pastry cooks and confectionery makers	0.185	0	0
1349	Professional services managers not elsewhere classified	0.192	0	0
7412	Electrical mechanics and fitters	0.200	0	0
1323	Construction managers	0.207	0	0
1411	Hotel managers	0.207	0	0
3221	Nursing associate professionals	0.222	0	0
2330	Secondary education teachers	0.231	0	0
7411	Building and related electricians	0.240	0	0
3259	Health associate professionals not elsewhere classified	0.250	0	0
5151	Cleaning/housekeeping supervisors in offices, hotels and others	0.250	0	0
2142	Civil engineers	0.259	0	.
2149	Engineering professionals not elsewhere classified	0.261	0	.
2642	Journalists	0.267	0	.
1321	Manufacturing managers	0.286	0	.
2611	Lawyers	0.296	0	.
2359	Teaching professionals not elsewhere classified	0.304	0	.
2144	Mechanical engineers	0.308	0	.
3251	Dental assistants and therapists	0.321	0	.
3411	Police inspectors and detectives	0.321	0	.
3256	Medical assistants	0.333	0	.
2166	Graphic and multimedia designers	0.345	0	.
2631	Economists	0.346	0	.
7233	Agricultural and industrial machinery mechanics and repairers	0.346	0	.
7522	Cabinet makers and related workers	0.348	0	.
2512	Software developers	0.357	0	.
5414	Security guards	0.357	0	.
9112	Cleaners and helpers in offices, hotels and other establishments	0.357	0	.
7119	Building frame and related trades workers not elsewhere classified	0.360	0	.
2421	Management and organization analysts	0.370	0	.
5153	Building caretakers	0.370	0	.
7112	Bricklayers and related workers	0.370	0	.
9412	Kitchen helpers	0.385	0	.
3257	Environmental and occupational health inspectors and associates	0.400	0	.
7231	Motor vehicle mechanics and repairers	0.400	0	.
2431	Advertising and marketing professionals	0.407	0	.
7212	Welders and flame cutters	0.407	0	.
1324	Supply, distribution and related managers	0.414	0	.
3359	Regulatory government associate professionals	0.423	0	.
5223	Shop sales assistants	0.423	0	.
7543	Product graders and testers (excluding foods and beverages)	0.458	0	.
3115	Mechanical engineering technicians	0.462	0	.
2262	Pharmacists	0.500	0	.

ISCO-08-4 Code	ISCO-08-4 Name	Mean	Mode	Consensus
9629	Elementary workers not elsewhere classified	0.500	0	.
7214	Structural metal preparers and erectors	0.520	1	.
7523	Woodworking machine tool setters and operators	0.520	1	.
8219	Assemblers not elsewhere classified	0.538	1	.
3353	Government social benefits officials	0.556	1	.
3352	Government tax and excise officials	0.571	1	.
8212	Electrical and electronic equipment assemblers	0.577	1	.
9332	Drivers of animal-drawn vehicles and machinery	0.577	1	.
7223	Metal working machine tool setters and operators	0.583	1	.
3322	Commercial sales representatives	0.593	1	.
3323	Buyers	0.593	1	.
3334	Real estate agents and property managers	0.607	1	.
4120	Secretaries (general)	0.607	1	.
2411	Accountants	0.633	1	.
7321	Pre-press technicians	0.640	1	.
9329	Manufacturing labourers not elsewhere classified	0.640	1	.
9333	Freight handlers	0.652	1	.
8160	Food and related products machine operators	0.667	1	.
9334	Shelf fillers	0.692	1	.
9621	Messengers, package deliverers and luggage porters	0.692	1	.
3118	Draughtspersons	0.720	1	.
3313	Accounting associate professionals	0.731	1	.
4110	General office clerks	0.750	1	1
8322	Car, taxi and van drivers	0.759	1	1
8131	Chemical products plant and machine operators	0.792	1	1
8332	Heavy truck and lorry drivers	0.793	1	1
8121	Metal processing plant operators	0.800	1	1
8122	Metal finishing, plating and coating machine operators	0.800	1	1
4321	Stock clerks	0.828	1	1
4412	Mail carriers and sorting clerks	0.862	1	1
3324	Trade brokers	0.867	1	1
4322	Production clerks	0.875	1	1
4312	Statistical, finance and insurance clerks	0.897	1	1
5230	Cashiers and ticket clerks	0.897	1	1
3321	Insurance representatives	0.900	1	1
4222	Contact centre information clerks	0.900	1	1
4323	Transport clerks	0.926	1	1
4311	Accounting and bookkeeping clerks	0.933	1	1

Table 2: The PIAAC survey asked employees in Austria and Germany about how frequently they undertake the following 39 tasks at work.

Task Description	Task Group	PIAAC Code
Sharing work-related information with co-workers	Human Interaction	human_share
Instructing, training or teaching people, individually or in groups	Human Interaction	human_train
Making speeches or giving presentations in front of five or more people	Human Interaction	human_speech
Selling a product or selling a service	Human Interaction	human_sell
Advising people	Human Interaction	human_advise
Persuading or influencing people	Human Interaction	human_influence
Negotiating with people either inside or outside one's firm or organization	Human Interaction	human_negotiate
Using email	IT Usage	itusage_email
Using the Internet in order to better understand issues related to one's work	IT Usage	itusage_internet
Conducting transactions over the Internet, e.g., buying or selling	IT Usage	itusage_buy
Using spreadsheet software, for example, Excel	IT Usage	itusage_excel
Using a word-processing package, for example, Word	IT Usage	itusage_word
Using a programming language to program or write computer code	IT Usage	itusage_code
Participating in real-time discussions over the Internet, e.g., online conferences	IT Usage	itusage_discuss
Working physically for a long period	Physical Work	physical_long
Using skill or accuracy with hands or fingers	Physical Work	physical_accurate
Planning one's own activities	Planning	planning_own
Planning the activities of others	Planning	planning_others
Organizing one's own time	Planning	planning_time
Solving simple problems, which require no more than 5 min of attention	Problem-solving	problem_simple
Solving complex problems, which require at least 30 min of attention	Problem-solving	problem_complex
Reading directions or instructions	Reading and Understanding	reading_instruction
Reading letters, memos or emails	Reading and Understanding	reading_letter
Reading articles in newspapers, magazines or newsletters	Reading and Understanding	reading_news
Reading articles in professional journals or scholarly publications	Reading and Understanding	reading_article
Reading books	Reading and Understanding	reading_book
Reading manuals or reference materials	Reading and Understanding	reading_manual
Reading bills, invoices, bank statements or other financial statements	Reading and Understanding	reading_bill
Reading diagrams, maps or schematics	Reading and Understanding	reading_graph
Writing letters, memos or emails	Writing and Calculating	wricalc_letter
Writing articles for newspapers, magazines or newsletters	Writing and Calculating	wricalc_news
Writing reports	Writing and Calculating	wricalc_report
Filling in forms	Writing and Calculating	wricalc_form
Calculating prices, costs or budgets	Writing and Calculating	wricalc_budget
Using or calculating fractions, decimals or percentages	Writing and Calculating	wricalc_fraction
Using a calculator (either hand-held or computer-based)	Writing and Calculating	wricalc_calculator
Preparing charts, graphs or tables	Writing and Calculating	wricalc_chart
Using simple algebra or formulas	Writing and Calculating	wricalc_simple
Using more advanced mathematics or statistics, such as calculus, complex algebra, trigonometry, or using of regression techniques	Writing and Calculating	wricalc_advanced

Table 3: Summary of characteristics

Name	Observations					
Age Group						
"<16-19"	104					
"20-24"	195					
"25-29"	255					
"30-34"	255					
"35-39"	273					
"40-44"	309					
"45-49"	267					
"50-54"	242					
"55-59"	119					
">60"	32					
Gender						
Male	1,002					
Female	1,049					
Firm - Sector						
"Public or NGO"	668					
"Private"	1,383					
Firm - Size						
"1-10"	458					
"11-50"	607					
"51-250"	480					
"251-1000"	326					
">1000"	180					
Job - Responsibility						
Yes	1,182					
No	869					
Job - Experience						
"<1 month"	585					
"1 to 6 months"	282					
"7 to 11 months"	157					
"1 or 2 years"	472					
"3 years or more"	555					
Job - Education						
"<ISCED 3"	252					
"ISCED 3-4"	1,169					
"ISCED 5+"	630					
Education		Min.	25%	Mean	75%	Max.
"Years in Full-time Education"		4.00	13.00	14.29	16.00	20.00
Skills						
Problem-solving		168.1	268.1	290.1	313.6	404.3
Numeracy		160.4	269.6	294.8	321.7	409.7 2
Literacy		156.8	263.6	285.8	310.5	396.2

Table 4: Models (1)-(6) work with a binary outcome of job digitalisation, while the outcome of model (7) is continuously measured between 0 and 1. The full binary model (6) with personal/firm-/job-level characteristics and tasks shows the best model fit.

	<i>Dependent variable</i>						
	Binary (1)	Binary (2)	Binary (3)	Binary (4)	Binary (5)	Binary (6)	Fractional (7)
Personal							
Age Group	0.069* (0.040)	0.106** (0.046)	0.175*** (0.057)	0.105 (0.068)		0.141 (0.094)	0.025 (0.037)
Gender (<i>Ref. male</i>)	-0.021 (0.192)	0.466** (0.225)	0.565** (0.253)	0.130 (0.337)		0.183 (0.419)	0.051 (0.166)
Education (<i>Years</i>)	0.952*** (0.283)	0.723** (0.305)	1.005*** (0.355)	1.411*** (0.419)		1.489*** (0.495)	0.133 (0.230)
Education ²	-0.050*** (0.011)	-0.038*** (0.012)	-0.049*** (0.014)	-0.071*** (0.017)		-0.070*** (0.020)	-0.008 (0.008)
Firm							
Firm - Sector (<i>Ref. public</i>)		2.300*** (0.240)	2.170*** (0.263)			1.695*** (0.454)	0.522*** (0.188)
Firm - Size (<i>0-4</i>)		0.085 (0.090)	0.129 (0.100)			0.408** (0.168)	0.104* (0.061)
Job							
Job - Responsibility (<i>Ref. no responsibility</i>)			-0.200 (0.264)			-0.979** (0.486)	-0.039 (0.178)
Job - Experience (<i>0-4</i>)			0.151* (0.087)			-0.006 (0.151)	-0.006 (0.055)
Job - Education (<i>0-2</i>)			-1.293*** (0.230)			-1.919*** (0.424)	-0.483*** (0.148)
Skill - Problem-solving (<i>Test Score</i>)			-0.0003 (0.006)			-0.018* (0.010)	-0.001 (0.004)
Skill - Numeracy (<i>Test score</i>)			0.021** (0.007)			0.008 (0.011)	0.003 (0.005)
Skill - Literacy (<i>Test score</i>)			-0.006 (0.008)			0.009 (0.013)	-0.003 (0.005)
Cooperate with Humans (<i>Frequency</i>)			-0.360 (0.342)			-0.307 (0.589)	-0.167 (0.225)
Tasks							
human_share				0.769 (0.507)	0.730 (0.480)	0.880 (0.619)	0.083 (0.254)
human_train				-0.263 (0.550)	-0.483 (0.522)	0.183 (0.688)	-0.090 (0.249)
human_speech				-2.445** (1.020)	-3.299*** (0.966)	-2.562** (1.188)	-0.257 (0.357)
human_sell				0.765* (0.455)	0.847** (0.411)	0.966* (0.550)	0.117 (0.214)
human_advise				-0.507 (0.443)	-0.560 (0.419)	-0.622 (0.519)	-0.109 (0.216)
human_influence				-1.236*** (0.474)	-1.081** (0.429)	-0.886 (0.559)	-0.249 (0.212)
human_negotiate				0.478 (0.555)	0.369 (0.494)	0.891 (0.660)	0.115 (0.236)
itusage_email				0.870 (0.621)	0.808 (0.572)	1.134 (0.763)	0.255 (0.284)
itusage_internet				0.688 (0.515)	0.422 (0.468)	0.727 (0.600)	0.044 (0.229)
itusage_buy				0.573 (0.632)	1.428** (0.624)	0.052 (0.711)	0.198 (0.270)
itusage_excel				0.612 (0.471)	0.717* (0.430)	1.080* (0.565)	0.224 (0.226)
itusage_word			29	-0.886* (0.517)	-0.714 (0.479)	-1.117* (0.641)	0.028 (0.228)
itusage_code				-1.780** (0.795)	-1.282* (0.771)	-2.234** (0.910)	-0.251 (0.423)
itusage_discuss				2.559 (1.604)	2.909* (1.654)	3.612* (1.939)	-0.163 (0.505)

	<i>Dependent variable</i>						
	Binary	Binary	Binary	Binary	Binary	Binary	Fractional
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
physical_long				-1.906***	-1.561***	-2.439***	-0.536**
				(0.435)	(0.406)	(0.529)	(0.212)
physical_accurate				-0.014	0.138	0.183	-0.059
				(0.387)	(0.356)	(0.471)	(0.174)
planning_own				-0.364	-0.580	-0.463	-0.196
				(0.424)	(0.394)	(0.504)	(0.186)
planning_others				-0.431	-0.459	0.193	0.014
				(0.576)	(0.520)	(0.692)	(0.271)
planning_time				-0.841*	-0.945**	-0.454	-0.003
				(0.459)	(0.425)	(0.532)	(0.216)
problem_simple				0.246	0.336	0.056	-0.004
				(0.439)	(0.412)	(0.509)	(0.202)
problem_complex				-0.217	-0.255	0.050	-0.075
				(0.557)	(0.534)	(0.652)	(0.266)
reading_instruction				0.865*	0.946**	0.801	0.085
				(0.465)	(0.422)	(0.520)	(0.201)
reading_letter				0.792	0.399	0.165	0.234
				(0.723)	(0.666)	(0.849)	(0.334)
reading_news				-0.443	-0.155	0.310	-0.011
				(0.520)	(0.471)	(0.659)	(0.229)
reading_article				-0.665	-0.720	-0.969	-0.047
				(0.781)	(0.718)	(0.940)	(0.322)
reading_book				-3.639***	-3.855***	-3.632***	-0.304
				(1.064)	(1.086)	(1.249)	(0.352)
reading_manual				-0.303	-0.341	-0.306	0.090
				(0.594)	(0.566)	(0.692)	(0.258)
reading_bill				0.697	0.689	1.227**	0.212
				(0.500)	(0.453)	(0.600)	(0.212)
reading_graph				0.156	0.236	0.192	-0.009
				(0.462)	(0.428)	(0.546)	(0.201)
wricalc_letter				-0.644	-0.614	-0.112	-0.218
				(0.661)	(0.638)	(0.762)	(0.304)
wricalc_news				2.055	3.158	4.665	0.148
				(3.602)	(2.784)	(4.245)	(1.017)
wricalc_report				-2.091***	-1.980***	-1.676***	-0.415**
				(0.446)	(0.422)	(0.534)	(0.207)
wricalc_form				-0.169	-0.135	-0.225	0.138
				(0.401)	(0.380)	(0.464)	(0.185)
wricalc_budget				0.006	0.016	-0.473	-0.034
				(0.511)	(0.467)	(0.604)	(0.228)
wricalc_fraction				0.861*	0.745	0.827	0.062
				(0.513)	(0.496)	(0.599)	(0.232)
wricalc_calculator				2.111***	2.097***	1.893***	0.478**
				(0.441)	(0.413)	(0.531)	(0.224)
wricalc_chart				0.363	-0.060	0.740	-0.079
				(0.695)	(0.648)	(0.809)	(0.287)
wricalc_simple				-0.408	-0.578	-0.535	0.032
				(0.533)	(0.517)	(0.640)	(0.237)
wricalc_advanced				2.041	0.800	2.647	-0.006
				(1.247)	(1.103)	(1.923)	(0.492)
Constant	-3.708*	-7.828***	-11.294***	-6.391**	0.154	-6.814*	-0.768
	(1.895)	(2.088)	(2.726)	(2.783)	(0.551)	(4.092)	(1.805)
Observations	541	541	541	541	541	541	995
Akaike Inf. Crit.	663.473	558.371	506.827	391.567	421.820	347.170	1,122.227

Note: *p<0.1; **p<0.05; ***p<0.01; Standard errors are shown in parentheses

Table 5: When comparing the outcome reported in past contributions with our findings, the choice of model clearly dictates the resulting probabilities. Models with a binary dependent variable lead to bimodal distributions with large high-risk groups. Fractional models yield a normal distribution with small high-risk shares.

Author	Initial Input	Model Type	Predicted Distribution	High Risk	Country
Frey and Osborne (2013)	Binary (0/1)	Classification	Bimodal	47%	US
Bowles (2014)	<i>transfer of Frey and Osborne (2013)</i>		Bimodal	54%	AT
Arntz et al. (2016)	Discrete (0-1)	Fractional	Normal	12%	AT
Nagl et al. (2017)	Discrete (0-1)	Fractional	Normal	9%	AT
<i>Own calculations</i>	Binary (0/1)	Logit	Bimodal	45%	AT
<i>Own calculations</i>	Discrete (0-1)	Fractional	Normal	12%	AT
<i>Own calculations</i>	Binary (0/1)	LDA	Bimodal	46%	AT

Table 6: The correlation matrix shows that there are no significant correlations across variables, except in the case of the test scores for problem-solving (PS), numeracy and literacy.

	Age Group	Gender	Education	Education ²	Firm - Sector	Firm - Size	Skills - PS	Skills - Numeracy	Skills - Literacy	Job - Resp.	Job - Education	Job - Experience
Age Group	1											
Gender	-0.031	1										
Education	0.120	0.001	1									
Education ²	0.108	0.001	0.992	1								
Firm - Sector	-0.153	-0.134	-0.177	-0.185	1							
Firm - Size	0.014	-0.169	0.101	0.104	-0.082	1						
Skills - PS	-0.298	-0.122	0.316	0.312	0.088	0.158	1					
Skills - Numeracy	0.018	-0.183	0.418	0.414	0.019	0.744	0.865	1				
Skills - Literacy	-0.110	-0.051	0.424	0.421	-0.025	0.810	0.865	1				
Job - Resp.	0.167	-0.220	0.138	0.135	0.021	0.024	0.096	0.058	1			
Job-Education	0.242	-0.013	0.581	0.576	-0.198	0.113	0.209	0.337	0.161	1		
Job-Experience	0.244	-0.196	0.197	0.194	0.126	0.108	0.064	0.105	0.302	0.300	1	