POLITICAL RESEARCH EXCHANGE
2024, VOL. 6, 2389910
https://doi.org/10.1080/2474736X.2024.2389910

Bankers are afraid of technology now: explaining perceived vulnerability to technological change among the higher-educated

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ABSTRACT
The higher-educated are typically seen as winners of technological change and automation, but recent evidence shows that many higher-educated workers are, in fact, concerned about losing their jobs to technology. The reasons why higher-educated workers are worried about technological change are not yet clear, however. We analyse survey data from 25 countries to resolve this puzzle. Our results indicate, in a nutshell, that many higher-educated workers are concerned about being replaced by 'artificial intelligence' (AI) and related technologies. Specifically, we find that perceived technological vulnerability among the higher-educated is strongly linked to working in the finance and IT sectors – which are known to be particularly heavily exposed to advances in AI technology. We discuss the implications of technological vulnerability among the higher-educated for social solidarity and political conflict in digitalizing economies.

ARTICLE HISTORY
Received 19 February 2024
Accepted 4 August 2024

KEYWORDS
Labour markets; technological change; artificial intelligence; perceived vulnerability

Introduction

The higher-educated were not supposed to be concerned about technological change. On the contrary, the higher-educated were supposed to benefit from the fact that technological advances, especially in computing, software, and robotics, usually directly complement their skill set, and thus raise their productivity, demand for their skills, and ultimately their incomes. Worries about technological change were supposed to be concentrated among lower- to medium-educated workers who are known to face high risks of being made redundant by technology (e.g. Autor 2015; Autor, Levy, and Murnane 2003; Goos, Manning, and Salomons 2014) and to suffer stagnating incomes and deteriorating job prospects as a result (e.g. Gallego, Kurer, and Schöll 2022; Kurer and Gallego 2019). Against this background, some even predicted a growing polarization of labour

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markets between higher-educated 'brains' and their lower- to medium-educated 'servants' due to technological change (Palier 2019; Rehm 2020).

Recent evidence indicates, however, that vulnerability to technological change increasingly affects the higher-educated as well – or, more accurately, that many higher-educated workers *feel* vulnerable to technological change. Specifically, two recent studies found that levels of concern about technology-induced job loss are only marginally lower among higher-educated workers compared to those without higher education (Busemeyer et al. 2023, 604), or that 'higher education only weakly attenuates subjective risk perceptions' (Kurer and Hausermann 2022, 154). These studies did not investigate further what exactly causes the increased perceived vulnerability among the higher-educated, but given that their analyses were based on separate data sets collected at different points in time (2020 & 2018, respectively) and in different countries, it is unlikely that their findings are mere accidents.

The increased vulnerability to technological change among the higher-educated could have profound political consequences. On the one side, it could help counteract recent trends toward a polarization of social risk exposure between the higher-educated and those without higher education (e.g. Palier 2019; Rehm 2020), which would in turn help stabilize support for risk-sharing and redistribution (Kurer and Hausermann 2022, 154, Rehm, Hacker, and Schlesinger 2012). However, given that there is also a known link between technological vulnerability and right-wing populist support (Kurer 2020), increased vulnerability among the higher-educated may also add further fuel to an already ongoing 'authoritarian turn' in the advanced democracies (Inglehart and Norris 2017). Therefore, it is essential for political science research to substantiate this pattern and to understand the causes of higher-educated vulnerability to technological change to be able to better anticipate future developments.

We contribute to this by providing a dedicated analysis of the drivers of perceived technological vulnerability among the higher-educated using comparative survey data from the OECD's 2020 *Risks that Matter* survey. Our main finding, in a nutshell, is that perceived technological vulnerability among the higher-educated is associated with exposure to 'artificial intelligence' (AI) technology.

More specifically, we confirm the above-mentioned findings that there is no difference in perceived technology risk between the higher-educated and others. Second, we use random forest modelling (Breiman 2001) to identify the main correlates of perceived vulnerability among the higher-educated and find a strong role of working in the finance and insurance and the information technology and communication (IT) sectors, a pattern that exists in all but a few countries. We then offer an account for this pattern by drawing on recent economic research on the spread of AI technology across workplaces, which has identified precisely these sectors as the most exposed to advances in AI technology (e.g. Acemoglu et al. 2022; Brynjolfsson, Mitchell, and Rock 2018; Felten, Raj, and Seamans 2021; Jiang et al. 2021).

As the previous paragraph hints at, our approach in this study is inductive, and we want to be transparent about this so as not to mislead readers about our research process. We chose an inductive approach since perceived technological vulnerability among the higher-educated is, to our knowledge, a recent and relatively unexplored phenomenon and because we wanted to be able to uncover new and possibly unanticipated relationships. The exploratory nature of the research we report here also informed our choice of machine-learning methods. This approach does obviously not allow us to make strong claims about causal relationships, and our findings should instead be seen as a basis on which future (causal) analyses can build.

Data

We use data from the second (2020) round of the OECD's *Risks that Matter* (RTM) survey, which is a new source of cross-country comparative micro-level data on perceived exposure to life course risks, the perceived adequacy of social protection systems, and demands and support for social protection and redistribution. The 2020 round (overall $N = 25\,814$) was conducted in 25 advanced economies on online respondent panels, using quotas for gender, age, education, income, and labour market status.[1]

The 2020 round of the RTM survey included dedicated items to measure attitudes toward technological change and digital transformation (used also in Busemeyer et al. 2023; Busemeyer and Tober 2022) one of which is a direct measurement of respondents' concerns about getting replaced by different forms of new technology:

> How likely do you think it is that the following will happen to your job (or job opportunities) over the next five years: My job will be replaced by a robot, computer software, an algorithm, or artificial intelligence.

Respondents could indicate their perceived risk of being replaced on a four-level ordinal scale ranging from 'very unlikely' over 'unlikely' to 'likely' and 'very likely.'[2] We condense this to a dummy variable that identifies respondents who perceive themselves at risk of replacement (those who considered it 'likely' or 'very likely' that they could be replaced) and use this as our dependent variable.[3]

This operationalization obviously measures *perceived* rather than objective technology risk – but this is exactly what we are concerned with here. In addition, the item covers a range of different technologies and does therefore not immediately reveal which specific type of technology a given respondent is feeling vulnerable to. This, however, corresponds directly or very closely to the operationalisations used in the previous studies we build on Kurer and Hausermann (2022) and Busemeyer et al. (2023) – and it motivates our analysis here, which aims precisely at teasing out what the higher-educated are really concerned about.

Given our exploratory approach, we consider a broad range of socio-demographic attributes as potential explanatory variables in our main analysis (see Table 1 for a summary, and see Table A-1 in the Appendix for more detailed descriptions). We choose some variables that have previously been found to be linked to labour market risks such as the type of employment contract and exposure to 'gig work' (Häusermann, Kurer, and Schwander 2014), urban or rural residency (Jiang et al. 2021), the sector of employment (Felten, Raj, and Seamans 2021), or direct exposure to digital technology at work (Busemeyer et al. 2023), but we consider also other variables such as marital status to be able to uncover unexpected relationships.

Methods

We primarily rely on random forest modelling (RFM) to inductively uncover the most relevant predictors of perceived vulnerability to technological change. RFM is a type of

Table 1. Summary of the variables considered in the study.

Variable
Socio-demographics, education and social class
Gender
Age
Country
Education
Social class
Living arrangements
Size of town
Housing type
Marital status
Partner's employment
Children
Current job and employment status
Employment status
Type of employment
Type of contract
Professional status
Company size
Type of occupation
Industry
Online platform work and the use of digital technologies
Digital information
Complex Technology
Gig economy

machine-learning technique that is commonly used to develop predictive models where the precise effects of independent variables are not the main interest (see e.g. Breiman 2001). However, RFMs can also be used as a tool to identify relevant predictors of some outcome and to quantify their effects (e.g. Lupu and Warner 2022).

Random forests are, in essence, collections of large numbers of randomly composed 'decision trees' (i.e. a set of step-by-step instructions for how to segment a given dataset into different groups so that the resulting grouping accurately predicts an outcome of interest), where each tree includes only a small set of all predictors that are included in a given model.[4] Due to their random composition, each of the trees in a random forest will produce slightly different predictions. However, across a large number of random decision trees – i.e. in the entire random forest – some predictions will occur more frequently than others, and the prediction that is 'voted' for by most of the trees becomes the prediction of the random forest model as a whole.[5]

To assess the predictive power of individual variables, we use the variable importance measure and partial dependence (PD) coefficients. The variable importance measure can be thought of as a measure of the loss in the entire model's predictive power that results from removing a given predictor (see, e.g. Breiman 2001, 211 or Lupu and Warner 2022, 75). PD coefficients measure the effects of individual categories of variables as the change in the model's prediction when one assumes that all responses belong to a given category (and holding all other variables constant). To facilitate the interpretation of our results, we also transform PD coefficients into marginal changes in predicted probabilities.[6]

While the RFM models are the backbone of our analysis, we also use conventional logistic regression models to substantiate key results. We introduce the exact model specification in more detail below.

Results

As a very first step, we inspect our data descriptively and cross-tabulate perceived technology risk by education (see Figure 1). Overall, while most respondents are not concerned about technology-related job loss, there are sizeable minorities in both educational groups who report that they are concerned. More importantly, the data show only a small difference in perceived technology risk between those without and those with higher education: The share of higher-educated who feel technologically vulnerable is only slightly lower than the share of lower educated who feel vulnerable (ca. 32% vs. ca. 38%, corresponding to previous findings; see e.g. Busemeyer et al. 2023, 604).

To substantiate and contextualize this pattern, we run a first RFM on the entire dataset. As described above, the response variable here is perceived technology risk, and we include education as one potential predictor alongside all the others into the model. The left-hand side of Figure 2 presents the main results (in the form of variable importance scores) and highlights again the fact that perceived technology risk is, at best, weakly predicted by educational attainment: Out of the twenty predictors, education ranks 14th. This again corresponds to previous findings (Busemeyer et al. 2023; Kurer and Hausermann 2022) but runs counter to theory and past evidence suggesting that higher education should be linked to clearly lower (if not even no) vulnerability to technology (e.g. Anelli, Colantone, and Stanig 2021; Autor 2015; Autor, Levy, and Murnane 2003).

Next, we focus on the group of the higher-educated and try to find out what is behind their elevated level of concern about technology – i.e. who are the thirty per cent of higher-educated that feel vulnerable to technological change, and what distinguishes them from those higher-educated who do not feel vulnerable? To find out, we estimate a second RFM using the same potential predictors (except for education) but focus now exclusively on the variation *within* the higher-educated and thus exclude all respondents without higher education. The right-hand graph in Figure 2 presents the results. The most

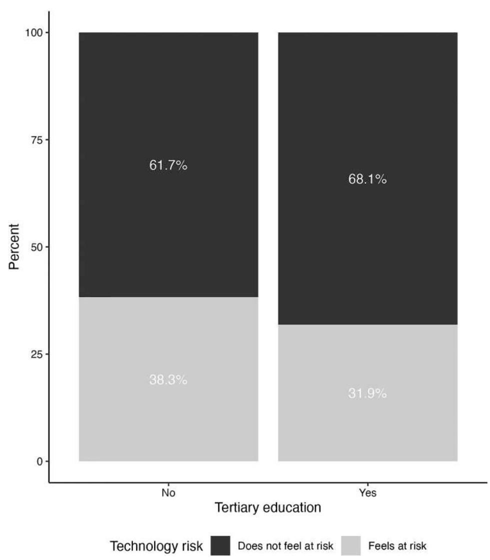
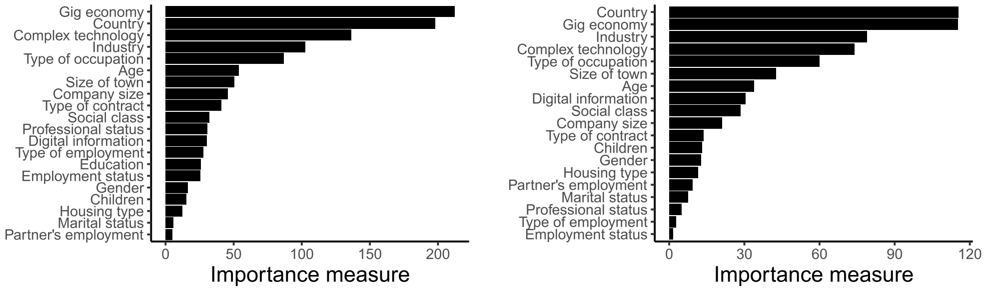


Figure 1. Perceived technology risk across education.



(a) (b)

Figure 2. Variable importance for perceived technology risk (random forest models). (a) Entire sample and (b) higher-educated only.

significant variables driving vulnerability among the higher-educated turn out to be again workers' involvement with the gig economy, their country of residence, their sector of employment, the extent to which they use complex technology at the workplace, their type of occupation, the size of the town where they reside, and their age group. The predictive power of these variables is also reflected in their selection for the final model that exhibits optimal predictive performance. Less important are exposure to digital information at work, social class, the company size of workers, employment status (employer vs employee), the type of employment (permanent vs temporary), and the professional status of workers (full-time, part-time). These latter variables are not included in the final model, reflecting their lower importance scores.

To further quantify the effects of those variables that were selected into the optimal model and received the highest importance scores, we present the estimated PD coefficients and marginal changes in predicted probabilities for the individual categories of those variables (see Tables 2 and 3). Starting with the country variable, only four countries covered by our analysis display positive PD coefficients, i.e. have higher-educated professionals who feel more at risk of being replaced by technology than those in other countries; all other variables held constant. These are Italy (PD = 0.04), Korea (PD = 0.09), Turkey (PD = 0.10) and the United States (PD =0.06). Translating these results into marginal effects, our model suggests that the average probability of feeling at risk would increase by 6.11 percentage points (pp) if all participants were from Turkey while all other characteristics remained the same. Similarly, this increase would amount to 6.01 pp if they were all assumed to be Korean, 5.03 pp if they were from the United States, and 4.63 pp if they were Italians. In contrast, the lowest chances of feeling at risk come from individuals in Austria (PD = −0.15), Belgium (PD = −0.15), Estonia (PD = −0.14), and Finland (PD = −0.14).

The PD coefficients also indicate an elevated probability of exposure in three particular economic sectors: the essential and primary sector (PD = 0.00), manufacturing (PD = 0.02), and the finance and insurance sectors (PD = 0.01). This would translate in, for example, an increase in the average probability of feeling at risk by 3.90 pp associated with working in finance and insurance, keeping all other characteristics constant. The information and communications and the leisure and hospitality sectors are not far behind with marginal effects of 3.15 pp. These effects are smaller than those of living in different countries (see

Table 2. Estimated partial dependence (PD) coefficients and marginal effects.

Variable	Code	PD	Marginal Marginal effect (pp.)
Average			46.35
Countries			
Austria	AUT	−0.15	−0.10
Belgium	BEL	−0.15	−0.09
Canada	CAN	−0.12	0.54
Chile	CHL	−0.10	1.04
Denmark	DNK	−0.13	0.36
Estonia	EST	−0.14	0.18
Finland	FIN	−0.14	0.21
France	FRA	−0.11	0.93
Germany	DEU	−0.13	0.44
Greece	GRC	−0.09	1.39
Irland	IRL	−0.12	0.60
Israel	ISR	−0.10	1.21
Italy	ITA	0.04	4.63
Korea	KOR	0.09	6.01
Lituania	LTU	−0.06	2.16
Mexico	MEX	−0.06	2.21
Netherlands	NLD	−0.09	1.47
Norway	NOR	−0.10	1.17
Poland	POL	−0.07	1.83
Portugal	PRT	−0.09	1.31
Slovenia	SVN	−0.11	0.93
Spain	ESP	−0.13	0.39
Switzerland	CHE	−0.11	0.83
Turkey	TUR	0.10	6.11
United States	USA	0.06	5.03
Industry			
Essential primary	EP	0.00	3.65
Manufacturing	MN	0.02	4.15
Construction and real estate	CR	−0.00	3.65
Wholesale and retail	WR	−0.03	2.90
Transportation and storage	TS	−0.03	2.90
Leisure and hospitality	LH	−0.02	3.15
Information and communications	IC	−0.02	3.15
Finance and Insurance	FI	0.01	3.90
Professional activities	PR	−0.12	0.65
Administration and support	AD	−0.13	0.40
Public administration	PA	−0.15	−0.09
Education	ED	−0.17	−0.59
Human health	HH	−0.18	−0.84
Other services	OS	−0.06	2.15
No information	NI	−0.03	2.90

above) – but they still amount to about a tenth and an eighth, respectively, of the overall average probability of feeling at risk among the higher-educated (see Figure 1). In contrast, human health (PD = −0.18) or education (PD = −0.17) are the two sectors where professionals feel least at risk.

We also find that higher-educated professionals without exposure to gig work are substantially less likely to feel at risk. In addition, we find that the more often professionals use complex technology at work, the more at risk they feel. For instance, if individuals were assumed to use complex technology in the workplace daily (PD = 0.01), the sample's average probability of feeling at risk would increase by 3.95 percentage points. In contrast, if they were assumed never to use such technology at work (PD = −0.22), this probability would decrease by 1.82 pp.

Table 3. Estimated partial dependence (PD) coefficients and marginal effects.

Variable	PD	Marginal effect	Variable	PD	Marginal effect
Average		46.35			
Gig economy			*Complex technology*		
Never	−0.16	−0.34	Everyday	0.01	3.95
Few Times	0.10	6.15	Sometimes	−0.07	1.87
Occasionally	0.09	5.90	Never	−0.22	−1.82
Regularly	0.06	5.15	No Info	−0.22	−1.82
Type of occupation			*Age group*		
Managers	−0.14	0.16	18–24	0.01	3.90
Professionals	−0.17	−0.59	25–34	−0.04	2.65
Technicians	−0.03	2.90	35–44	−0.07	1.90
Clerical	0.06	5.15	45–54	−0.10	1.15
Service	0.03	4.40	55–64	−0.14	0.16
Manual	0.02	4.15			
No Info	0.04	4.65			
Size of town					
<10k	−0.14	0.16			
10–100k	−0.09	1.40			
100k+	−0.00	3.65			
No information	0.02	4.15			

As shown in Table 3, perceived risk is also associated with age, as younger individuals feel more at risk than older ones. The results also show that feelings of being at risk increase with the size of the town or city people live in. Assuming all participants came from bigger cities (i.e. at least 100, 000 inhabitants), the average probability of feeling at risk would increase by 3.65 percentage points (PD = −0.00). By contrast, if they were all from a town of less than 10, 000 inhabitants (PD = −0.14), this probability would increase only by 0.16 pp.

Overall, our RFM analysis reveals several relevant predictors of elevated perceived risk among the higher-educated, the most important of which are exposure to the gig economy, the country of residence, and the sector of employment. Cross-country differences are, of course, generally to be expected, and the effect of gig work confirms an older finding that even the higher-educated are not immune to the effects of atypical or precarious employment (Häusermann, Kurer, and Schwander 2014). The strong effect of working in specific sectors – in particular in heavily numeric and data-intensive sectors such as finance and information technology – is more intriguing, however.

We conduct some additional descriptive analyses to substantiate these findings further and to get an image of the effect of the sector of employment (and its cross-country variation) that is not filtered through a complex model. First, we calculate the overall shares of respondents who feel at risk per sector of employment as well as the shares of higher-educated per sector to see if perceived technology risk and higher education really coincide in the above-named sectors as predicted by the model.[7] Figure 3 presents the results.[8]

The particular status of the finance and insurance and the information and communications sectors is immediately reflected here: Both sectors have levels of perceived technology risk comparable to those in sectors that are traditionally vulnerable to technological change, such as manufacturing, agriculture, or construction, despite being predominantly higher-educated. In this respect, these two sectors stand apart from those dominated by higher-educated workers, such as education or public administration, where workers feel much less vulnerable to technological change.

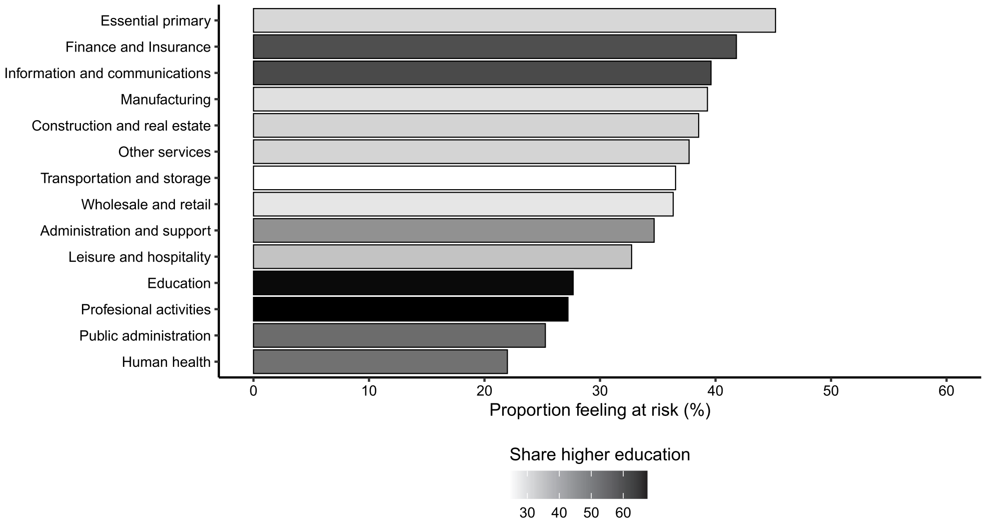


Figure 3. Perceived technology risk and skills across economic sectors (entire sample).

Notes: 'Feeling at risk' is measured as in the main analysis: Seeing it as 'likely' or 'very likely' that a machine, robot, or algorithm replaces one's job. See the text above for details. This figure is based on the entire sample (i.e. not only the higher-educated).

Second, to fully exploit the cross-country nature of our data (and since the country of residence was a strong predictor in the previous analysis), we also calculate the perceived vulnerability of the higher-educated both by sector and country, focussing here again on the higher-educated alone. To simplify the presentation, we aggregate sectors into groups, combining the finance & insurance and information & communication sectors into one group (Finance & IT) and the remaining sectors in a second group. We also provide the overall average per country as a baseline.

As can be seen in Figure 4, above-average levels of perceived technological vulnerability in the financial and IT sectors are fairly common across countries: Workers in these sectors almost always feel noticeably more at risk than those working in other sectors and the overall average.[9] There are exceptions, however. In Lithuania, the finance and IT sectors are less exposed than others (although not by much), while there are essentially no between-sector differences in Slovenia and Spain. It is finally also worth pointing out that countries differ in both the overall degree to which higher-educated workers feel at risk (Korea and Turkey lead the field here) and when it comes to the gap between the finance and IT sectors and the remainder (Poland, Portugal, the US, or France stand out as cases with particularly large gaps).

In the final step, we substantiate the previous findings using a conventional estimation method, logistic regression. Here, we regress the perceived technology risk dummy on being higher-educated (vs not), a dummy measuring being employed in the finance, insurance, or IT sectors (vs elsewhere), and add controls for age, being female, and a simple measure of labour market status (having a permanent contract vs a temporary or no contract). We also include a set of country-fixed effects. The left-hand graph in Figure 5 presents the results in the form of average marginal effects and shows that working in the finance and IT sectors is overall linked to a statistically and substantively

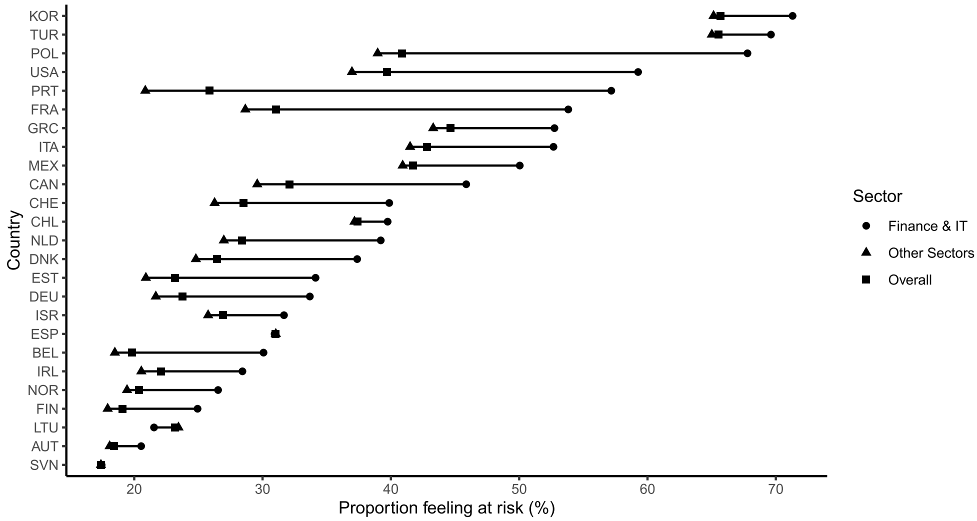


Figure 4. Perceived technology risk among the higher-educated across countries and economic sectors.

Notes: 'Feeling at risk' is measured as in the main analysis: Seeing it as 'likely' or 'very likely' that one's job is replaced by a machine, robot, or algorithm. See the text for details.

(by around ten percentage points, roughly corresponding to the sum of the marginal effects associated with these sectors in the RFM analysis above) higher perceived technology risk, net of all the controls.

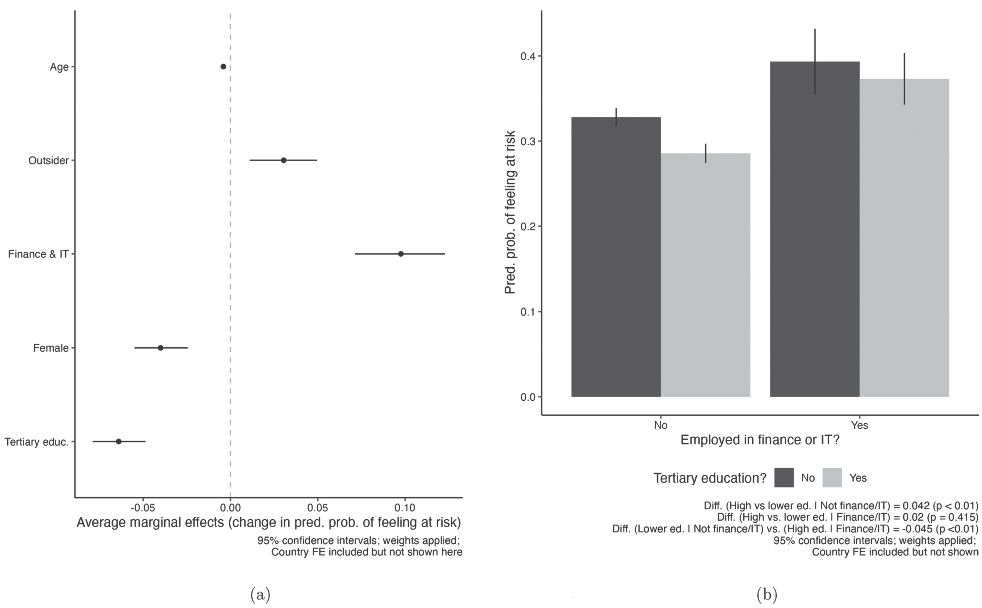


Figure 5. Education, sector of employment, and perceived risk. (a) Average marginal effects (add. model) and (b) Predicted probabilities (interact. model).

Notes: Based on logistic regression models. See Table A-5 in the Appendix for the complete and unprocessed estimation results.

In a second logistic regression model, we interact the finance & IT dummy with the higher education dummy to see to what extent the effect of working in finance or IT differs by level of education. The right-hand graph in Figure 5 presents the main result as predicted probabilities. On the one hand, working in finance and IT is associated with higher perceived technology risk across educational levels and the higher-educated have always lower levels of perceived risk.[10] At the same time, however, the difference between the higher and lower educated is cut in half (from around 4 to 2 percentage points) when working in finance and IT, and it is no longer statistically significant. In other words, higher education no longer protects against perceived technology risk among finance and IT workers. Finally, levels of perceived technology risk among the higher-educated in finance and IT are significantly higher than even the lower educated in other sectors, which again highlights that the higher-educated working in finance and IT are feeling particularly exposed, even compared to the lower educated working in other sectors.

Discussion: what exactly are bankers afraid of?

Our analysis points to the sector of employment – particularly being employed in finance, insurance, or IT – as a critical driver of perceived technological vulnerability among both the lower- and the higher-educated. The elevated levels of concern among the lower-educated are arguably not very surprising given that they are known to be exposed to technological change in general, including the types of technologies (esp. computers & software) that are heavily used in these two sectors (e.g. Autor 2015; Autor, Levy, and Murnane 2003). In contrast, the fact that perceived technological risk among the higher-educated is so strongly linked to working in these sectors seems to raise more questions than it answers: Intuitively, if any group of people should be *best* suited to not only cope with but actively benefit from current technological change, then this should be higher-educated professionals in fields such as finance or IT, where strong numerical or IT skills are often a precondition for employment.

However, recent research in labour market economics points to a highly plausible cause: machine learning and algorithmic decision-making (i.e. 'artificial intelligence', AI) technology. More specifically, several recent studies in this field have measured the spread of AI technology and of workers' exposure to it (i.e. the overlap between AI's and workers' capabilities), and these studies consistently find that exposure to AI technology is strongest among higher-educated white-collar workers, and especially those working in sectors that involve a high degree of information processing and decision-making (e.g. Acemoglu et al. 2022; Felten, Raj, and Seamans 2021; Georgieff and Hyee 2022; Jiang et al. 2021). Felten, Raj, and Seamans (2021, 2203) explicitly name financial examiners or actuaries as occupations and the finance, accounting, or insurance industries as sectors with particularly high levels of AI exposure. Similarly, Acemoglu et al. (2022) analysed the spread of AI technology across US workplaces by looking at the extent to which vacancy descriptions include AI-related skills as requirements and found that the IT and finance sectors were among the sectors with the highest growth in AI-related job vacancies since 2010. Comparative studies find that levels of AI exposure vary little across countries (see (Georgieff and Hyee 2022), 11) which fits well with our finding that workers in the finance and IT sectors feel particularly exposed in almost all of the countries we have data for (see above).

An important driver of this development is the fact that work in these sectors typically requires a great degree of decision-making, classification, and pattern recognition – all tasks that AI technology is specifically designed for (Felten, Raj, and Seamans 2021). For example, workers in the finance industry must routinely interpret written or spoken information when providing investment advice based on a customer's portfolio, income, or spending patterns (Grennan and Michaely 2020), and pattern recognition is central for fraud detection, an important task in both the insurance and finance sectors – and precisely these tasks are now increasingly taken over by digital technology, and specifically AI. Machine-learning algorithms, for example, are frequently used to help detect and prevent bank fraud or money laundering (e.g. Hildebrand and Bergner 2021), and according to a 2018 *Select USA* study, most trading volumes in the equity and foreign exchange markets are now conducted through algorithmic trading (25–75 per cent and 90 per cent-plus, respectively).[11]

Although research on the effects of AI technology on workers has so far not found evidence that AI is systematically replacing human workers at a large scale, some displacement effects have already been observed. For one, different studies have pointed to changes in skill demands by employers, who increasingly demand software or even directly AI-related skills in addition to substantive, sector-related competencies. Jiang et al. (2021) find this in the US finance sector, where firms increasingly demand a combination of finance-related and software skills, partly at the expense of workers without strong software skills (see also Acemoglu et al. 2022). However, and secondly, some studies also find more tangible negative effects of AI and related technologies such as job or income loss among exposed higher-educated workers (Grennan and Michaely 2020; Lane, Williams, and Broecke 2023).

Overall, exposure to AI and related technologies does therefore provide a plausible explanation for the high levels of perceived technological vulnerability among higher-educated workers in the finance, insurance, and IT sectors that our analysis revealed, and thus for the findings mentioned above in previous research (Busemeyer et al. 2023; Kurer and Hausermann 2022). We can, of course, not completely rule out that *some* of the variation in perceived exposure among the higher-educated could be attributable to 'traditional' technologies. Still, it is unlikely to be a major factor given that exposure to non-AI technologies is so strongly focussed on workers with lower or medium levels of education (see e.g. Kurer 2020, 1803).

Our analysis also revealed two other important patterns: Cross-country variation in overall perceived exposure among the higher-educated in general (i.e. across all sectors) and also cross-country variation in the *gap* between the higher-educated in finance and IT and those in other sectors. AI exposure is unlikely to be an explanation here given its relative uniformity across countries (Georgieff and Hyee 2022), and we, therefore, consider other potential drivers.

Regarding overall levels of perceived technological vulnerability, social protection systems may be a potential explanation since those countries with higher overall levels of vulnerability (e.g. Poland, Turkey, or the United States) tend to have less well-developed welfare states than countries with lower levels of risk (e.g. Austria, Norway, or Finland; see Figure 4). However, it is not clear that the generosity of social protection systems can also explain the variation in the gap in perceived risk between the finance & IT sectors and the rest, which we also find (see Figure 4 above). In particular, we find relatively small gaps in some countries with developed social protection systems (notably Austria) but also in countries with less developed systems (notably Chile). Similarly, we find significant gaps in countries with generous systems (especially France) and in countries with less generous systems (e.g. Poland).

Tentatively, we suggest that the structure of the finance and insurance sectors and, in particular, its degree of regional concentration (e.g. Wójcik and MacDonald-Korth 2015) could be a possible explanatory variable here. Both we and others (Jiang et al. 2021) found that being located in a large metropolitan area is associated with increased exposure to technology and perceived risk among the higher-educated. It might, therefore, be that a high degree of centralization of the financial system within one large regional hub and a small set of globally active banks and insurances increases the pace at which new technology is adopted and thus the exposure of those working in finance and insurance to this change relative to the rest of the higher-educated workforce. Unfortunately, we lack relevant comparative data on this aspect and therefore suggest investigating the role of the financial sector's regional concentration for perceived risk among the higher-educated as an avenue for future research.

Conclusion

We have analysed the drivers of perceived vulnerability to technological change among higher-educated workers using cross-country comparative survey data and machine-learning methods. Overall, our results, in combination with findings from other research (e.g. Felten, Raj, and Seamans 2021; Jiang et al. 2021), indicate that perceived vulnerability to technological change among the higher-educated is linked to working in the finance and IT sectors and, therefore, likely results from these sectors' high exposure to technological innovations in the area of AI.

Our results lead to some interesting avenues for future social and political research on the implications of technological change and digitalization. For one, it would be worthwhile to investigate more closely the cross-country variation in levels of perceived vulnerability among the higher-educated, and our earlier discussion suggests some possible explanations that could be tested. Second, a relevant question from a political science perspective is what this increasing exposure to technological change among the higher-educated means in terms of the politics of social protection and redistribution. Theoretically speaking, the fact that vulnerability to technological change seems to be spreading more evenly over the skill distribution opens possibilities for cross-class coalitions of high- and low-skilled vulnerable workers that share a common interest in a generous and protective welfare state (as others have also noted before; see Kurer and Hausermann 2022, 154). Such coalitions have historically led to a stable political consensus around risk-sharing via a generous and inclusive welfare state (Baldwin 1990; Rehm 2016; Rehm, Hacker, and Schlesinger 2012), and they could now counteract current polarizing tendencies that threaten to undermine social solidarity and welfare states (Iversen and Rehm 2021, 2022; Rehm 2020). Exploring this further would also be a fruitful avenue for future research.

A final question is whether this exposure to the negative consequences of technological change among the higher-educated also leads to tangible changes in electoral behaviour – specifically, whether we can expect that higher-educated workers will increasingly form a new electoral base for parties or candidates that champion generous benefits and other forms of social protection (Häusermann, Kurer, and Schwander 2014) – or a new reservoir of support for populist right-wing parties (similar to lower-skilled workers before; see e.g. Kurer 2020)?

Notes

1. The dataset contains only a small share of missing observations (see Figure A-1 in the Appendix.) We use weights in our estimations to account for any divergence of the obtained sample from the target quotas.
2. Respondents were also given the option to answer 'Can't choose'.
3. Figure A-2 in the Appendix shows the original variable broken down by our other main variable of interest, educational attainment, and reveals no strong variation in the degrees of (dis-)agreement that would be lost by collapsing the variable.
4. We grow random forests of 500 trees each. Since high-skilled respondents who do not feel at risk outnumber those who feel vulnerable in our sample (see also below), the class of interest represents a minority. We therefore train our models using Random Oversampling Examples (ROSE) (Lunardon, Menardi, and Torelli 2014).
5. The predictive performance of a given RFM can be gauged via metrics based on confusion matrices such as the model's overall accuracy and the *F*-score. We use an accuracy level of at least 70% and an *F*-score of more than 55% as minimum values that models need to meet to ensure that the model correctly classifies most cases. Our final model achieves an F-score of 58.24% and an accuracy level of 70.36%.
6. This is done by relating a given PD coefficient to the overall average predicted probability estimated by the model.
7. We use the entire dataset here, i.e. we do not limit the analysis to the higher-educated.
8. See Table A-2 in the Appendix for the detailed figures.
9. See Table A-3 in the Appendix for the detailed numbers.
10. This is also reflected in an insignificant coefficient on the interaction term; see Table A-5 in the Appendix (but see also Mood 2010, on the limited interpretability of coefficient estimates from logistic regression models).
11. Financial Times. (2022, July 8). 'Rule books alone cannot govern the rise of the robots.' Accessed November 28, 2022, https://www.ft.com/content/973efb17-6b8b-420e-a89d-dbddee06adf4.

Disclosure statement

No potential conflict of interest was reported by the author(s).

Funding

This work was supported by Center Enterprise 4 Society and Université de Lausanne.

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