Human capital investment and perceived automation risks: Evidence from 16 countries☆

Stefania Innocenti [a,*], Marta Golin [b]

[a] *Smith School of Enterprise and the Environment, University of Oxford, United Kingdom*
[b] *Department of Economics and Jacobs Center for Productive Youth Development, University of Zurich, Switzerland*

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ABSTRACT

Robotics and artificial intelligence are transforming jobs and career paths, and equipping workers with the ability to gain new skills has become a strategic policy imperative. Previous studies showed that investment in human capital depends on locus of control, risk preferences and impatience. Yet in a changing world of work, the perceived risk of being replaced by a machine or an algorithm might also affect workers' decisions to gain new professional skills. Using novel survey data from representative samples of working individuals in 16 countries, this paper shows that fear of automation is positively associated with workers' intentions to invest in training activities outside their workplace. This effect is robust to controlling for other known behavioural traits. We also show that fear of automation reinforces the effect that internal locus of control exerts on retraining intentions.

1. Introduction

New developments in robotics and artificial intelligence are rapidly changing people's jobs and career paths. Consequently, the debate around the effects of technology on workers' career opportunities and job security has been intensely revived. Some scholars contend that technological unemployment represents a serious threat for the workforce. Technology might in fact substitute workers, especially those who carry out repetitive routine and manual tasks and are employed in low-skilled occupations.[1] However, large uncertainty remains concerning the magnitude and implications of the substitution effect for existing jobs.[2] Acemoglu and Restrepo (2018, 2019) clarify in fact that technological advancements can also complement workers' skills, triggering changes in the employment structure along the skill dimension. Further, the intensity of the substitution effect might differ across occupations and depend on workers' skills (Blanas et al., 2020).

[1] See Autor et al. (2003), Autor (2015), Autor et al. (2015), Brynjolfsson and Mitchell (2017), Frey and Osborne (2017), Brynjolfsson et al. (2018).
[2] See Arntz and Zierhan (2016), Frey and Osborne (2017), Nedelkoska and Quintini (2018).

These recent debates have renewed the discussion on the importance of education. Equipping workers with the ability to thrive in this changing labour environment has consequently become a strategic policy imperative (OECD, 2019). National governments and international organisations alike aim to facilitate continuous, lifelong investment in education to make sure that workers' skills remain up to date, firms continue to be competitive, and inequality does not increase. Investment in human capital and higher educational attainment are thought to be key to shelter workers from the adverse effects of the current wave of automation, especially for those in jobs where technological improvements are common (Bessen, 2020).[3]

In this paper, we study how workers' perceived risk of unemployment due to automation affects their intention to invest in human capital. Previous literature in behavioural labour economics has focused on the role of locus of control, impatience and risk preference as determinants of individuals' decision to invest in human capital.[4] Multiple studies suggest that individuals who hold internal locus of control are more likely to invest in human capital compared to those who do not feel in control of their lives (Coleman and DeLeire, 2003; Offerhaus, 2013; Fouarge et al., 2013; Jaik and Wolter, 2016).[5] Equally, it has been shown that impatience is negatively associated with educational investment and attainment.[6] Scholars have also hypothesised that risk preferences are related to investment in human capital, but empirical work remains inconclusive (Caliendo et al., 2020a).[7] However, the effect of perceived automation risks on human capital investment is yet to be studied in the economics literature.

In this paper we take a first step at closing this gap. We focus on a specific type of human capital investment, namely investment in further training outside one's workplace. According to the OECD (2018), training provision outside the workplace could contrast the selective offerings and durations of on-the-job training across occupations and could prove extremely beneficial to those workers in occupations severely affected by new technological advancements. Our objective is, thus, to analyse the impact of perceived automation risks on workers' propensity to acquire new professional skills outside their workplace while accounting for locus of control, risk preferences and impatience.

To answer our research question, we exploit novel survey data from a sample of around 18,000 workers across 16 countries. The survey data were collected as part of a larger project initiated by a large insurance company with the goal of investigating households' financial situation and workers' careers. The survey included questions to purposely elicit workers' perceptions about the future impact of technological advancements on their current jobs and careers, their locus of control, risk tolerance and impatience as well as their intentions to acquire further training in their free time. We first document heterogeneities in the extent to which workers are worried about automation across countries and background characteristics. Second, advancing on the recent literature that incorporates behavioural traits into models of investment in human capital, we estimate a model of intentions to retrain that explicitly takes into account the contribution of perceived automation risks.

We provide two main sets of findings. First, through a descriptive analysis, we show that 30% of respondents in our sample are worried about being displaced by a machine or algorithm, although there are large heterogeneities across the 16 countries included in this study. On an unconditional basis, we find that women, younger workers and those who earn a low income are more likely to be worried about automation-induced unemployment. Further, we find that perceived automation risks are positively correlated with impatience and external locus of control.

Our second set of findings emerges from the estimation of logit regressions for workers' intentions to invest in further training in their free time, as a function of their perceived automation risks, locus of control, risk preferences, impatience and other background and job characteristics. Our estimates pool together respondents from all countries in our sample and show that, even when accounting for locus of control, risk preferences and impatience, workers' perceived automation risk increases the estimated probability of taking further training by 6%. Additionally, we show that the effect of perceived automation risk differs depending on individual predispositions. Perceived automation risk reinforces the positive effect that internal locus of control exerts on retraining intentions: those individuals who simultaneously have internal locus of control and are concerned about the future impact of technology on their work activities are 30% more likely to express intentions to gain new professional skills in their free time. The effect of perceived automation risks on retraining intentions is instead not qualitatively different across patient or impatient individuals. Similarly, fear of automation increases the predicted probability of retraining independently from risk tolerance.

With no claim of causality, the results from this paper suggest that perceived automation risks are linked to investment in human capital. This is particularly true for those workers who are more likely to invest in further training to begin with,

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[3] Nedelkoska et al. (2015) analysed job transitions of displaced workers in Germany between 1975 and 2010 and found that, while those workers who upgraded their skillset did not experience long-term earnings losses, those who did not retrain experienced large protracted shortfalls in income.

[4] Locus of control is a psychological trait that is best described as a "generalised attitude, belief or expectancy regarding the nature of the causal relationship between one's own behaviour and its consequences" (Rotter, 1966). Those with internal locus of control tend to consider much of what happens in life as the result of their own behaviour, whereas those with external control are inclined to believe that life's outcomes are determined by external factors such as luck, chance, fate or the actions of others.

[5] For the effect of locus of control on wage differentials, job search and engagement in entrepreneurial activities, and reservation wages, see also Hansemark (2003), Caliendo et al. (2015), McGee (2015), Caliendo et al. (2016), Piatek and Pinger (2016), Schnitzlein and Stephani (2016).

[6] See Meier and Sprenger (2007), Lusardi et al. (2010), Golsteyn et al. (2014), Cadena and Keys (2015), Falk et al. (2018) for evidence on the relationship between patience and educational attainment.

[7] Guiso and Paiella (2008) show that investment in education can be seen as a risky endeavour, and results from Belzil and Leonardi (2007) suggest that risk averse individuals are more likely to drop out from school. Interestingly, they observe a sign reversal before entering college, which is consistent with viewing schooling as an insurance at higher grades and a risky decision at lower grades.

namely those with an internal locus of control. The strong complementarity between fear of automation and internal locus of control could thus contribute to widening existing labour market inequalities. In the event of biased beliefs about the displacing effect of automation and heterogeneous perceived returns to training, designing policies which could inform workers of the actual benefits of retraining is therefore of crucial importance. Arguably, automatic opt-out retraining programmes could prove useful to prepare workers for new jobs and shelter them from automation risks, especially for those individuals who are least likely to take actions on their own account.

Our contribution to existing literature is threefold. First, we build on previous literature on behavioural labour economics which has become increasingly interested in topics related to skills and technological change (Dohmen, 2014), but has so far not investigated the effect of perceived automation risks on human capital investments. Risk tolerance, impatience and locus of control condition human capital investments through workers' subjective expectations about the relationship between training and future wage growth. However, whereas most studies have concentrated on these traits, in a changing world of work, workers' concerns about the likely effects of technology on their daily jobs cannot be neglected. Ours is the first study to analyse the relation between workers' perceived automation risks and their willingness to acquire new skills while also accounting for risk aversion, impatience and locus of control.

Equally, our second contribution consists of systematically integrating behavioural insights in the literature concerned with the impact of technology in the current world of work. It has been shown that not all workers are equally affected by the advent of cutting-edge technologies and carefully accounting for the task content of the job workers are currently carrying out is crucial (Autor et al., 2003; Autor, 2015). To date, this literature has been agnostic about people's perceptions of technological advancements as well as behavioural traits and the likely effects these might have on labour markets and on workers' capacity to adapt to these evolving environments. In our analysis, we explicitly take into account workers' occupation and tasks to examine heterogeneity in perceived automation risks and how these relate to differences in individual intentions to gain new professional skills.

Third, whereas previous studies on either the determinants of human capital investment or the effect of technological advancement have tended to concentrate on single labour markets (Fouarge et al., 2013; Acemoglu and Restrepo, 2019), we carry out our empirical analysis on a wide set of countries. We rely on an original large survey which was conducted in 16 countries with representative samples of workers aged between 20 and 70 and whose goal was to investigate individual abilities to adapt to changing labour markets. This is amongst the first surveys of its kind.

2. Survey design

To study the association between perceived automation risks and investment in further training, we rely upon a large international survey implemented between February and March 2019. The data were collected as part of a multi-country study launched by Zurich Insurance through a survey administered online by Epiphany, a Dutch professional survey company. The survey was conducted in Australia, Brazil, Finland, Germany, Hong Kong, Ireland, Italy, Japan, Malaysia, Mexico, Romania, Spain, Switzerland, the United Arab Emirates (UAE), the United Kingdom (UK) and the United States (US). In each country, the original sample was selected to be representative in terms of age, gender and region. Quota-based sampling was used to ensure representativeness across these characteristics. Subjects were eligible to participate in the study if they reported being in work at the time of data collection, and aged 20–70.

The survey company engaged respondents through a network of panel providers which guaranteed both global reach and access to local knowledge and expertise in panel management. The providers' panel management practices were compliant with jurisdiction-specific data protection and privacy laws. Only respondents who completed the survey received rewards. These depended on the panel provider customary compensation scheme and included points-programmes, gift cards, vouchers, charitable contributions and prize draws.

The survey was explicitly designed to investigate how workers are adapting to the rapidly changing world of work. It was comprised of several sections that we describe below.[8]

Work situation The first five sections of the survey were devoted to eliciting information from respondents on their work situation. We collected detailed information on the respondents' work status, occupation, their contract type and the type of organisation they work for, the number of hours worked per week, the task composition of their job, and the total number of jobs they have had since the beginning of their career.

Intentions to retrain Respondents were also asked about their willingness to acquire new skills by investing in further training. More precisely, respondents were asked to state their intention to attend training programmes to improve their professional skills, when such investment would take up one evening a week of their leisure time for 6 months. The time commitment makes the hypothetical investment quite substantial. Answers were given on a four-points Likert scale ranging from 1 "Very unlikely" to 4 "Very likely". We construct a binary variable taking value 1 if respondents state it is somewhat or very likely that they will participate in further training, and 0 otherwise. We use this indicator as our main dependent variable in the analysis.

We note that our dependent variable measures workers' intentions to invest in further training, rather than actual training participation. The cross-sectional nature of the survey, and the lack of information on past training history of respon-

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[8] The exact formulation of all questions used in this paper is provided in order of presentation in Appendix C.

dents prevent us from being able to internally validate the intentions to retrain question against actual (past or future) training decisions. However, recent work in the human capital literature has made use of similar questions about the likelihood of educational investment decisions or occupational choice, and found self-reported intentions to correlate highly with actual choices (see for example Boneva and Rauh, 2017; Arcidiacono et al., 2020).[9] In the specific context of professional retraining choices, Fouarge et al. (2013) show that differences in willingness to take further training by education group are important drivers of the discrepancies in actual training participation between low- and highly-educated workers. Based on this evidence, the correlation between retraining intentions, as measured in our survey, and actual training decisions is likely to be high.

Perceptions about technology Participants to the study were also asked questions about their perceptions of the disruptive potential of technology and its consequences for their work situation. Our main explanatory variable is constructed from a question which asked respondents to report the extent to which they feared losing their job over the next 5 years because of technological advancements. More precisely, the question read as follow:

> *To what degree are you worried about losing your job in the next 5 years because your tasks will be replaced by a machine or a computer programme?*

Original answers to the question were given on a four-points Likert scale ranging from 1 "Not worried at all" to 4 "Very worried". We construct a binary indicator that takes value 1 if the respondent is moderately or very worried, and 0 otherwise. This is the key explanatory variable that we use in our analysis.[10] In what follows, we interpret this binary variable as capturing respondents' "perceived automation risks", their "concerns about the displacing effect of automation" or their "fear of automation". We use these terms interchangeably in the text.

We also collected information on perceptions about the influence of past technological advancements on labour markets by asking survey participants to reflect on the extent to which technological innovations have changed labour market conditions over the last 15 years.

Attitudes and behavioural traits In the sixth and seventh section of our survey, we elicited proxies of respondents' patience, risk aversion and locus of control. Our survey does not contain direct questions on time preferences. However, the well-known Cognitive Reflection Test (CRT) (Frederick, 2005) was included in the survey. We consider the number of correct answers individuals were able to provide to the 3 questions that make up the test. Given the strong correlation between the CRT score and time preferences (Frederick, 2005), in what follows we construct a binary indicator that takes value 1 for respondents who answered none of the CRT questions correctly, and 0 otherwise and use this variable as a proxy for impatience.

To elicit an individual's degree of risk aversion, we adapted for the survey the experimentally validated method elaborated by Charness and Villeval (2009) and Charness and Gneezy (2010). We asked each participant how much of an hypothetical $100 of savings they would want to invest in a risky asset that yields 2.5 times the amount invested with 50% probability, and 0 otherwise. The lower the amount invested in the risky asset, the higher is the degree of risk aversion. Conversely, risk loving or risk neutral individuals will invest the whole $100.[11] We first construct a variable that captures the difference between 100 and the amount the individual would be willing to invest. The variable thus ranges from 0 to 100, with 100 indicating the highest degree of risk aversion. We then construct a binary variable that takes value 1 if individuals are more risk averse than their country's median and 0 if their degree of risk aversion is lower than the country median.

Finally, we measure locus of control from answers to the questions on how much control each person thinks they have over their life and how much freedom of choice they have in their life. These two questions are based on a regular survey item included in the World Value Surveys. Although different from the Rotter (1966) scale, these questions have been used to proxy locus of control or 'perceived fate control' by Veenhoven (2000), Inglehart et al. (2008), Verme (2009), Williamson and Mathers (2011), Nikolaev and Bennett (2016). Answers to both questions range from 1 "No control at all" to 5 "A great deal" of control. We take the average of the answers to the two questions and classify individuals as having an internal (external) locus of control if their value is above (below) their country's median.

Socio-demographic characteristics The last sections of our survey tackled the socio-demographic profiles of respondents. We specifically collected information on the respondents' age, gender, whether they have migrant origins, the number of years they spent in education and whether they have children. The survey data also includes information on the respondents' broad income category relative to their country of residence.

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[9] Stated intentions have also been shown to strongly relate to actual behaviour in the context of voting (Delavande and Manski, 2010).

[10] In Appendix Table B.2 we provide evidence of the fact that our results remain unaltered when using the categorical variable.

[11] Crosetto and Filippin (2013) compare various risk elicitation tasks. They show that in the laboratory conditions the investment game elaborated by Charness and Villeval (2009) and Charness and Gneezy (2010) yields estimated degrees of risk aversion comparable to that obtained by means of a Bomb Risk Elicitation Task (Crosetto and Filippin, 2013), a multiple price list as in Holt and Laury (2005) or an ordered lottery choice as implemented by Eckel and Grossman (2002, 2008).

3. Data

3.1. Sample selection

The original survey data included 18,019 subjects across 16 countries. We restrict the sample in several ways. First, we exclude individuals who, despite being in work, primarily identify themselves as students or retirees. This is because our focus is on working individuals whose perceptions of automation risks may drive their training choices. We also eliminate members of the armed forces. Additionally, we exclude from our sample responses from individuals who did not answer the occupation question or declared to be civil servants but provided no other indication of their occupation. Some respondents provided answers to the occupation questions that could not be classified into ISCO-08 occupation codes. We retain these observations and assign them a separate occupation code.[12] Finally, we restrict the sample to individuals for whom we have information on the type of contract they are employed under, or the type of employment (employee vs self-employed) they fall within, the number of jobs they have worked in the past and their income category. Eliminating observations as per the above criteria leaves us with a sample of 15,889 individuals across 16 countries.

3.2. Data description

Table A.1 provides descriptive statistics for the final sample. Starting with our main dependent and independent variables, the first two rows of Table A.1 show that around 63% of workers in our sample would be willing to invest part of their free time in training programmes to acquire additional professional skills, and 30% of survey participants report being moderately or very worried about the potential adverse effects of automation.

Turning to background characteristics, around 46% of the respondents in our final sample are female. On average, individuals have completed around 14 years of education and have around one child each. A significant share (i.e. 15%) of workers in our sample are of foreign origins. Looking at variables related to the respondents' work situation, we divide respondents between those who are employees and have a permanent contract, and those who do not. Generally, this taxonomy reflects what in the literature are often referred to as typical versus atypical work arrangements.[13] 38% of individuals work in atypical work arrangements, and the vast majority of the sample (71%) works 35 h per week or more. When asked to classify the task content of their job, 51% of respondents reported performing predominantly manual tasks as opposed to knowledge-based tasks, and 39% reported performing creative rather than routine tasks.[14]

At the bottom of Table A.1 we report summary statistics for measures of impatience, risk preferences and locus of control. Respondents to our survey on average answered 0.78 questions from the CRT correctly, and 54% of them are classified as impatient according to our binary measure. Our continuous measure of risk aversion shows that workers in our sample are on average willing to invest only $41 on the risky asset - hence displaying a considerable degree of risk aversion. Finally, over 61% of respondents hold internal locus of control, as shown in the last row of Table A.1.

4. Who fears automation?

Overall, 30% of respondents in our sample are concerned about the disruptive potential of technological advances.[15] We note that answers to our survey question, given its framing, could mask different concerns. Although we are fundamentally interested in respondents' concerns about the displacing effect of automation due to skill obsolescence, the answers could also encapsulate a more general concern about short-term unemployment, general pessimism about the impact of technological advancements and apprehension about the possibility of finding a new, suitable job following an unemployment spell.

Other questions from our survey allow us to partially clarify the extent to which these concerns taint the interpretation of our main explanatory variable. In particular, we look at an indicator that takes value 1 if respondents think it is likely or very likely that they will lose their job over the next 12 months as a proxy for general concerns about short-term unemployment. Further we construct a binary variable that captures whether respondents think technological innovations have worsened labour market conditions over the last 15 years and use it as a proxy for pessimism about technological advancements. We

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[12] Answers to the occupation question were provided as a free text. After translating the text answers to English, manual assignment of entries to standard occupational codes was performed. Often-appearing words were matched to detailed descriptions of standard ISCO occupational categories available at https://www.ilo.org/public/english/bureau/stat/isco/isco08/. Whenever the answer text was too short for the match to be successful, respondents are assigned a separate occupation code of 99. Table B.1 in Appendix shows that our main results are robust to dropping these observations.

[13] The definition of non-standard forms of employment encompasses all forms of employment other than a full-time permanent contract (Eurofound, 2017). The same definition is used in recent work on atypical work arrangements - see for example Datta et al. (2019).

[14] We follow the approach in Acemoglu and Autor (2011) and construct a measure of task content from the self-reported answers about respondents' classification of their jobs. In particular, we use answers to two questions where we asked respondents to report the fraction of their job they think is "manual or knowledge based" and "creative or routine". We classify a job as manual (creative) if the answer to the first (second) question is above 50%, and as knowledge-based (routine) otherwise. This results in the following four task types: manual-routine, manual-creative, knowledge-routine and knowledge-creative.

[15] A more nuanced view of the extent to which respondents are worried about being displaced by algorithms or machines can be gathered observing Fig. A.1 where we pull all countries together and plot answers to the fear of automation question by its original four-points Likert scale.

note that both variables are positively correlated with our measure of fear of automation (corr. = 0.22 and 0.16 respectively). However, in a robustness check presented in Table B.3, which we discuss in Section 5.3, we show that perceived automation risks significantly influence workers' willingness to take up further training *over and beyond* the impact of perceived generic short-term unemployment risks and workers' perceptions about the past influence of technological advancements. In this sense, our measure of perceived automation risks arguably reflects the extent to which workers believe that their skills would become obsolete given the expected labour markets' changes.

Additionally, our independent variable could conceal workers' concerns about finding a new job. Put differently, if a worker, given her abilities and skills, can transition to a high number of jobs, the advent of robotics and artificial intelligence might appear less threatening. As our dataset does not contain information on the work activities that our respondents carry out in their job, we cannot compute a measure of skill transferability and thus of the extent to which workers could transition to different occupations, should they become unemployed. We acknowledge that concerns about both skill obsolescence and transferability might be driving the results that we uncover.

We now proceed to explore how workers' concerns about automation vary across different groups. First, we note that there is large heterogeneity in the extent to which people fear the advent of automation across the countries in our dataset (see Fig. A.2). Overall, the countries where people fear automation the least are Germany and Finland with 13 and 14% of respondents reporting being worried about losing their job because of a computer or algorithm. In contrast, the UAE and Malaysia are the countries where workers expect technological disruptions to be the highest – 51 and 50% of respondents in these countries report being worried about the effect of automation on their work activities.

Next, we pool together respondents across all countries to look at which individual characteristics and traits are correlated with higher perceptions of automation risk. Figure 1 shows that women, young workers and those earning lower incomes are significantly more likely to be worried about the displacing effect of automation. Similarly, workers who are impatient and have external locus of control are more worried about automation than patient workers and those who feel more in control of their lives. We find no unconditional heterogeneity in the extent to which workers fear automation by levels of risk aversion.

Finally, we use a logit regression model to look at heterogeneities in fear of automation across a wide set of individual and job characteristics, conditional on a full set of controls (see Table 1). Column (1) shows that older respondents and medium and high income workers are significantly less likely to report being worried about losing their job to a computer or algorithm compared to low income workers. This is consistent with the fact that older individuals face a shorter time horizon during which technological advancements could disrupt their career paths, and high income workers tend to be employed in occupations that are less likely to be automated.

In Column (2) we additionally control for respondents' personality and preferences to understand the extent to which these shape workers' concerns about automation-induced unemployment. Results show that individuals who hold internal locus of control are significantly less likely to worry about automation than workers with an external locus of control. Further, workers' fear of automation is negatively correlated with their risk aversion, and workers who are impatient are more likely to report being worried about the disruptive potential of technology.

In Column (3) we add job and employment status characteristics to our vector of control variables to examine heterogeneities in concerns about automation depending on the type of jobs workers are performing. Indeed, the future substitution effect of automation is likely to differ depending on the type of job and tasks workers are performing, and the occupation they work in. We find that, controlling for occupation fixed effects, demographics and personality traits, workers who report carrying out knowledge-based tasks are significantly less worried about automation compared to workers employed in manual jobs. Working longer hours correlates negatively with perceived automation risks. All other relationships described above survive the inclusion of these additional controls, although the income gradient becomes somewhat less pronounced once we control for job characteristics.

4.1. Correlation with other existing measures of automation

We also compare the perceived automation risks elicited in our survey with automation probabilities as estimated by Frey and Osborne (2017) and Nedelkoska and Quintini (2018).[16] Table A.2 reports the individual-level conditional and unconditional correlation between these estimates and our survey-based measure of fear of automation. It suggests that those who are employed in occupations that are more at risk of automation are also more worried about being displaced by a machine or algorithm. We also collate together the three measures across occupational categories in Fig. A.3. The figure shows that automation probabilities from Nedelkoska and Quintini (2018) closely follow the measure from Frey and Osborne (2017): some occupations, such as general office clerks, appear to be clearly more exposed to automation risks

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[16] To achieve comparability between the various measures, we collapse the automation probabilities from Frey and Osborne (2017) at the ISCO-08 2-digit level, which is the level at which we classify occupations in our dataset. To do so, for each ISCO-08 2-digit occupation we take the unweighted average for the automation probabilities of the ISCO-08 4-digit sub-categories. Automation probabilities from Nedelkoska and Quintini (2018) are already available at the ISCO-08 2-digit level. For this comparison, we use the categorical measure of automation risks from our survey data and take the average within occupations.
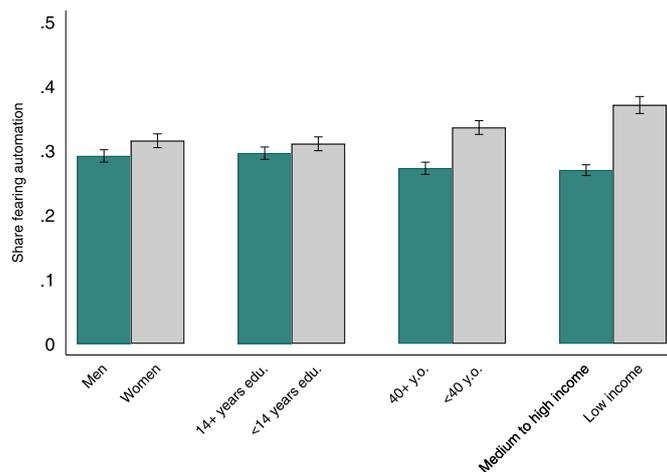
(a) Individual characteristics
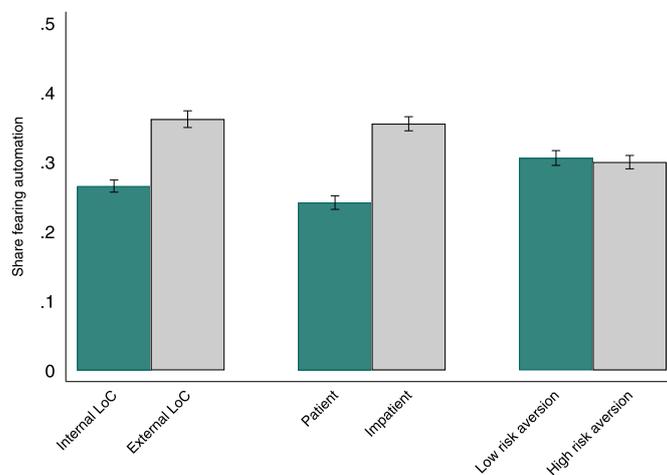
(b) Preferences

Fig. 1. Fear of automation by individual characteristics and preferences. *Notes*: Share of respondents who reported being moderately or very worried about automation, separately by different background characteristics and preferences. Black caps represent 95% confidence intervals.

than others (e.g. health professionals). Conversely, this pattern is somewhat less evident in our survey data, where people's perceptions of technological disruptions are fairly homogenous across occupations.[17]

The discrepancy between our measure of perceived automation risks and automation probabilities from Frey and Osborne (2017) and Nedelkoska and Quintini (2018) might originate from different sources. First, our measure is calculated from individual-level subjective assessments of automation risks. It reflects the extent to which workers believe that, because of technological advancements, their skills would become obsolete and thus they would lose their job. Conversely, the automation probabilities from Frey and Osborne (2017), Nedelkoska and Quintini (2018) are calculated at the occupation-level. They reflect the possibility that machines or computer algorithms could replace workers for part or all of their tasks.[18] In this sense, these probabilities can be interpreted as technically capturing the potential for automation-induced unem-

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[17] At the occupation level, i.e. collapsing our dataset to the mean values of the fear of automation variable and automation probabilities by occupational category, our binary measure of perceived automation risk has a correlation of 0.41 (*p*-value < 0.01) and 0.36 (*p*-value = 0.018) with automation probabilities from Nedelkoska and Quintini (2018) and Frey and Osborne (2017), respectively.

[18] Probability estimates from Frey and Osborne (2017) are obtained from expert valuations of the likelihood of automability for different occupations, based on various bottlenecks to computerisation (creativity, persuasion, and social intelligence required for certain occupations). Nedelkoska and Quintini (2018) follow a similar approach but use individual-level data collected through the Survey of Adult Skills (PIAAC) to estimate the risk of automation for individual jobs.

Table 1
Determinants of fear of automation.

	(1)	(2)	(3)
Age (years)	−0.0169***	−0.0169***	−0.0161***
	(0.0031)	(0.0031)	(0.0031)
Female	0.0962	0.0449	0.0492
	(0.0686)	(0.0671)	(0.0621)
Educational attainment	−0.0610***	−0.0378**	−0.0118
	(0.0191)	(0.0178)	(0.0181)
Number of children	0.0562***	0.0533**	0.0518**
	(0.0214)	(0.0219)	(0.0221)
Migrant	0.1548	0.1489	0.1476
	(0.0979)	(0.0946)	(0.0956)
Medium income	−0.3040***	−0.2592***	−0.2114***
	(0.0675)	(0.0663)	(0.0652)
High income	−0.6339***	−0.5315***	−0.4547***
	(0.0743)	(0.0707)	(0.0674)
Internal LoC		−0.4265***	−0.4129***
		(0.0683)	(0.0666)
Risk averse		−0.0896*	−0.0815*
		(0.0470)	(0.0447)
Impatience		0.4782***	0.4448***
		(0.0455)	(0.0442)
Number of past jobs			0.0020
			(0.0042)
Task-type			
Manual-Creative			0.1450***
			(0.0477)
Knowledge-Routine			−0.1536***
			(0.0557)
Knowledge-Creative			−0.1267***
			(0.0468)
Atypical work arrangement			−0.0012
			(0.0536)
Private sector			0.0799
			(0.0521)
Hours worked			−0.0248*
			(0.0148)
Constant	−0.1197	−0.2195	−0.3220
	(0.1710)	(0.1891)	(0.2512)
Observations	15,889	15,889	15,889
Pseudo R^2	0.0777	0.0922	0.1013
Country F.E.	yes	yes	yes
Occupation F.E.	no	no	yes

Notes: Logit regressions. Standard errors clustered at the country level are reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. The dependent variable is a binary indicator taking value of one if the respondent reports being moderately or very worried about automation, and zero otherwise. Occupation dummies refer to the ISCO 2-digit classification of occupations.

ployment, which is likely to differ from the actual replacement rate. Indeed, recent work by Arntz et al. (2017) shows that occupation-level measures tend to yield to an overestimation of automation risks.[19]

Additionally, part of the difference between our measure and estimates from the literature may arise as a consequence of the mapping of free-text answers to the occupation question into ISCO occupational titles. Lastly, the measures might differ because people have biases in their perceptions of automation risk, possibly due to misinformation regarding the likely impact of technology on different types of jobs and its potential to create new jobs. Whether workers generally misperceive automation risks cannot be analysed with our data, but remains an interesting and open question.

5. Fear of automation and intentions to retrain

5.1. Empirical specification

The core of our empirical analysis relies on the estimation of a logit model with country and occupation fixed effects to analyse the association between perceived automation risks and intentions to invest in further training, conditional on a

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[19] We also compared our survey data with the Suitability for Machine Learning measure elaborated by Brynjolfsson et al. (2018). The result of this comparison is available from the authors upon request.

broad set of individual, job and employment characteristics. The basic specification is:

$$\Pr(Retrain_{i,c,j} = 1) = \Lambda\left(\alpha_0 + \alpha_1 Fear_{i,c,j} + \alpha_2 \mathbf{X}_{i,c,j} + u_c + u_j + \epsilon_{i,c,j}\right) \qquad (1)$$

where $Retrain_{i,c,j}$, our dependent variable, indicates a respondent's intention to take further training to improve her professional skills at the expenses of one evening per week of her leisure time, where i indicates the respondent, c her country of residence and j her occupation. $Retrain_{i,c,j}$ is equal to 1 if the individual declares she wants to take further training, and 0 otherwise.

The term u_c stands for the country fixed effects which are included in all our regressions to remove the impact on training intentions of fixed country characteristics that are potentially correlated with our main regressors. u_j refers to a set of occupation dummies. $Fear_{i,c,j}$ is a dummy variable which takes value 1 if the agent declared to be worried or very worried about losing her job to a machine or an algorithm in the next 5 years. This is the key regressor in our analysis.

$\mathbf{X}_{i,c,j}$ identifies a vector of controls. Firstly, we include other behavioural traits such as risk aversion, impatience and locus of control that the literature on human capital accumulation have found to be strong correlates of investment decisions. In augmented specifications, we look at the interaction between fear and all behavioural traits to analyse the possible heterogeneous effect that fear of automation might exert on intentions to retrain.

We also include a battery of individual characteristics such as age, gender, income categories, presence of children in the family, educational attainment and migration background. These variables are included as they might independently influence individual perceptions of the need for further training or simply act as barriers to investments in human capital.

Finally, we add to our empirical specification a suite of variables capturing job and employment characteristics. We include a dummy identifying whether the respondent works in the private or public sector, the number of hours worked per week and whether the respondent's work arrangement is atypical in nature. We obtain this information combining responses to questions which inform us on whether the respondent has a non-permanent working contract and non-standard employment (i.e. is a freelancer, worker-on-demand or simply self-employed). To ascertain that fear of automation is not just a proxy of past work experience, we control for the respondent's employment history, i.e. the number of past jobs she has been employed in. Importantly, we include indicators for self-perceived task-types which are meant to identify whether, in the respondent's opinion, her job mostly entails carrying out routine-manual, routine-knowledge based, non-routine-manual or non-routine-knowledge based tasks.

Since we specify a logit model to represent choice behaviour, $\Lambda(\cdot)$ refers to the cumulative distribution function of the logistic distribution.

5.1.1. Threats to identification

Whilst we make no causal claims about the associations that we document, we now discuss three potential identification issues that arise when analysing the relation between individual intentions to take further training and perceived automation risks.

First, fear of automation is likely to be non-random. Specifically, the extent to which individuals are concerned about the advent of automation clearly depends on their jobs and on the institutional measures in place to offset the effects of technology disruptions. This might *a priori* shape their inclination to take further training to counteract these risks. We address this issue by including country- and occupation-fixed effects as well as a set of task-type dummies in our model specifications.

The second important issue to consider regards omitted variables. Concretely, our dataset does not contain any information on whether respondents expect the cost of training to be paid by the employer or the worker. It is reasonable to expect that intentions to acquire new professional skills increase if the employer pays for worker's training. Additionally, workers whose employer is willing to offer them the possibility to retrain might perceive their employer as more invested in protecting their jobs from the substitution effect of new automation waves. Under this assumption, perceptions about the disruptive effect of technology might actually decline if the employer bears the cost of retraining. Therefore, the effect that perceived automation risks has on retraining intentions would in our case be downward biased. Equally, as we lack information on the cost of training, it can be argued that the relationship between retraining and perceived automation risks results from self-selection into training due to wealth reasons. Although, we have no means to alleviate these concerns directly, we always control for income in our specifications. Additionally, in one of our robustness checks we partition the sample by broad income levels and examine whether the effect of fear of automation on intentions to retrain changes along the income distribution (see Table B.4).

Personality traits are also omitted from our analysis due to data availability. In particular, we believe that conscientiousness and openness to experience would be relevant to our analysis. As conscientious individuals are found to cope better in situations in which they are exposed to threats (O'Connor et al., 2009) and tend to find effective ways to overcome stress (Murphy et al., 2013), we expect conscientiousness to be negatively correlated with perceived automation risks. Simultaneously, conscientiousness has in the past been found to reduce intentions to retrain (Fouarge et al., 2013; Caliendo et al., 2020a). Its omission is thus likely to lead to an overestimation of the true impact of automation risks on intentions to retrain. We appreciate the potential bias of our estimator. Turning to openness to experience, recent literature has shown that this trait positively affects self-reported career success (van den Born and van Witteloostuijn, 2013) and job mobility (Nieß and Zacher, 2015). It was also found to have a very modest positive effect on retraining (Fouarge et al., 2013; Caliendo et al., 2020a). Thus, its omission is likely to lead to an underestimation of the true impact of automation risks on intentions to

retrain, and therefore bias our results towards finding a null result. To ascertain the possible bias arising from the omission of openness to experience, in a robustness check we control for intentions to leave one's job voluntarily or to become a freelancer, as a proxy for openness to experience (see Table B.5, which we discuss in the next section).

Lastly, our specification is affected by a simultaneity bias whereby perceived automation risks affect people's willingness to retrain, but retraining intentions also affect workers' concerns about automation. Whilst we have no means to mitigate this bias, in line with Fig. 1 which suggests that more educated workers are less worried about technological unemployment, we would expect an increase in training to reduce workers' automation concerns, suggesting that this might bias our estimates downward.

For the reasons listed above, although we conduct numerous robustness checks to mitigate concerns regarding our identification, we do not make strong causal claims about the effect of perceived automation-induced displacement risks on intentions to acquire further skills in one's free time.

5.2. Main results

We report our main results on how perceived automation risks relate to retraining intentions in Table 2. We start, in Column (1), with a baseline logit specification that only accounts for fear of automation and the country dummies.[20] The estimated coefficient shows that fearing the disruptive effect of technology increases the probability of stating positive intentions to gain new professional skills from 0.62 to 0.66. Put differently, the odds of expressing positive intentions to retrain for those who fear automation are 1.20 times (i.e $e^{(0.179)}$) larger than those of individuals who are not concerned about the impact of technology.[21]

We then proceed to estimate four richer specifications. In Column (2) we add individual characteristics. Adding these controls somewhat reduces the effect of fear of automation on intentions to retrain, nonetheless the coefficient remains positive and significant. Older individuals are less likely to state they intend to retrain. We also observe a pronounced gradient of retraining intentions by income levels, whilst we do not find any evidence of a gender effect on intentions to retrain.

Column (3) additionally controls for individual risk tolerance, impatience and locus of control. As mentioned, these factors have all been shown to affect individuals' intentions to gain new skills. Compared to column (2), the estimates from column (3) show that the positive association between fear of automation and intentions to retrain becomes stronger when controlling for risk aversion, impatience and locus of control. Being worried about the advent of cutting edge technologies increases the probability of considering acquiring new skills by roughly 6% compared to the baseline, with predicted probabilities increasing from 0.63 in baseline to 0.67. This suggests that fear of automation matters for workers' intentions to retrain over and beyond workers' background characteristics, locus of control, risk and time preferences. Looking at the effect of other behavioural traits on intentions to retrain, we find that holding an internal locus of control increases the predicted probability of retraining, which is in line with Fouarge et al.'s (2013) and Caliendo et al.'s (2020b) findings. Risk averse individuals are less likely engage in retraining activities, suggesting that investing in further professional training outside the workplace is seen as a risky endeavour. Impatience instead does not appear to significantly affect intentions to invest in further training, once fear of automation and other behavioural traits are accounted for.

In Column (4) we observe that the effect exerted by perceived automation risks on workers' intentions to invest in human capital is not undermined by job and employment characteristics: conditional on all other characteristics, fearing the disruptive effect of technology increases the probability of stating the intention to gain new professional skills to 0.67 from a baseline probability of 0.63, i.e by around 6%.[22] It is shown that working in the private sector or having an atypical work arrangement does not influence intentions in a significant manner. All other relationships described above remain robust in this full model.

5.3. Robustness

As mentioned in Section 4, our measure of fear of automation could reflect general short-term unemployment concerns and a more general pessimism about the past effect of technology on labour markets. To clarify these issues, in Table B.3 we present results from specifications where we add proxies for each of these concerns to our vector of controls.

Specifically, in Column (1) we control for an indicator that takes value 1 if the worker thinks her perceived likelihood of losing their job in the next 12 months is moderately or very high. In Column (2) instead we include in our model an indicator that takes value 1 if the worker perceives the current job situation as moderately or very worse relative to 15 years ago, due to the effect of science and technology. Finally, in Column (3) we control for both concerns simultaneously.

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[20] Our results are robust to probit and multinomial logit estimation procedures. The estimates are available from the authors upon request.

[21] For ease of interpretation, in what follows we will report our results in terms of probability of intending to retrain while constantly keeping all covariates at their mean. Such probability is obtained dividing the odds in favour of positive retraining intentions by one plus the odds of positive retraining intentions.

[22] These results are robust to decreasing the disaggregation in the set of occupation dummies and using the ISCO-08 1-digit rather than the 2-digit classification.

Table 2
Fear of automation and intentions to retrain.

	(1)	(2)	(3)	(4)
Fear of autom.	0.1799***	0.1099**	0.1659***	0.1927***
	(0.0546)	(0.0522)	(0.0532)	(0.0488)
Age (years)		−0.0214**	−0.0136	−0.0231**
		(0.0094)	(0.0098)	(0.0104)
Age squared		−0.0286**	−0.0365***	−0.0279**
		(0.0118)	(0.0123)	(0.0128)
Female		−0.0101	0.0084	0.0503
		(0.0630)	(0.0607)	(0.0595)
Educational attainment		0.0841***	0.0849***	0.0470***
		(0.0198)	(0.0190)	(0.0167)
Number of children		0.0692***	0.0630***	0.0683***
		(0.0108)	(0.0125)	(0.0138)
Migrant		0.1465**	0.1487**	0.1345**
		(0.0593)	(0.0600)	(0.0597)
Medium income		0.1368***	0.0891**	0.0219
		(0.0437)	(0.0436)	(0.0433)
High income		0.2361***	0.1481***	0.0042
		(0.0285)	(0.0293)	(0.0348)
Internal LoC			0.5193***	0.5077***
			(0.0494)	(0.0492)
Risk averse			−0.2867***	−0.2873***
			(0.0307)	(0.0311)
Impatience			−0.0606	−0.0202
			(0.0453)	(0.0460)
Number of past jobs				0.0169***
				(0.0040)
Task-type				
Manual-Creative				0.1988***
				(0.0763)
Knowledge-Routine				0.2023***
				(0.0445)
Knowledge-Creative				0.4601***
				(0.0612)
Atypical work arrangement				0.0076
				(0.0531)
Private sector				−0.0850*
				(0.0475)
Hours worked				0.0698***
				(0.0137)
Constant	0.1950***	1.2572***	1.0335***	0.8996***
	(0.0134)	(0.1988)	(0.2132)	(0.2195)
Observations	15,889	15,889	15,889	15,889
Pseudo R^2	0.0673	0.1104	0.1234	0.1342
BIC	19,624	18,795	18,551	18,352
Country F.E.	yes	yes	yes	yes
Occupation F.E.	no	no	no	yes

Notes: Logit regressions. Standard errors clustered at the country level are reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. The dependent variable is a binary indicator taking value of one if the respondent reports being willing to invest in further training in their free time, and zero otherwise. Occupation dummies refer to the ISCO 2-digit classification of occupations. The reference category for task-types is 'Manual-Routine' tasks.

Results from Table B.3 show that the effect of perceived short-term unemployment risks are significant predictors of retraining intentions, but their effects are additional to that played by fear of automation. Further, controlling for the perceived past influence of technology does not alter the magnitude or significance of our measure of perceived automation risks. These results suggest that our measure of fear of automation captures concerns about the displacing effect of technological advancements that are mostly related to skill obsolescence.

As highlighted in Section 5.1.1, the omission of information on the cost of retraining and individual personality traits may bias our estimates of the effect of fear of automation on retraining intentions. In Table B.4 we partition the sample into broad income categories calculated on the basis of each country's income distribution, and we examine whether workers choose to retrain depending on their income and whether the effect of perceived automation risk on retraining intentions varies along the income distribution. The results show that, whilst the effect of fear of automation on retraining intentions is indeed stronger for high income workers, even workers on low income are significantly more likely to be willing to invest in further training if they are worried about technology-induced unemployment.

Moreover, in Table B.5 we run our baseline specification and additionally control for workers' intentions to leave their job voluntarily and to become freelance, as proxies for openness to new experiences. Adding these controls does not curtail the effect of fear of automation on workers' retraining intentions, thus reducing our concern about the potential bias in our estimates caused by the omission of this personality trait.

Finally, as an additional robustness check we also run country-level regressions. In fact, the pervasiveness of automation and the functioning of labour markets are likely to differ across countries. This in turn is likely to lead to differences in the association between fear of automation and intentions to retrain across countries. Table B.6 shows the coefficient estimates for fear of automation from regressions for each individual country in our sample. Fear of automation is positively associated with retraining intentions in almost all countries in our sample.[23]

5.4. Perceived automation risks and other behavioural traits

We also investigate whether the impact of fear of automation on intentions to retrain is heterogeneous, depending on workers' locus of control, risk preferences and impatience.

It could *a priori* be argued that individuals with internal locus of control might react differently from those who believe that life's outcomes are externally driven when evaluating the impact of technology on their working life and ultimately form intentions to gain new professional skills. The coefficients of the interaction term yield very interesting insights, summarised graphically in Fig. 2a. The effect of fear of technology-induced unemployment on retraining intentions is positive and significant if and only if the agent is already convinced that she controls life's events. Agents who believe they can control life's outcomes and fear the advent of automation are *ceteris paribus* 30% more likely to think about investing in human capital compared to those who have external locus of control and are not worried about being replaced by machines or algorithms, with probabilities increasing from 0.57 in baseline to 0.74.[24]

Similarly, the effect that fear of automation exerts on intentions to retrain might differ depending on individual risk attitudes. Figure 2b shows that perceived automation risk increases the predicted probability of retraining intentions independently from risk tolerance. Fearing automation shifts the probability of retraining intentions for individuals with high risk aversion from 0.60 to 0.64, roughly a 6.5% increase. Fearing automation instead increases intentions to retrain by 7.5% for individuals whose risk aversion is lower than their country median, bringing the probability from 0.66 to 0.71.

As investment in human capital yields delayed payoffs, those who discount the future more heavily might be less inclined to retrain, even more so if the risks of technology-induced unemployment are considered low. The coefficients of the interaction term between our proxy for impatience and fear of automation are reported in Fig. 2c. The effect of perceived automation risks on retraining intentions is not qualitatively different across patient or impatient individuals.

6. Discussion and conclusion

In the current world of work, designing learning programmes to assist workers to keep their skills up to date is key, but embarking on such a mission requires additional knowledge about workers' intentions to acquire new skills. In particular, why are some workers more likely than others to invest in human capital? Are perceived automation risks likely to incentivise investments in retraining?

Using novel survey data for representative samples of working individuals in 16 countries, we show that workers' perceived automation risk is positively correlated with retraining intentions, even after controlling for multiple behavioural traits that previous literature has found to impact investments in human capital. We also show that fear of automation strongly reinforces the well-known positive effect of locus of control on skills' accumulation: those workers who are worried about technology-induced unemployment and simultaneously hold internal locus of control are 30% more likely to think about investing in further training compared to those who have external locus of control and are not worried about being replaced by machines or algorithms. Turning to other behavioural traits, our analyses show that the effect of perceived automation risks on retraining intentions is not qualitatively different across patient or impatient, risk averse or risk seeking individuals.

Taken together, our results are clearly suggestive of a positive relationship between intentions to acquire new skills and perceived automation risks. Additionally, the complementarity between fear of automation and internal locus of control could widen existing labour market inequalities. This is consistent with evidence that participation in general training is lowest among workers with an external locus of control, because their subjective expected returns to the retraining investment are considerably lower than the perceived returns of workers with an internal locus of control (Caliendo et al., 2020b).

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[23] We also conducted two additional robustness checks. Labour market policies meant to protect workers from disruptions caused by technology clearly have the potential to influence workers' concerns and intentions to retrain. Equally, in countries which use more robots, automation appears to be more tangible and might shape workers' willingness to gain new skills. Controlling for countries' expenditure on labour market policies, be they passive or active, or the density of robots used in the manufacturing sector does not alter the effect exerted by perceived automation risks on workers' intentions to invest in additional human capital. The related estimates are available from the authors upon request.

[24] In Fig. B.1 we show the coefficient estimates for the interaction between fear of automation and internal locus of control, from regressions for each individual country in our sample. The Figure clearly shows that the reinforcing effect of fear of automation and internal locus of control that we have uncovered appears to be valid in all countries. However, for some of them – namely Brazil, Ireland and Germany – the coefficient of the interaction term is not statistically different from 0 at the 10% level.
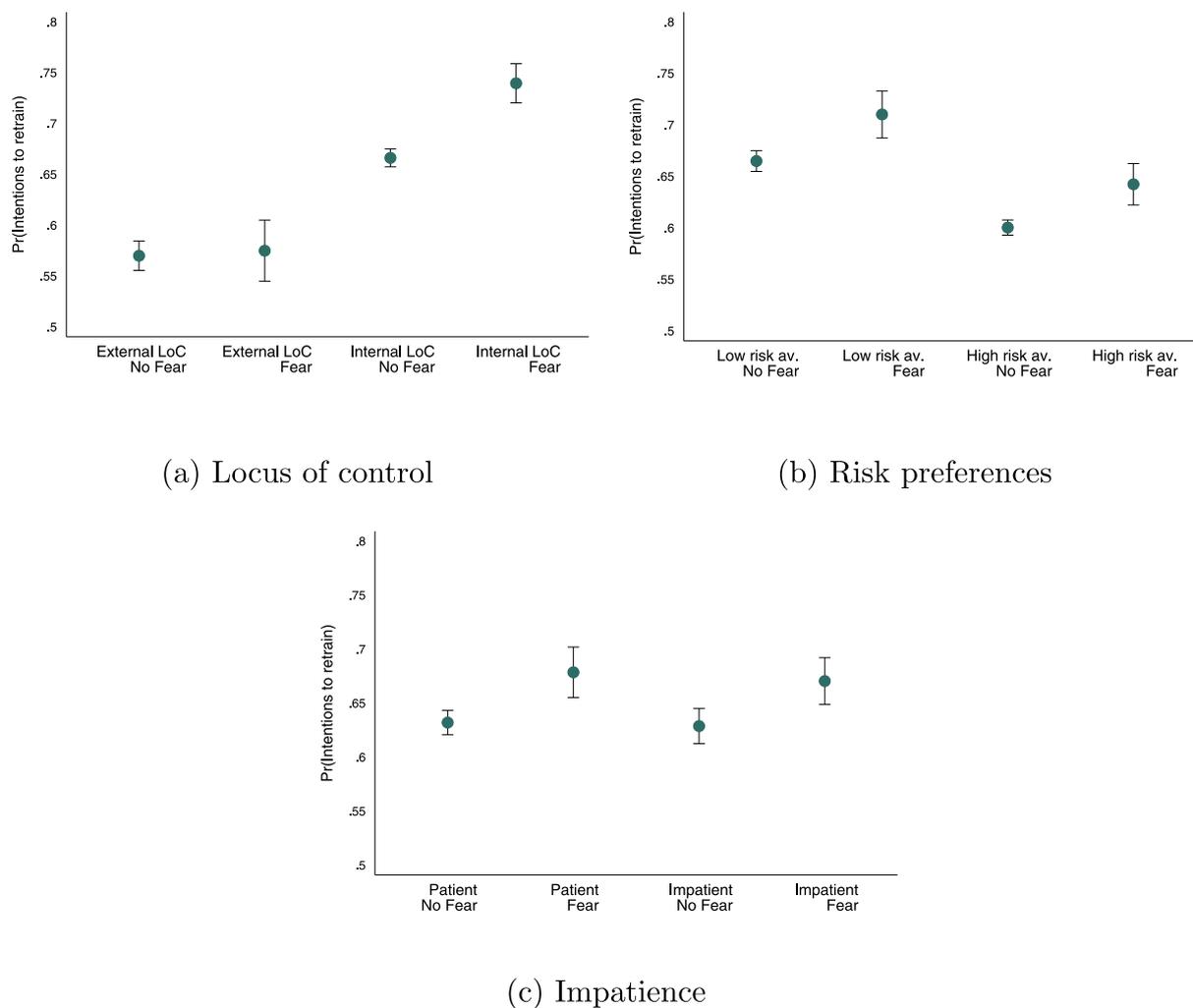
(a) Locus of control

(b) Risk preferences

(c) Impatience

Fig. 2. Predicted probability of retraining intentions by locus of control, risk and time preferences. *Notes*: Predicted probability of retraining intentions for the four possible combinations of locus of control and fear of automation (panel a), risk tolerance and fear of automation (panel b), impatience and fear of automation (panel c). Respondents are classified as fearing automation if they reported being moderately or very worried about losing their job to a machine or computer algorithm. The dots represent marginal effects from the interaction variable, and the bars show 95% confidence intervals. All regressions include the full set of control as per Table 2 column (4).

Therefore, designing adequate policies which aim at building a learning culture (Berger and Engzell, 2020) and providing workers with information on the benefits of retraining activities is key to promote mobility in the automation age.

We believe that research on systematic changes in the decisions to accumulate skills in the current technological era and their relation to behavioural factors will therefore appeal to policy makers. This is because the speed of technological change is notable, and routine-biased technological change is likely to increase following the coronavirus economic crisis, as it did after other recent economic downturn episodes (Hershbein and Kahn, 2018). Further, changes in the propensity to invest in human capital will bring about changes in labour markets' structure and dynamics, and consequently in aggregate economic and socio-political outcomes. In fact, if people do not retrain and fall into prolonged unemployment spells, the sustainability of the welfare state is endangered. Thus, it is in the policy makers' interest to design active labour market policies that are aligned to labour markets' needs and bypass self-selection into retraining.

To effectively equip workers with the ability to adapt to a changing world of work, governments could envision retraining programmes targeted to workers whose future employment opportunities are low due to automation. As a matter of fact, workers consider training assistance the best way to respond to adverse labour market developments generated by the adoption of labour-saving technology (Di Tella and Rodrik, 2020). Yet, few of such schemes currently exist. The Australian and Austrian governments, in collaboration with industry associations, have implemented targeted employment assistance to support individuals in sectors impacted by structural change to transition to new jobs (OECD, 2019). At present, these schemes do not entail automatic opt-out enrolment. Yet, in light of our results, such feature could be crucial to carry people through their employment history, especially for those individuals least likely to take actions and engage in retraining on their own account.

This study opens several avenues for further research. First, due to data availability, our study did not investigate actual behaviour. Instead, we focused on the relation between perceived automation risks and intentions to gain new professional skills. The theory of planned behaviour (Ajzen, 1991) suggests that stronger intentions to engage in certain behaviours are more likely to produce those behaviours. As mentioned above, it is thus plausible to hypothesise that the positive association linking fear of automation and retraining intentions survives even when evaluating actual enrolment into training. However, further work is needed to ascertain the validity of this hypothesis.

Equally, we believe that concentrating on training outside the workplace was the most sensible first step given the known heterogeneity in the availability of on-the-job training across occupations which specifically penalises workers in automatable jobs. Nonetheless, a more systematic analysis of the effects of fear of automation on other types of training is an important area for future work.

Third, alleviating the omitted variable bias affecting our estimation strategy appears to be a crucial avenue for future research. Further, designing an experiment to mute the reverse causality channel linking retraining intentions and perceived automation risks appears to be a promising step forward to causally identify the effect that fear of automation exerts on human capital accumulation.

Finally, there is great need for empirical evidence on the actual effectiveness of training programmes in tackling the substitution effect of automation. An evaluation of skills accumulation schemes should be conducted while accounting for people's *ex ante* concerns about technological advancements and personal dispositions and traits.

Declaration of Competing Interest

The authors have no financial interests to disclose.

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.jebo.2021.12.027.

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