How Scary is the Risk of Automation?
Evidence from a Large Scale Survey Experiment

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Abstract

Technological advancements have historically reshaped labor markets; now, emerging AI innovations like ChatGPT may put previously "safe" occupations at risk of automation. This study investigates individuals' willingness to pay for reduced automation risk through a discrete-choice experiment involving nearly 6,000 participants. Results reveal that respondents would accept a salary reduction equivalent to almost 20% of the Swiss median annual gross wage for a 10 percentage point lower automation risk. While preferences are generally homogeneous, differences exist among demographic groups. Men, younger and risk-tolerant individuals, and those with higher education show lower willingness to pay for reduced automation risk.

Keywords: Artificial intelligence, automation, willingness to pay, survey experiment

JEL classification: J24, O33

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The authors are grateful for the financial support from the Swiss State Secretariat for Education, Research and Innovation through its Leading House on the Economics of Education (ECON-VPET). The experiment presented in this study is registered in the AEA RCT Registry (AEARCTR-0011903).

1 Introduction

In recent decades, advances in digital technologies have profoundly transformed labor markets in developed economies, particularly by automating human work in many low-skilled and routine occupations, leading to job loss and socio-economic decline for affected workers (Katz & Murphy, 1992; Autor et al., 2003; Cortes, Jaimovich & Siu, 2020). Initial studies on recent AI innovations such as ChatGPT suggest that they may increase the risk of job displacement in occupations previously considered safe from automation (Eloundou et al., 2023; Hui et al., 2023). As a consequence, the question of how individuals respond to the growing threat of automation is receiving increasing attention in the literature (e.g., Di Giacomo & Lerch, 2023; Goller, Gschwendt & Wolter, 2023; Lergetporer, Wedel & Werner, 2023).

Research on the impact of digitalization on labor markets has shown, first and foremost, that it affects workers heterogeneously, depending on their skill level and the task content of their occupations. While workers with higher levels of education and individuals working in occupations that predominantly involve cognitive and non-routine tasks have experienced an increase in demand due to workplace digitalization in recent decades, digital innovations such as computers and robots have increasingly been used to substitute human workers in routine intensive occupations (Katz & Murphy, 1992; Autor et al., 2003). As a result, most labor markets in developed economies have experienced a general upgrading and a decline in routine employment, oftentimes accompanied by widespread job loss and socioeconomic decline among routine workers (e.g., Goos et al. 2009; Cortes, Jaimovich & Siu, 2020; Jaimovich & Siu, 2022).

In contrast, recent innovations in generative AI are likely to affect occupations that require highly skilled workers and primarily involve non-routine and cognitive tasks such as writing, programming, or designing (Eloundou et al., 2023; Felten et al., 2023). In fact, a first study showed that the introduction of three generative AI models has had negative employment and wage effects for workers providing non-routine cognitive work that these AI models are specialized in (Hui et al., 2023). This is particularly important because, while most developed economies, such as Switzerland, so far navigated the digital transformation without much harm to its workers (Gschwendt, 2022), their workforce, characterized by a high level of education and a high proportion of non-routine cognitive workers, as such is poised to face a greater degree of exposure to these new digital innovations than previous ones, i.e., software and robot technology.[1]

While the empirically observed behavior in response to increased automation risks is not unambiguous as research on labor market choices and policy preferences shows (e.g., Busemeyer & Sahm, 2022; Gallego et al., 2022; Golin & Rauh, 2022; Hess, Janssen & Leber, 2023; Lergetporer, Wedel & Werner, 2023, Petrova et al., 2024), recent studies find that individuals adjust their educational and occupational choices in order to reduce their risk of job automation. A recent paper on study choices shows that young people have responded to the introduction of industrial robots by increasing investment in higher education, with increased college enrollment (Di Giacomo & Lerch, 2023). Similarly, in response to the introduction of ChatGPT, prospective apprentices adjusted their occupational choices away from occupations that primarily involve cognitive tasks or require high language skills and are thus more likely to be affected by generative AI technologies (Goller, Gschwendt & Wolter, 2023).

While these studies indicate that considerations of minimizing the risk of job loss due to automation play an important role early in career choices, the subjective monetary value that people attach to a reduced probability that their trained occupation could be displaced by

[1] Not surprisingly, AI skepticism has increased significantly since the public launch of ChatGPT, according to surveys conducted before and after the launch of ChatGPT by the Digital Society Initiative of the University of Zurich (https://www.dsi.uzh.ch/de/current/news/2024/dsi-insights-ki-schweiz-skepsis.html). Here too, however, the results were mixed. While the proportion of respondents who would leave decisions to machines fell significantly after the launch of ChatGPT, the proportion of respondents who would allow ChatGPT to do some of their work was quite substantial. Three quarters of the respondents would delegate work of teachers, webdesigners or journalists to a machine.

technological progress is unknown. We add to this emerging literature by quantifying the willingness to pay (WTP) for occupations with lower exposure to automation risks.

To do this, we conducted a discrete-choice experiment among a representative sample of 5'952 adult residents in Switzerland in Fall 2023, almost one year after the launch of ChatGPT and other tools of generative artificial intelligence. We elicit their preferences for a hypothetical child's educational and career path. The empirical analyses of the preferences of the respondents for a particular career for a 40-year-old hypothetical child show that they would be willing to accept a scenario with an almost 20% lower gross annual wage if they could, at the same time, reduce the exposure to automation risk by 10 percentage points. The WTP to reduce automation risk varies by respondent characteristics, such as education level, nationality, gender, age, and risk aversion. The identified extremely high WTP reflects major concerns about automation-induced job losses and their implications. After all, since automation technology generally affects tasks and occupations across firms and industries, job loss due to automation typically implies diminished opportunities to secure similar positions.

The remainder of this paper is structured as follows: In the next section, we outline the experimental setup. Section 3 describes the collected data and used methods. Section 4 presents the results, both for our overall sample as well as for relevant subgroups, and Section 5 concludes.

2 Experimental Setup

Discrete Choice Experiments (DCEs) have gained growing popularity in economics for eliciting the preferences of individuals in various domains of life.[2] As a well-established stated

[2] Overviews are provided in, e.g., Ryan et al. (2008), Bliemer and Rose (2021), and Shang and Chandra (2023).

preference method, DCEs are rooted in the economic frameworks of random utility maximization (McFadden, 1974) and Lancaster's theory of consumer choice (Lancaster, 1966).

The fundamental idea of DCEs is that an individual's utility can be deconstructed into the utility derived from the essential characteristics, or attributes, of the respective good or service. These attributes must be known by individuals and are valued differently by them, rendering some combinations of attributes more and some less attractive. Therefore, DCEs require that individuals make choices involving trade-offs among the given attributes, often in hypothetical decision scenarios with two or more alternatives. In this paper, we leverage the methodology of DCEs to study how selected career path attributes relate to preferences for career choices for hypothetical children.

Our DCE methodology offers a solution to two major challenges encountered when using realized choice data to elicit individuals' preferences for career paths. First, identifying an individual's factual alternatives to their realized career path is extremely difficult. Second, the presence of correlations between observable and unobservable career characteristics may bias results based on such realized choice data. In contrast, our DCE enables us to observe individuals' repeated choices between two varying hypothetical career paths, each defined by a distinct set of attributes of interest. Moreover, explicitly clarifying that the career choices solely differ in these specified attributes helps mitigate the risk of omitted variable bias.

Despite the growing popularity of DCEs across various fields of economics, reservations persist regarding stated preference methods' external validity, notably concerning potential biases stemming from their hypothetical nature (e.g., Loomis 2011). In fact, meta-analyses have found a significant 'hypothetical bias' in studies directly asking individuals about their WTP for public goods, such as natural resource conservation, leading to an overestimation of WTP for such goods (e.g., List & Gallet, 2001; Murphy et al., 2005).

However, our approach is very different from that of these studies, both in terms of methodology and the good being evaluated. First, by conducting a DCE, we indirectly estimate individuals' WTP for career attributes instead of directly asking them to assign monetary values to them, which should reduce the hypothetical bias (OECD, 2018). Second, while valuing non-market public goods may indeed prove challenging for non-experts, often resulting in arbitrary valuations, for the markets of interest here, i.e., the labor and education market, individuals have taken previous consideration to their own career choices and thus have real-life reference points (Datta 2019). Notably, in health markets, where such reference points are also available to individuals, studies find that DCEs produce reasonable predictions of actual health-related behaviors (Mohammadi et al., 2017; Quaife et al., 2018). Moreover, Mas and Pallais (2017) conducted both a DCE and a field experiment, finding that preferences for job characteristics in a call center, as revealed in their DCE, closely mirror those observed in the field experiment, indicating that well-designed survey-based choice experiments yield responses that closely approximate real market choices. Similarly, Wiswall and Zafar (2017) found that individuals' education and job preferences, as estimated in a DCE, strongly correlated with their later actual education and job choices.

The approach of asking respondents about their preferences for the education and occupation of a hypothetical child aged 40, rather than asking respondents directly about their own WTP for a lower automation risk, is justified by several considerations. First, we can thus present all respondents with comparable alternatives to choose from, which—as under laboratory conditions—differ only in the attributes we have defined. Second, regardless of the age, education, gender, or professional experience of the respondents, we can choose a realistic scenario in which the decisions are to be made for people who are all almost at the peak of their professional careers (in terms of salary and hierarchical position), i.e., at an age at which no major changes should occur without external influences, but at the same time they are still so far away from retirement that they could not simply escape an exogenous shock by taking early retirement. Third, by asking respondents to consider their hypothetical child for whose well-being they will be concerned about, we prompt respondents to make choices that—in their view—benefit that person.

In other words, the choice is to be made for a person close to the respondent (hypothetical child) who, in the event of a higher risk of automation of the current occupation, could no longer react simply (i.e., only at great cost) by undergoing a new education or by ending their working life. Even though this scenario does not take into account the life situations of the interviewees, but deliberately abstracts from them, they are included in the analysis. This is because they can be examined as determinants of the heterogeneity of WTP. Finally, by randomly allocating hypothetical sons and daughters to the respondents, the setting allows us to verify whether preferences vary with the gender of the concerned person (the hypothetical child).

The initial attributes that describe the alternatives and the levels that capture the relevant variation in the attributes were selected based on the literature regarding automation, preferences for different educational degrees, prestige associated with different occupational and educational choices, and experts' opinions. Regarding the latter, we consulted experts in the field of education and labor economics from academia as well as practitioners. We asked them about the selection of attributes and the chosen levels. The final list and wording of the attributes and levels were done in consultation with a focus group with a total of 33 participants, where we tested whether the terms used were clear and could be understood by the general population. Given the objective of our study, we consider the four attributes shown in Table 1 to be the most relevant for our analysis. Other attributes used to describe career paths, such as job satisfaction, the possibility to work part-time, or flexible working hours, were excluded, as they would have greatly increased the number of choice sets without significantly contributing to answering our main research question. In the particular case of job satisfaction, consultation with our focus group showed that the respondents would have seen this as a dominant characteristic across choice sets, with the danger that they would have disregarded the levels of other attributes. To avoid confusion, we explicitly instructed respondents during the survey to assume that any career features not mentioned in the description were the same across the alternatives, particularly job satisfaction and workload.

Regarding the levels of the attributes, yearly wages were selected based on median wages for people aged between 35 and 45 with different education backgrounds working full-time, obtained from the Swiss Labor Force Survey (SLFS) 2022. The levels for the risk of automation were chosen based on what could be realistic to expect in the next ten years, according to the scientific literature (Frey & Osborne, 2017; Arntz et al., 2016; Webb, 2019). Importantly, we explicitly specified the automation risk to the respondents as "the probability that the job could be completely replaced by digital technologies such as robots or artificial intelligence within 10 years." Consequently, this risk is very different from the risk of "only" losing a particular job for a specific firm because it affects all jobs in the given occupation.

The three levels of the highest educational attainment were chosen according to the most prevalent degrees in Switzerland among Swiss residents between 35 and 45 years of age. Among people with upper secondary level as the highest educational degree, vocational education and training is the most frequent one (28% of the relevant population). In addition, a university degree and a university of applied sciences degree are included as levels, the most prevalent tertiary degrees in the relevant population (18% and 12%, respectively). Importantly, in Switzerland, a Baccalaureate school degree is almost always followed by a tertiary education degree, with more than 90% starting studies in a higher education institution. This fact, together with the feedback received from the focus group, convinced us to exclude a separate level for a Baccalaureate school degree. For hierarchical position, a high, top-management position and a low, non-management position were included. [3] The final selection of attributes and the attribute levels are summarized in Table 1.

Table 1

Career path attributes and levels

Attribute	Level
Annual gross wage (CHF)[4]	75,000
	100,000
	115,000
	130,000
Automation risk (%)	30
	45
	60
Highest educational attainment	Apprenticeship certificate
	University of Applied Sciences degree
	University degree
Hierarchical position	Low (without management function)
	High (top management)
Job satisfaction	Satisfied
Weekly working time	42 hours

The next step in the development of the DCE was the selection of choice sets to be shown to the study participants. With four attributes, each with between two and four levels, plus the framing of a son or a daughter, the total number of possible choice sets in the DCE was 2,556. In order to generate a smaller number of choice sets that would still be able to efficiently capture the key trade-offs that are the focus of our study, we decided on a D-efficient block design using the software Ngene. The final design consisted of 21 choice sets split into three blocks with

[3] We piloted a different version with three levels of hierarchical positions but did not find differences in the preferences between middle management and high management functions.

[4] 1 CHF = approximately 1.1 US$ or 1 Euro.

seven choice sets containing two alternatives each.[5] Each participant was randomly assigned to answer one of the blocks, and the order in which choice sets were presented to respondents within each block was also randomized. In addition, we randomly assigned respondents to one of two subgroups, one asking about preferences for a hypothetical daughter and the other asking about preferences for a hypothetical son. An example of a choice set, including the introduction, is shown in Figure 1.[6]

Figure 1

Example of a Choice set

«Imagine you now have a 40-year-old son (daughter). We will show you 7 sets of two choices of occupational situations and educational qualifications. The two choices differ only in 4 characteristics: Highest educational attainment, hierarchical position in the job, gross annual wage in Swiss Francs and automation risk.*

We would like to know which of the two choices you would prefer for your 40-year-old son (daughter). Assume that your son (daughter) is equally satisfied and that the actual working week is 42 hours in all choices.

**By automation risk, we mean the risk that the occupation could be completely replaced by technologies such as robots or artificial intelligence within 10 years.*

Which of the two choices would you like your 40-year-old son (daughter) to have, option A or option B?»

	Alternative A	**Alternative B**
Highest educational attainment	University of Applied Sciences degree	University degree
Hierarchical Position	High (top management)	Low (without management function)
Annual Gross Wage (CHF)	115,000	130,000
Automation Risk	30%	30%
Your choice		

[5] The full choice set universe is shown in Table A.1 in the appendix.

[6] A screenshot of an actual choice set is shown in Figure A.1.

3 Data and Methods

The DCE described in the previous section was fielded as part of the fifth *Survey of Public Opinion on Education*, which was conducted in Switzerland between September and October 2023 by *Intervista AG*, a private market research institute, on behalf of the Centre for Research in the Economics of Education of the University of Bern. The survey was carried out online. The analysis sample contains information on a total of 5'952 Swiss residents from all three main language regions (German, French, and Italian) aged between 25 and 60. The sample is based on a random draw from the Intervista Internet Panel, with over 120,000 actively recruited persons who are compensated for their participation. To ensure the representativeness of the sample for the Swiss population, quotas for age, gender, region, and education were used. The Italian-speaking region, which is the smallest in size, was oversampled to obtain more accurate estimates and avoid small cell sizes. The response rate was 91%, and panelists were invited to the survey on a rolling basis until the quotas were filled. In all our empirical analyses, we employ survey weights to ensure the sample's representativeness with respect to the national population.

The comprehensibility of the questionnaire and the criteria of the choice sets were first tested in focus group interviews with 33 participants. After ensuring that the questions were understood as we intended, the model was tested by Intervista with a sample of around 100 respondents. This pilot test showed that the originally planned division of the hierarchy levels into 3 categories, namely no supervisor function, middle management and top management, was not expedient because the respondents made no difference in their preferences between the top and the middle management position. Therefore, for this attribute, in the final study a distinction was only made between a low position without a management function and a top management position.

Intervista monitors the survey responses of its panelists for inattentiveness and randomly answered questions, and removes such individuals from the panel. Nevertheless, to additionally check whether respondents who progressed rather swiftly through the choice sets bias the results, Table B.1 in the Appendix shows results using a reduced sample that excludes all respondents who either spent less than 60 seconds on the introduction page for the DCE or less than 30 seconds on one of the choice sets. The results of the reduced sample are virtually identical to those of the full sample.

Our analysis is based on McFadden's (1974) random utility model. The utility that respondent i derives from choosing alternative j for his/her hypothetical son or daughter g in choice set s is given by:

$$U_{isjg} = CP_{isjg} + e_{isjg} \qquad i = 1,\ldots,N;\ s = 1,\ldots,7;\ j = A,B;\ g = 1,2 \tag{1}$$

where CP_{isjg} represents the systematic component of the overall utility, and e_{isjg} is a random term. We assume the individual chooses that alternative, A or B, if it delivers a higher utility than the other alternative in the choice set. Assuming e_{isjg} to be independently extreme value type-I distributed, the probability of choosing j takes the form:

$$\text{Prob}(y_{isg} = \text{j}) = \frac{exp(\text{CP}_{\text{isjg}})}{\sum_{l=A,B} exp(CP_{islg})} \tag{2}$$

where y_{isg} denotes the choice observed for i in choice set s for the daughter/son subsample g. We first used a conditional logit model (McFadden, 1974) to approximate respondents' preferences for career path attributes. Here, we consider a linear specification for CP_{isjg} of the form:

$$CP_{isjg} = \alpha\text{jg} + A_{isj}{'}\delta_g \tag{3}$$

where A_{isj} is the vector of the four attributes describing alternative j for individual i in choice set s. The parameter vector δ_g is the main interest of our study as it describes the individuals' preferences for the different career path attributes, while α_j is an alternative-specific intercept estimated alongside δ_g. As usual, α_{jg} must be interpreted in relative terms describing general preferences of individuals for one alternative (in our case option B) over the other alternative (in our case option A).

While the preference parameters δ_g delineate the marginal utility of the various attributes, it is often more straightforward to interpret these parameters in monetary values and as a marginal rate of substitution with a monetary reference attribute. This helps convey individuals' WTP per unit of each attribute. Derived from contingent valuation theory, WTP assesses how much consumers are willing to pay on average for a change in a specific attribute, keeping their level of utility the same. WTP can be positive or negative depending on whether individuals derive a utility or disutility from the given change of the attribute. We estimate the model in the preference space, which gives a better goodness-of-fit (see also Hole and Kolstad, 2012), where parameters have utility units, and then we compute the WTP by dividing the parameters by the parameter associated with the wage attribute.

Because preferences for different alternatives for career paths or parameters are likely to differ across individuals, we used a mixed logit model in a second step to approximate preferences for career path attributes more flexibly. In the mixed logit (see, for example, McFadden & Train, 2000), individual heterogeneity is accounted for by assuming individual-specific parameters, in our case assuming δ_{gi} and α_{jgi} in equation (4) instead of fixed parameters δ_g and α_{jg}. We assume the parameters in the mixed logit to be normally distributed except for the wage parameter, which we assume to follow a log-normal distribution. All random parameters are allowed to correlate with each other.[7]

[7] For a detailed description of mixed logit models and their estimation, see McFadden & Train (2000).

Table 3 shows summary statistics of our sample. Sociodemographic characteristics are reported overall and by respondent gender. Of the 5'952 respondents, the majority are from the German-speaking area of Switzerland (71%), followed by the French- and Italian-speaking regions (25% and 4%, respectively). The gender distribution is comparable to official statistics reported by the Federal Statistical Office. The mean age in the sample is 43 years, and 42% of the sample has completed a tertiary degree. The only significant gender differences observed in the chosen variable are the proportion of people who completed a tertiary degree, which is 44% for men and 40% for women, and the proportion of people who self-defined as risk-seeking, which is 12 percentage points higher for men than for women.

Table 3

Background characteristics of the sample by respondent gender

	Full Sample	Female	Male
Male	0.503	0.000	1.000
Mean Age	43.118	43.106	43.131
German Region	0.712	0.709	0.715
French Region	0.248	0.251	0.246
Italian Region	0.040	0.040	0.039
Below Secondary Degree	0.060	0.073	0.047
Secondary Degree	0.517	0.523	0.512
Tertiary Degree	0.423	0.404	0.442
Swiss Citizen	0.727	0.728	0.726
Parents	0.517	0.544	0.490
Patient	0.425	0.416	0.433
Risk-seeking	0.421	0.363	0.478

4 Results

4.1 Conditional Logit Estimates and WTP for Lower Automation Risk

As a starting point for analyzing career preferences, we consider the conditional logit model under the assumption of homogeneous preferences, and we pool the sample across sons and daughters. Table 4 displays the results. Column 1 shows our baseline specification with all attributes included in the model. The signs of the wage and automation coefficients are as expected, i.e., individuals prefer alternatives with higher wages, and, most importantly, they clearly dislike a higher automation risk. Note that we scaled the wage attribute to CHF 10,000 per year and the variable for the risk of automation to 10 percent point values. Furthermore, all things equal, people are less prone to choose a career path with a university degree, which can be explained by the fact that ceteris paribus people prefer a shorter education time, and, therefore, less costs associated with it. It could further be related to the general popularity of the vocational education track in Switzerland, as there is no clear preference between a secondary-level vocational degree or a degree from a university of applied sciences, the latter usually being the tertiary qualification for people having a vocational qualification at the upper-secondary level. Finally, a top management position is preferred to a regular employee position.

To assess potential differences in preferences between the subsamples for sons and daughters, columns 2 and 3 report results for extended conditional logit models that additionally include interactions between automation risk, and all attributes, respectively, and a binary variable denoting whether observations belong to the son subsample. Based on previous literature (e.g., Jacobs et al, 2006; Tungodden & Willén, 2023), it would be possible that labor market expectations and preferences for risk vary depending on the gender of the child. This might be because of different role expectations, or expectations to adapt to such new risks. However, given the insignificant coefficients of the interactions, preferences regarding our attributes of interest do not appear to differ by the gender of the hypothetical child.

Table 4

Conditional logit estimates and WTP for career path attributes

	Estimated coefficients			WTP
	(1)	(2)	(3)	(4)
Lower automation risk (10 ppt.)	0.532***	0.517***	0.512***	16368.1***
	(0.0149)	(0.0171)	(0.0209)	(287.4)
University degree	-0.351***	-0.351***	-0.378***	-10797.0***
	(0.0229)	(0.0229)	(0.0327)	(840.4)
UAS degree	-0.00879	-0.00876	-0.0458	-270.2
	(0.0219)	(0.0219)	(0.0311)	(676.5)
Top management position	0.0475**	0.0475**	0.0514*	1460.3**
	(0.0158)	(0.0158)	(0.0224)	(472.1)
Annual gross wage (10'000 CHF)	0.325***	0.325***	0.324***	
	(0.00712)	(0.00712)	(0.0101)	
Automation risk × son		0.0295	0.0413	
		(0.0176)	(0.0298)	
University degree × son			0.0533	
			(0.0459)	
UAS degree × son			0.0737	
			(0.0437)	
Top management position × son			-0.00799	
			(0.0316)	
Annual gross wage × son			0.00160	
			(0.0142)	
N	83,328	83,328	83,328	83,328

Notes: For columns 1 to 3, the outcome is a dummy variable on whether or not a career path is chosen or not. *son* is a dummy variable equal to one if respondents are in the son subsample and equal to zero if they are in the daughter subsample. WTP in column 4 is calculated by the ratio of the estimate for the respective career path attribute and the estimate for annual gross wage in column 1, times 10'000 CHF. Population weights are applied, standard errors are shown in parentheses, and * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Finally, column 4 illustrates the WTP for different career attributes as derived from the conditional logit model estimates in column 1. Specifically, it indicates that the WTP for a 10-

percentage-point reduction in the risk of job automation is approximately CHF 16,368 in annual gross wage. This value is calculated as the ratio of the coefficient 0.532, representing the effect of automation risk reduction on the likelihood of choosing an alternative, to the coefficient 0.325, representing the effect of the annual gross wage on the likelihood of choosing an alternative, multiplied by 10,000. Given that the median yearly income of an employee was around 88,000 CHF in 2022 (Federal Statistical Office, 2023), this would mean that people are willing to pay around 19% of a median yearly income for a 10 ppt. lower automation risk. In comparison, individuals are only willing to forgo CHF 1,460 (or 1.65 percent) per year for the benefit of having a top hierarchical position.

4.2 Mixed Logit Estimates and WTP for Lower Automation Risk

Table 5 presents the results of the mixed logit models, using the same specifications as in conditional logit models shown in Table 4, but allowing for individual heterogeneity in preferences by specifying random parameters for all attributes. Correspondingly, column 1 shows the mean estimates of the distributions of random coefficients for our baseline model, only including main effects, columns 2 and 3 show the mean estimates for the two extended models, including interactions of the son subsample dummy with automation risk and with all attributes, respectively. Again, column 4 reports the WTP calculations based on the estimates in column 1. Additionally, the estimated standard deviations of these distributions can be found in Table B.4 in the appendix.

Qualitatively, the mixed logit results are very similar to the results of the conditional logit model, but there are also some important differences and additional insights generated by the mixed logit model. First, the standard deviations for all random coefficients are significantly different from zero (Table A.3, column 1), highlighting substantial heterogeneity in preferences for the career path attributes.

Second, the mean WTP estimates show that respondents would be indifferent between choosing a job with a given automation risk and a job with a 10 percentage points higher risk if the increase in yearly wages is around CHF 15,300 (around 17% of the average yearly income), which is roughly CHF 1000 less than the WTP estimated in the conditional logit model. One reason is that the marginal utility of a wage increase is estimated larger in the mixed logit at 0.513, while the marginal disutility of a higher automation risk is also larger but relatively less than in the conditional logit.

Table 5
Mean mixed logit estimates and WTP for career path attributes

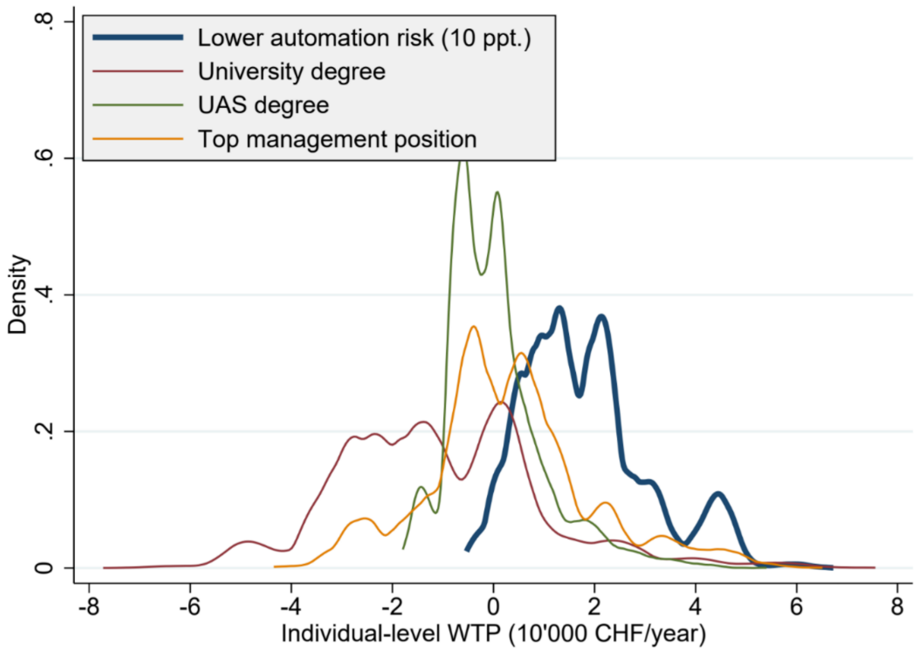
	Mean estimated coefficients			WTP
	(1)	(2)	(3)	(4)
Lower automation risk (10 ppt.)	0.787***	0.777***	0.763***	15333.1***
	(0.0243)	(0.0289)	(0.0333)	(366.8)
University degree	-0.560***	-0.565***	-0.592***	-10910.1***
	(0.0417)	(0.0422)	(0.0590)	(912.3)
UAS degree	-0.0301	-0.0288	-0.0765	-586.6
	(0.0325)	(0.0327)	(0.0471)	(638.6)
Top management position	0.0670**	0.0668**	0.0616	1305.9**
	(0.0253)	(0.0255)	(0.0361)	(485.2)
Annual gross wage (10’000 CHF)	0. 513***	0.519***	0.520***	
	(0.0128)	(0.0131)	(0.0227)	
Automation risk × son		0.0348	0.0514	
		(0.0317)	(0.0481)	
University degree × son			0.0554	
			(0.0854)	
UAS degree × son			0.0723	
			(0.0666)	
Top management position × son			-0.00757	
			(0.0524)	
Annual gross wage × son			0.00695	
			(0.0226)	
N	83,328	83,328	83,328	83,328

Notes: For columns 1 to 3, the outcome is a dummy variable on whether or not a career path is chosen or not. *son* is a dummy variable equal to one if respondents are in the son subsample and equal to zero if they are in the daughter subsample. WTP in column 4 is calculated by the ratio of the estimate for the respective career path attribute and the estimate for annual gross wage in column 1, times 10'000 CHF. Population weights are applied, standard errors are shown in parentheses, and * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Another reason could be the underlying heterogeneity in preferences for a lower automation risk, where the conditional logit model imposes the restriction of homogeneous preferences. Figure 2 depicts the distribution of posterior estimates of the individual-specific estimates of the WTP for all attributes. The graph shows that the WTP for a lower automation risk of 10 percentage points ranges from about CHF -5,000 to CHF 50,000 in yearly wages, i.e., some respondents would be willing to give up a relatively large amount of wages in order to reduce the risk of automation in the job, while for others, the marginal disutility of higher automation risk is close to zero, or even positive in very few cases, showing a form of risk-seeking behavior.

Figure 2

Distribution of individual-level WTP for career path attributes



Concerning the other specific career path attributes, the mean WTP for a vocational education and training degree in comparison to a university degree is around CHF 11’036 CHF. This is comparable to the results of the conditional logit model, which indicates once again that people prefer a vocational education rather than a university education for the same yearly wage, hierarchical position, and automation risk. The results also show that individuals would be willing to forgo around CHF 1,300 of a yearly wage for a top managerial position, which is slightly less than what was obtained from the conditional logit model, but the distribution of individual-level estimates of the WTP (Figure 2) again shows substantial heterogeneity.

Given the apparent large heterogeneity in preferences, in the following two subsections, we examine the WTP for lower automation risk in more detail, which is the primary focus of this paper. Leveraging the mixed logit model setup, we investigate how WTP for lower automation risk varies across various respondent characteristics. Moreover, we explore the interplay between WTP for lower automation risk and our remaining career path attributes, namely type and level of education and hierarchical position.

4.3 WTP for Lower Automation Risk by Respondent Characteristics

Along with our large-scale survey experiment, we collected a wide variety of respondent characteristics, enabling us to uncover how WTP for lower automation risk varies among distinct respondent demographics. Table 6 presents the results of a multivariate regression of WTP for lower automation risk on key respondent characteristics, including gender, age, language region, education, nationality, parenthood, and whether respondents are patient or risk-seeking, respectively. Results are reported for the full sample in column 1 and for the daughter and son subsamples in columns 2 and 3, respectively.

Most importantly, the results indicate that gender, age, education, nationality, and risk-seeking behavior are significantly associated with the WTP for a lower automation risk. Male respondents show a mean WTP that is CHF 686 lower than that of female respondents, which implies that a 10-percentage points reduction in the automation risk is valued higher by women than men. Concerning age, people aged 50 and older need around CHF 2,102 more to counteract an increase in automation risk in comparison to people younger than 35.

Table 6

Individual determinants of WTP for a lower automation risk

	(1) Full sample	(2) Daughter subsample	(3) Son subsample
Male	-686.4*	-457.7	-873.9
	(333.7)	(468.1)	(475.5)
35–49	717.8	1131.3	291.9
	(427.7)	(610.7)	(599.7)
50+	2102.0***	2621.3***	1641.3*
	(482.1)	(690.3)	(673.6)
French region	-170.8	830.0	-1171.6*
	(387.6)	(551.8)	(545.0)
Italian region	522.3	1051.7	-2.629
	(485.7)	(703.0)	(670.7)
Below secondary degree	2367.7**	1813.3	2860.3*
	(814.0)	(1114.0)	(1188.5)
Secondary degree	1953.6***	1858.4***	2011.5***
	(353.3)	(492.3)	(507.8)
Swiss citizen	1244.4**	370.9	2102.4***
	(384.3)	(560.0)	(530.9)
Parent	-433.6	-497.9	-435.9
	(358.1)	(512.9)	(501.4)
Trait: patient	151.2	-151.7	463.0
	(341.4)	(476.8)	(487.2)
Trait: risk-seeking	-989.5**	-832.5	-1178.9*
	(339.6)	(481.4)	(480.6)
Constant	15943.8***	15783.0***	16160.1***
	(527.1)	(746.7)	(747.5)
N	5948	2975	2973

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: The multivariate regression is based on a reduced sample of 5948 because the nationality of four respondents could not be determined. The constant states the WTP estimation for a female non-Swiss citizen from the German-speaking region below the age of 35 with tertiary education, no children, and impatient and risk-averse traits.

The reason behind this may be that older people have more labor market experience and have already lived through one or more technological and employment changes in labor market conditions, and may even have experienced some periods of unemployment as a result and are, therefore, in a better position to understand or predict changes in labor market dynamics, while younger respondents, who are more familiar with new technologies, feel more secure to cope with these changes.

Furthermore, respondents with tertiary education have a lower WTP for a lower exposure to automation, which could indicate that due to their educational qualifications, they feel more confident in coping with technological changes compared to respondents with lower educational levels. Reassuringly, individuals who are more risk-seeking also have a lower WTP for a reduction of the automation risk, which is a clear sign that respondents perceive the automation risk presented in our experiment as a genuine risk.

Finally, columns 2 and 3 suggest differences in WTP between the daughter and son subsamples for respondents from the French region and Swiss citizens. While the coefficient for the French region is not significant and close to zero in the full sample, respondents in the son subsample exhibit a CHF 1,172 lower WTP for lower automation risk, while conversely, respondents in the daughter subsample are willing to pay CHF 830 more, albeit the latter coefficient is not significant. On the other hand, the positive and significant coefficient for Swiss citizens in the full sample appears to be driven almost solely by responses in the son sample, while the coefficient in the daughter sample is much smaller and not significant.

4.4 Interactions with Other Career Path Attributes

In a final step, we investigate how the WTP for lower automation risk varies depending on the levels of our remaining career path attributes, i.e., the level and type of education and hierarchical position. Column 1 of Table 7 reports the mixed logit WTP results from Table 5, while the model in column 2 additionally includes interactions between automation risk and the other career path attributes. For simplicity and readability reasons, only the WTPs for automation risk are reported. The extended model, including the interaction terms, reveals two main new results. First, while “at baseline,” i.e., with a vocational education diploma and a lower hierarchical position, the WTP for a 10 percentage points lower automation risk is CHF 13,880; it increases by CHF 777 with a concurrent top management position. This is likely due to the fact that losing a top management job often entails accepting a lower position and salary in a new role, likely prompting individuals to be more willing to pay to minimize this risk.

Table 7

Mixed logit WTP for lower automation risk with interactions

	(1)	(2)
Automation Risk (10 ppt.)	15333.1***	13879.6***
	(366.8)	(659.5)
Automation Risk × University Degree		2439.8***
		(550.5)
Automation Risk × UAS Degree		71.91
		(467.1)
Automation Risk × Top Management Position		776.9*
		(302.6)
N	83,328	83,328

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Second, the WTP for a lower automation risk greatly depends on the type of education, being much higher with a concurrent University degree. At first sight, this may seem counterintuitive, given that previous waves of digitalization have benefited individuals with general and tertiary education and the observation that survey respondents with tertiary education have a lower WTP. However, one factor might outweigh these considerations. Compared to a vocational or UAS diploma, obtaining a university degree represents a significantly greater investment in time and forgone income. Consequently, individuals may be more inclined to pay for a lower risk of automation if they had invested more in education before (ceteris paribus). Moreover, people's notion that university graduates will easily find new roles in different occupations due to their flexibility, given their complementarity with digital technologies, may no longer be (as) prevalent, as recent generative AI innovations have shown that they are likely to partially break this complementary relationship.

5 Conclusions

Even if, from a macroeconomic perspective, the automation of activities in the past has always led to more jobs, albeit sometimes only after transitional periods, and generally to better-paid and less strenuous jobs, it can still have a lasting negative impact on the careers of those affected. With the new changes brought about by generative artificial intelligence, the idea that one can protect oneself against technological shocks in the labor market simply by more and longer education is also being shaken, as these technologies are partly used to substitute non-routine cognitive activities that require long and demanding training. With this in mind, in this paper, we ask how threatened a representative cross-section of today's adult population feels by job automation. The subjectively perceived degree of threat is represented by the WTP that the respondents show in order to reduce the risk that an occupation can be automated. The WTP to reduce this risk by 10 percentage points, measured in a discrete choice experiment among nearly 6,000 adults in Switzerland, amounts to almost 20 percent of a gross annual salary.

Although we found significant heterogeneity in the WTP, such as that women, older people, those with a lower level of education, or those with a higher risk aversion have a higher WTP than men, younger people, those with a tertiary education and those with a higher risk tolerance, the differences are small in magnitude and do not call the average value into question. The absolute and relative level of this value is also reflected, for example, in the fact that the

WTP is more than ten times higher than respondents would be prepared to pay for a top hierarchical position compared to an employee position.

The extremely high WTP is, therefore, an expression of great uncertainty and fear of the possibility that the automation of work tasks could lead to job losses, the implications of which are fundamentally different from those of job terminations due to other reasons, e.g., corporate cost-cutting. In general, automation technology affects tasks and occupations across firms and industries. Thus, workers' training and experience in occupations affected by automation technology may become partially worthless, resulting in a substantially reduced value of their human capital and, in turn, diminished labor market opportunities. In other words, a worker facing job loss due to automation typically experiences diminished opportunities to secure similar positions.

The estimated WTP could manifest itself in a wide variety of forms. The most obvious, of course, is the willingness to switch to professions and economic sectors which, despite lower wage levels, are expected to be more resistant to the process of automation of human activities. But in many cases, after years of investing in the acquisition of specific professional qualifications, such a change is not easily possible and would require significant financial and time investment. However, there are other ways in which the high WTP could manifest itself, such as the willingness to invest more money in further training or to save more at an older age, thus allowing early retirement and reducing the risk of being affected by future job automation. Finally, at a political level, this high individual WTP could also be expressed in the fact that the population is more willing to spend taxpayers' money on job security and to agree to regulations, even if these are associated with costs for the economy as a whole. It is precisely in this sense, the potential economic and socio-political consequences, that the findings presented here are probably the most significant.

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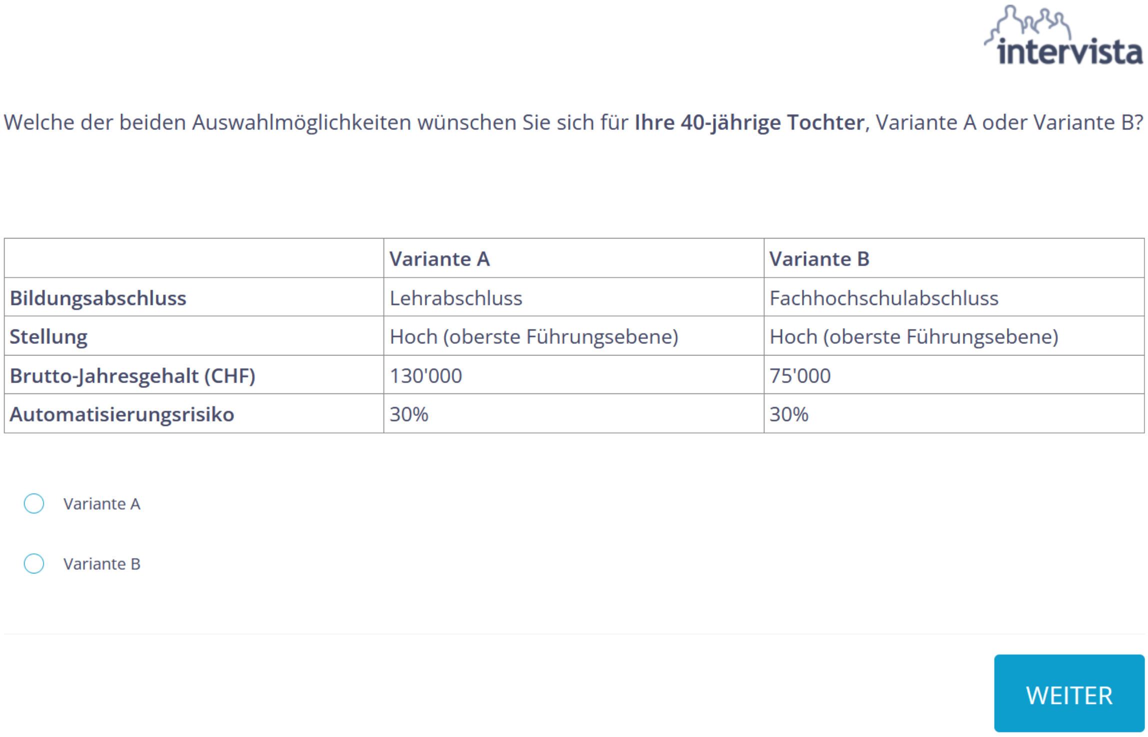
Appendices

Appendix A: Discrete Choice Experiment

Figure A.1

Screenshot of a German Choice Set



Welche der beiden Auswahlmöglichkeiten wünschen Sie sich für **Ihre 40-jährige Tochter**, Variante A oder Variante B?

	Variante A	**Variante B**
Bildungsabschluss	Lehrabschluss	Fachhochschulabschluss
Stellung	Hoch (oberste Führungsebene)	Hoch (oberste Führungsebene)
Brutto-Jahresgehalt (CHF)	130'000	75'000
Automatisierungsrisiko	30%	30%

Variante A

Variante B

WEITER

Table A.1

Choice sets used in the DCE

Choice set	Alternative	Highest educational attainment	Hierarchical position	Annual gross wage (CHF)	Automation risk (%)	Block
1	1	University of Applied Sciences degree	High (top management)	115,000	45	3
1	2	University degree	High (top management)	100,000	30	3
2	1	University of Applied Sciences degree	Low (without management function)	100,000	60	1
2	2	Apprenticeship certificate	High (top management)	130,000	60	1
3	1	University degree	High (top management)	75,000	30	1
3	2	Apprenticeship certificate	Low (without management function)	115,000	45	1
4	1	Apprenticeship certificate	Low (without management function)	115,000	60	1
4	2	University of Applied Sciences degree	High (top management)	75,000	60	1
5	1	Apprenticeship certificate	High (top management)	115,000	30	2
5	2	University of Applied Sciences degree	Low (without management function)	115,000	30	2
6	1	University degree	High (top management)	75,000	30	2
6	2	University degree	Low (without management function)	130,000	45	2
7	1	University degree	Low (without management function)	130,000	45	3
7	2	University of Applied Sciences degree	High (top management)	75,000	30	3
8	1	University degree	Low (without management function)	130,000	30	1
8	2	University of Applied Sciences degree	High (top management)	115,000	30	1
9	1	University degree	High (top management)	100,000	45	2
9	2	University degree	Low (without management function)	115,000	45	2

10	1	University of Applied Sciences degree	Low (without management function)	100,000	30	3
10	2	Apprenticeship certificate	Low (without management function)	130,000	45	3
11	1	University degree	Low (without management function)	100,000	45	2
11	2	University degree	High (top management)	130,000	60	2
12	1	University degree	High (top management)	75,000	60	3
12	2	Apprenticeship certificate	Low (without management function)	100,000	60	3
13	1	University of Applied Sciences degree	Low (without management function)	115,000	60	3
13	2	University of Applied Sciences degree	High (top management)	100,000	45	3
14	1	Apprenticeship certificate	High (top management)	100,000	60	2
14	2	University degree	Low (without management function)	100,000	60	2
15	1	University of Applied Sciences degree	High (top management)	130,000	60	1
15	2	Apprenticeship certificate	High (top management)	115,000	45	1
16	1	University of Applied Sciences degree	High (top management)	75,000	60	2
16	2	Apprenticeship certificate	High (top management)	75,000	30	2
17	1	Apprenticeship certificate	High (top management)	75,000	30	1
17	2	University degree	Low (without management function)	75,000	45	1
18	1	Apprenticeship certificate	High (top management)	130,000	30	3
18	2	University of Applied Sciences degree	High (top management)	75,000	30	3
19	1	Apprenticeship certificate	Low (without management function)	130,000	45	2
19	2	Apprenticeship certificate	High (top management)	130,000	60	2
20	1	Apprenticeship certificate	Low (without management function)	75,000	45	3

20	2	University of Applied Sciences degree	Low (without management function)	100,000	60	3
21	1	University of Applied Sciences degree	Low (without management function)	115,000	45	1
21	2	University degree	Low (without management function)	75,000	30	1

Appendix B: Additional Results

Table B.1

Reduced sample conditional logit estimates and WTP for career path attributes

	Conditional logit estimates			WTP
	(1)	(2)	(3)	(4)
Lower automation risk (10 ppt.)	0.556***	0.539***	0.540***	16735.1***
	(0.0173)	(0.0198)	(0.0241)	(327.3)
University degree	-0.348***	-0.348***	-0.366***	-10469.5***
	(0.0266)	(0.0266)	(0.0377)	(947.8)
UAS degree	-0.00756	-0.00757	-0.0372	-227.6
	(0.0254)	(0.0254)	(0.0358)	(768.3)
Top management position	0.0505**	0.0504**	0.0497	1520.4**
	(0.0183)	(0.0183)	(0.0259)	(536.4)
Annual gross wage (10’000 CHF)	0.332***	0.332***	0.335***	
	(0.00827)	(0.00827)	(0.0116)	
Automation risk × son		0.0338	-0.0319	
		(0.0205)	(0.0347)	
University degree × son			0.0367	
			(0.0532)	
UAS degree × son			0.0596	
			(0.0508)	
Top management position × son			0.00108	
			(0.0367)	
Annual gross wage × son			-0.00587	
			(0.0165)	
N	61,992	61,992	61,992	61,992

Notes: The reduced sample does not include any survey respondents who spent less than 60 seconds reading the DCE introduction or less than 30 seconds for any of the choice sets. For columns 1 to 3, the outcome is a dummy variable on whether or not a career path is chosen or not. *son* is a dummy variable equal to one if respondents are in the son subsample and equal to zero if they are in the daughter subsample. WTP in column 4 is calculated by the ratio of the estimate for the respective career path attribute and the estimate for annual gross wage in column 1, times 10’000 CHF. Population weights are applied, standard errors are shown in parentheses, and * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table B.2

Standard deviations of mixed logit estimates for career path attributes as shown in Table 5.

	(1)	(2)	(3)
Lower automation Risk (10 ppt.)	0.666***	0.666***	0.667***
	(0.0242)	(0.0252)	(0.0264)
University Degree	1.363***	1.373***	1.389***
	(0.0579)	(0.0583)	(0.0603)
UAS Degree	0.729***	0.752***	0.710***
	(0.0551)	(0.0526)	(0.178)
Top Management Position	1.061***	1.070***	1.069***
	(0.0349)	(0.0351)	(0.0358)
Annual Gross Wage (10'000 CHF)	0.593***	0.610***	0.603***
	(0.0274)	(0.0274)	(0.0593)
Automation Risk × Son Subsample		0.0745	0.157
		(0.123)	(0.146)
University Degree × Son Subsample			0.00978
			(0.557)
UAS Degree × Son Subsample			0.328
			(0.737)
Top Management Position × Son			0.0217
Subsample			(0.444)
Annual Gross Wage × Son			0.0288
Subsample			(0.266)
N	83,328	83,328	83,328

Notes: Standard errors in parentheses, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.