Automation Risk Affects Young Adults Occupational Preferences

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Abstract

Researchers have long been interested in technological development and its effect on human outcomes, but we know little about how automation risk affects occupational and educational choices. I used a pre-registered online experiment and provided respondents with information about the automation risk for teachers, economists, office clerks, and registered nurses to investigate how automation risk affects attractiveness and the expected probability of entering these occupations. Respondents revised their beliefs for all occupations conditional on the provided information. Economists and office clerks receive reduced occupational attractiveness. No effect was found for teachers and nurses. Next, I found that the expected probability of becoming an office clerk decreased, while there was no effect for the remaining occupations. In addition, the effects differ by gender and race. The findings are also related to changed perceptions regarding the occupations of economists and office clerks, where they are perceived to have lower future salaries, social status, and job stability.

JEL Classification: A13, C90, J20, J24

Keywords: *Automation risk, Occupational choice, Job preferences, Technology, Experiment*

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I. INTRODUCTION

John Maynard Keynes famously predicted technological unemployment "due to our discovery of means of economising the use of labour outrunning the pace at which we can find new uses for labour" (Keynes, 1930, p.3). However, his prediction proved incorrect. While machines and computers have substituted human labor in the past, new, more advanced jobs have been created (Autor, 2015). For example, in 2000, 2 percent of the US workforce worked in agriculture compared to 41 percent in 1900 (Autor, 2014). Thus, technological development has been an important driver for aggregate outcomes.[1] To this day, Keynes's thoughts are still relevant due to concerns about whether robots and AI will substitute human labor. Research has focused on how technology affects workers. Also, Acemoglu and Restrepo (2020a) estimated the negative effects of robots and found a decrease in wages by 0.42 percent and a 0.2 percent lower employment-to-population ratio.[2] Frey and Osborne (2017) has attempted to quantify the automation risk for several occupations.[3] Despite the rapid development of automation and AI, we still know little about how automation risk affects individuals sorting into occupations. However, studying occupational choices brings econometric challenges, such as omitted variable bias and reverse causality.

In this paper, I attempt to overcome these econometric challenges by leveraging an online experiment to analyze the effects of automation risk on preferences. More specifically, I document the causal effects of automation risk on attractiveness and the expected probability of entering a specific occupation. Experiments are ideal for identifying causal effects and analyzing theoretical predictions. I limit my study to four occupations with different automation risks: teachers, economists, office clerks, and registered nurses. To guide my predictions of the outcome and construct the experiment, I modified a model by Wiswall and Zafar (2018), which predicts that an information shock forces the individual to revise their beliefs about

[1] Autor et al. (1998) documents a strong and persistent growth in the demand for college graduates in response to skill-biased technological change. Autor et al. (2003) showed that routine jobs correlate negatively and non-routine cognitive correlates positively with computerization, which now is known as the "routinization" hypothesis. The "routinization" hypothesis predicts that machines easily substitute middle-skilled occupations. The hypothesis is formalized in Acemoglu and Autor (2011).

[2] More empirical evidence is provided by Acemoglu et al. (2023).

[3] For a sample of these studies see: Arntz et al. (2017); Paolillo et al. (2022). An additional sample of studies related to automation risk is Acemoglu and Restrepo (2019); Acemoglu and Restrepo (2020b); Gentili et al. (2020).

an occupation. Based on the mechanisms from my model, I pre-register hypotheses that the information treatment affects occupational attractiveness but not the expected probability of entering the occupation. To the best of my knowledge, I am the first to study how automation risk affects occupational attractiveness and the expected probability of entering a specific occupation using an online experiment.

In total, 600 respondents participated in the experiment through Prolific. I constructed an information provision experiment with one treatment group and one control group (Haaland et al., 2023). The treatment group was provided with information about computerization and the automation risk computed by Willrobotstakemyjob.com (2024) for the four occupations. Respondents answered questions about their background and job preferences before being randomized to treatment. Afterward, respondents answered occupational-specific questions. I also included questions about retirement, labor market outcomes, education, and political change. These questions relate to the social debate regarding the impact of computerization. Prior to beginning my analysis, I checked to see if respondents knew the correct automation risk for the occupations. I document that respondents underestimated the automation risk for economists and office clerks and overestimated it for teachers and nurses. Next, my main analysis suggests small to medium-sized negative effects on occupational attractiveness for economists and office clerks. Male and white respondents pronounce the effect. No effect was found for teachers and registered nurses. Lastly, the information treatment does not affect the expected probability of becoming a teacher, economist, or registered nurse. However, I find a small decrease in the likelihood of becoming an office clerk, where men and non-whites particularly pronounce the effect.

I explain my findings by providing evidence that respondents have revised their beliefs due to incorrect beliefs about automation risk. First, I show that treatment did not impact respondents with initially correct beliefs, meaning they did revise but did not change their beliefs. Moreover, respondents who underestimated the automation risk prescribe a lower occupational attractiveness for all occupations. Still, the direction is less distinct for respondents who overestimated the automation risk. The effect on expected probability if overestimating or underestimating the automation risk is near zero for all occupations except for office clerks. Next, I show that the main effects are related to changes in occupational-specific perceptions. I find that the decline in occupational attractiveness among treated respondents relates to beliefs that economists and office clerks will be lower paid in the future, have lower social status, and lower job stability. An interesting finding is the belief in improved job security for teachers and nurses, which can be due to the low automation risk. I continue my analysis of mechanisms by analyzing changes between occupations. The treatment group ranked the teaching occupation higher and office clerks lower, and there were no differences for economists and registered nurses. I conclude that respondents with initially incorrect perceptions revised their beliefs based on the information provided.

Next, I turn to my supplementary analysis, examining outcomes related to labor outcomes, education, retirement, and political change that are affected by correct information on automation risk. My results indicate that men expect to study more and are less in favor of imposing regulations on technological development. Finally, I analyze the effect of the information treatment on the expected choice of college major. Men were less likely to choose humanities and other social sciences as college majors, but overall, the information treatment does not seem to affect the expected college major.

This paper makes several contributions. Despite being the first study of its kind, my paper speaks to the literature by Card et al. (2012), Coffman et al. (2017), Belot et al. (2019), and Jones and Kofoed (2020), who used experimental designs to analyze how information provision affected occupational choices. These studies find that information provision affects occupational choices. I add to this literature by providing evidence of how automation risk affects occupational beliefs. My paper also speaks to the literature regarding determinants of occupational choice (Roy, 1951; Zarkin, 1985). Next, my methodology is related to papers using information provision experiments to prompt individuals to update their beliefs. Armantier et al. (2016), which used price information to update inflation expectations, Wiswall and Zafar (2015b) used an information provision experiment to study decisions under uncertainty and biased expectations, and Wiswall and Zafar (2015a), which used information treatment to study updated beliefs and preferences on college majors. My paper speaks to this literature by providing evidence that respondents update their beliefs, mechanisms, and how they differ between individuals.

Next, I complement the existing literature on determinants of college majors, future events, and workplace preferences. Specifically, I add to the experimental literature focusing on the role of social status in occupational sorting (Gola, 2024), level of competitiveness when choosing college major (Reuben et al., 2017), beliefs about how college major will affect future events (Beffy et al., 2012, Zafar, 2013; Wiswall and Zafar, 2015a; Wiswall and Zafar, 2015b; Wiswall and Zafar, 2021; Wiswall and Zafar, 2018; Delavande and Zafar, 2019; He et al., 2021). These studies emphasize that future events, such as expected wage, job flexibility, enjoyment, family life, and job stability, have proven to be determinants for college majors. In addition, preferences differ by gender and race. For example, women particularly pronounced family expectations and were more willing to pay for non-pecuniary outcomes. Men, on the other hand, had a higher willingness to pay for higher-paying jobs. I build on this literature by analyzing how automation risk affects perceptions of non-pecuniary and educational outcomes. My paper also relates to Arcidiacono et al. (2020), who found that non-pecuniary outcomes influence the decision not to choose the highest-paying occupation. They also found that the probability of choosing an occupation is highly predictive of the actual outcome two to six years later. Their results are meaningful for my study, as I only observe the expected outcome.

Finally, my study also speaks to the literature about job insecurity. Manski (2004) examines cross-sectional and time-series variation across respondents' perceptions of job insecurity. Age and job loss expectations are negatively related, and if a job search is necessary, the expected outcome tends to be better. Additionally, job loss and years of schooling are negatively related, while years of schooling and expected outcomes are positively related if a job search is needed. Finally, perceptions about job security vary little between genders but significantly by race, where the perceptions of a job loss were nearly double as high for blacks compared to whites. I advance this literature by providing evidence of how automation risk affects job preferences by gender and race.

The remaining structure is as follows. Section II describes the impact of technological development on labor markets and provides a theoretical framework. Section III describes the experimental design. Section IV presents the results, heterogeneity, and supplementary analysis. Section V concludes.

II. BACKGROUND

II.A. The impact from automation on labor

The introduction of AI is considered the fourth industrial revolution and will yield positive and negative effects (Gentili et al., 2020). Manyika et al. (2017) argues that AI will increase productivity and economic growth, but its impact on jobs and employment has raised concerns. Automation tends to reduce the labor share in production (Bessen, 2019, Acemoglu and Restrepo, 2019, Acemoglu and Restrepo, 2020a). Moreover, Gentili et al. (2020) argues that employment and wealth polarization as a response to the introduction of improved technology is a negative concern and should be targeted by politicians. According to Acemoglu and Restrepo (2020b), although many tasks have been automated, this has led to stagnated labor demand, lower productivity, and national income as there is an insufficient focus on creating new tasks. Still, there is a concern that the wrong type of AI will be implemented, which implies security risks. On the other hand, Aghion et al. (2018) and Noy and Zhang (2023) argue that AI will transform the production of goods and services, enhance idea creation, and boost productivity. Still, Aghion et al. (2018) and Acemoglu and Restrepo (2020b) emphasize that the importance of how AI is implemented today is essential for future events.

Previous industrial revolutions have mostly replaced low-skilled workers in the agricultural sector who moved to urban areas. The fourth industrial revolution concerns experts as it may affect medium-skilled and skilled workers, including those in cognitive jobs. Attempts have been made to predict which profession is subject to automation risk (Acemoglu and Restrepo, 2020a; Arntz et al., 2017; Autor and Dorn, 2013; Frey and Osborne, 2017; Paolillo et al., 2022). Frey and Osborne (2017) calculated the automation risk for around 700 existing occupations using a Gaussian method. The method follows a complex, nonlinear interaction between variables. For example, one variable may only be important if another variable is sufficiently high. Their approach relies on subjective expert classifications of job automation. However, Frey and Osborne (2017) were aware of this issue and attempted to reduce the subjective bias in their assessment and had workshops, and they also examined their classification. Later developments have been made by Willrobotstakemyjob.com (2024) where they have again computed the automation risk for most of the profession in Frey and Osborne (2017), with a similar methodology. Both studies use data from O*NET developed by the US Department of Labor. The database contains a rich set of occupations, key features, and attributes for each occupation. O*NET also assigns two values for each attribute: importance and level. Thus, it is possible to quantify the risk of automation as machines can more or less substitute different attributes.

II.B. The model

Set up of the model

A theoretical framework should help evaluate individuals sorting into occupations and the impact of automation risk.[4] I build on the theoretical framework by Wiswall and Zafar (2018) where I shock individual beliefs. Before formalizing the model, let me provide the intuition behind it. Assume an individual has to choose to enter an occupation but does not have perfect information about the occupation and future events that might follow. Suppose the individual gets shocked by some information about occupational automation risk. When facing a shock, individuals revise their beliefs about the occupation conditional on the shock.

Let an agent i choose between jobs $j \in J$. In turn, an agent only chooses between a subset of all jobs, $J \in \mathcal{J}$, where $\mathcal{J}$ is finite. Each job has N characteristics described by $(x_{1j}, x_{2j}, x_{3j}, ..., x_{Nj}) = \mathbf{x}_j$. For example, $\mathbf{x}$ contains wages, job flexibility, and job security. Individuals have preferences over job characteristics. However, this model does not assume that the agent maximizes income or consumption. Individual preferences are given by the function $f_i(\mathbf{x}_j) \in \mathbb{R}$. All remaining unobserved preferences and characteristics for a job j, are denoted by $\mu_{ij} = (\mu_{i1}, \mu_{i2}, \mu_{i3}, ..., \mu_{in}) \in \mathbb{R}$. Utility of job j is given by:

$$U_{ij} = f_i(\mathbf{x}_j) + \mu_{ij} \tag{1}$$

The utility function has all conventional properties (see Mas-Colell et al., 1995). Agents prefer occupations such that $U_{ij} \geq U_{ij'}$ for all $j \neq j'$.[5]

[4] Roy (1951) made an early attempt to theorize occupational sorting and emphasized the distribution of skills and available technology.

[5] In practice, agents are restricted in their occupation choice because they are not qualified or find a job unacceptable. This constraint will not affect the theoretical framework provided.

Information shocks

Suppose individuals face a shock σ_j, which can be any information about job j. The reaction depends on previous unobserved beliefs and can be described by the function θ_i. Thus, the reaction depends on the initial beliefs and the shock size. Rewrite the utility function as:

$$U_{ij} = f_i(\mathbf{x}_j) + \mu_{ij} + \theta_i(\mu_{ij}, \sigma_j) \tag{2}$$

If these unobserved beliefs are affected by a shock, σ_j, individuals will revise their beliefs, and the change is given by $\theta_i(\mu_{ij}, \sigma_j)$. In the absence of a shock $\theta_i(\mu_{ij}, \sigma_j) = 0$. If no shock occurs, the unobserved characteristics are unchanged. Similar to Wiswall and Zafar (2018), I assume that agents are rational decision-makers. The probability of choosing j is given by:

$$p_{ij} = \int 1\left\{U_{ij} > U_{ij'},\ \forall\ j \neq j'\right\} dH_i(\mu_i) \tag{3}$$

where $H_i(\mu_i)$ is i's beliefs of the distribution of $(\mu_{i1}, \mu_{i2}, \mu_{i3}, ..., \mu_{iJ})$. The value for each μ is unknown when running the experiment - choices are hypothetical. Thus, agents face hypothetical J jobs with characteristics $(x_1, x_2, x_3, ..., x_J)$ and choose a job with probability p_{ij} depending on their individual distribution of all unobserved factors μ_{ij}.

I end this section by summarizing the model's insights. When facing an information shock, individuals will revise their beliefs, and depending on the size of the shock, the utility will be affected differently. Note that all shocks are interpreted individually depending on the initial beliefs. If a shock is of a size such that $\theta_i(\mu_{ij}, \sigma_j) < 0$, then the utility of job j will be affected negatively, lowering the probability of entering.

III. EXPERIMENTAL DESIGN

To study the effects on occupational attractiveness and the expected probability of entering an occupation, I used an online experiment programmed in Qualtrics.[6] An experimental design is ideal for identifying causal effects as I want to analyze my model's theoretical predictions

[6] I pre-registered my analysis at the American Economic Association RCT Registry under the RCT ID AEARCTR-0013424.

and the complex decision process for occupational choice. The experiment included 600 participants aged 18-21 in the US and UK. Respondents were recruited and pre-screened through Prolific, where I paid participants $1.2 for a 6-minute online survey. Prolific is an online platform with a large pool of respondents with various characteristics. The advantage of using Prolific is that it allows access to a wide range of respondents.[7]

Respondents answered a survey consisting of four blocks. In the first block, respondents filled in their background information. In the second block, respondents are asked to report job preferences such as social status, expected earnings, flexibility, family, and job stability. Additionally, individuals are asked to estimate the automation risk for nurses, teachers, economists, and office clerks. I subjectively chose as broad occupations as possible with various automation risks in the list of jobs provided by Willrobotstakemyjob.com (2024).[8] The questions concerning individual job preferences are unrelated to any profession. Instead, these questions related to previous research determinants of college majors and job preferences.[9] After the second block, respondents were randomized to the treatment group or the control group.

The treatment group was provided an information treatment with brief background information about AI, recent developments such as ChatGPT, and the occupational automation risk computed by Willrobotstakemyjob.com (2024). The automation risk for teachers is 9 percent; for economists, 51 percent; for office clerks, 100 percent; and for registered nurses, 10 percent. The information treatment can be found in the Appendix. Respondents were asked to read the information carefully. The final block consists of questions related to the four occupations. All questions related to the four occupations were presented randomly to prevent biased answers. The experimental procedure is displayed in Figure I, and the complete survey can be found in the Appendix. Measures provided by Willrobotstakemyjob.com (2024) build on the methodology by Frey and Osborne (2017). The former used data from O*NET,

[7]Before the experiment, I performed a power analysis assuming an absolute effect of 0.3 and a standard deviation of 1.3. To obtain a statistical power of 80 percent and a significance level of 0.05, I needed 592 answers. I rounded upwards and aimed for 600 answers. More information is found in the pre-analysis provided at the AEA RCT Registry.

[8]Many occupations were specific and may be unknown to respondents. Thus, I attempted to choose well-known and broad occupations that respondents may have beliefs of.

[9]See for example: Gola (2024), Wiswall and Zafar (2021), Goldin (2014), Bloom et al. (2015), Kiessling et al. (2024) and Wiswall and Zafar (2015a).

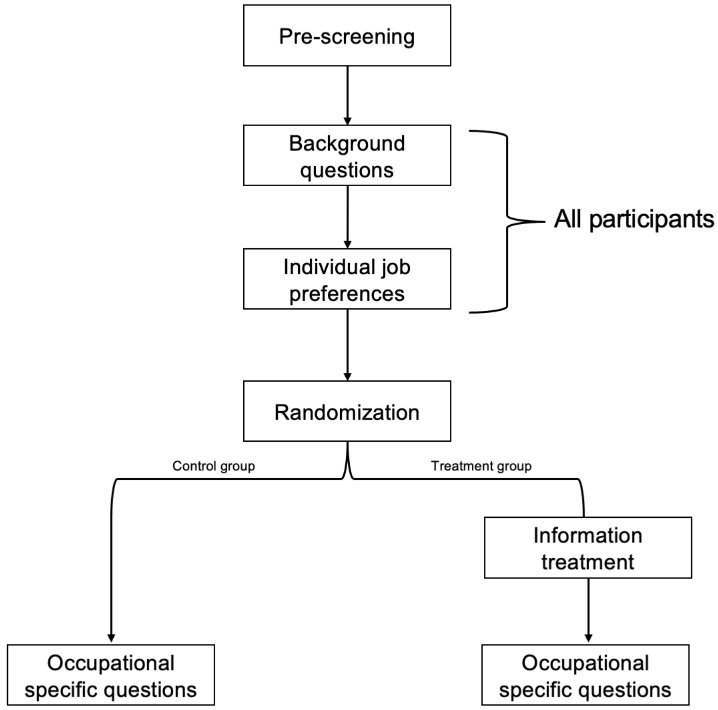

Figure I: Structure of survey and experimental procedure

Notes: All participants were pre-screened in Prolific to match the chosen sample. All participants answer the same questions in the first two blocks. Respondents were then randomized to either the control group or treatment group. The treatment group then receives information about the automation risk for four occupations. Finally, all respondents answered the same questions regarding the four occupations.

which includes attributes required for the job. The calculations performed by Willrobotstakemyjob.com (2024) in January 2023 used O*NET data from November 2022. Significant differences exist in the automation risk between Frey and Osborne (2017) and Willrobotstakemyjob.com (2024). Thus, it is more reliable to use the later estimates as it considers the latest technological developments and AI.

Since I do not observe the actual occupational choice, I focus on determinants of actual behavior. Given the intuition from my theoretical framework, providing respondents with correct information will force them to revise their beliefs about the attractiveness of entering the profession. The individual's response will depend on their initial belief and the information provided, leading to hypothesis 1.

Hypothesis 1: *Correct information about automation risk does affect the attractiveness of entering the occupation.*

Next, I am interested in whether correct information about automation risk affects the expected probability of entering the occupation. Respondents will revise their beliefs conditional on the information treatment. Given the treatment provided, I believe it is more difficult to affect an individual's willingness to enter an occupation, as it probably requires treatment with several more dimensions. Thus, I hypothesize that the second hypothesis will not be rejected.

Hypothesis 2: *Correct information about automation risk does not affect the expected probability of entering the occupation.*

My hypotheses apply to all occupations. How do the two hypotheses differ from each other? The first hypothesis focuses on how attractive an occupation is, whereas the second hypothesis focuses on the subjective probability of entering. Thus, the first hypothesis is a weaker form of interest in the occupation.

I deviated from the pre-registered analysis by changing the pre-screening process. The initially planned sample consisted of respondents aged 18 to 20 living in the US. However, due to time constraints to collect data and a small pool of respondents, I changed the screening criteria by including the UK and increased the maximum age from 20 to 21. This change was not optimal, as an older sample may catch respondents already choosing an occupation or deciding on a college major to pursue. Including the UK may result in less precision for my estimates due to cultural differences.

To simplify the interpretation, I constructed standardized values.[10] I relate to the theoretical model in Section II.B and exogenously shock respondents by informing them about the automation risk for teachers, economists, office clerks, and nurses. I estimate the specification with robust standard errors:

$$y_{ij} = \beta D_i + \alpha \text{AUTO-RISK}_{ij} + \delta' \mathbf{x}_i + \psi' \mathbf{z}_i + \varepsilon_{ij} \tag{4}$$

where y is the outcome variable, such as the expected probability of choosing a profession j, D_i, takes the value one if the respondent is in the treatment group and zero otherwise, AUTO-RISK_i indicates the estimated automation risk by respondents for occupation j, $\mathbf{x}$ is a

[10] $\mathrm{y}_{\mathrm{SD}} = \frac{\mathrm{z(value)} - \mathrm{z(mean)}}{\mathrm{z(std)}}$

vector of individual characteristics respondent i, $\mathbf{z}$ is a vector of individual job preferences, and ε is the error term. Moreover, the research design yields full compliance in the treatment group since there is no self-selection into treatment. Hence, all estimates show the average treatment effect on the treated.

IV. RESULTS

IV.A. Balance check

Table I shows descriptive statistics and balance checks for a set of background variables and individual job preferences. Data for these variables was collected before the treatment group was treated. I present a sample of all characteristic variables and p-values from the t-test. The sample of respondents consists of 42 percent who identify as men and are of similar age. Respondents have, on average, similar socioeconomic backgrounds. Both the control group and treatment group have similar views on job preferences. Interestingly, on a Likert scale, the mean is 6 of 7 for job stability, where seven stands for *strongly agree*. Turning to the believed automation risk for all occupations is statistically different from the calculated automation risk by Willrobotstakemyjob.com (2024). The respondents underestimated the automation risk for economists ($p < 0.00$) and office clerks ($p < 0.00$) but overestimated it for teachers ($p < 0.00$) and nurses ($p < 0.00$).[11] Thus, treated respondents should revise their beliefs due to the information shock.

The table shows that respondents' characteristics seem balanced except for the proportion of men and the belief about office clerks' automation risk, which showed statistically significant differences. The difference in the proportion of men is considered weak due to the larger control group and the smaller fraction of men participating in the study. Moreover, the difference is only significant at the 10-percent level, indicating weak significance. Next, there is a significant difference between the beliefs of automation risk for office clerks. It differs by about five percentage points, which is considered small. Thus, the latter difference is negligible. I conclude that the randomization has been successful, and the control and treatment groups seem balanced.

[11] I performed a one-sample mean comparison test where the hypothesized means is the automation risk by Willrobotstakemyjob.com (2024).

Table I: Descriptive statistics and balance check

	Full sample					Control group					Treatment group					
	Mean	SD	Min	Max	N	Mean	SD	Min	Max	N	Mean	SD	Min	Max	N	P-value
Individual characteristics																
Men	0.42	0.49			600	0.45	0.5			318	0.38	0.49			282	0.067
Year born	2003	1.07	2002	2006	600	2003	1.04	2002	2006	318	2003	1.09	2002	2006	282	0.63
Income ($)	16,088	21,054	0	100,000	600	16,679	21,274	0	100,000	318	15,421	20,821	0	100,000	282	0.47
Education mother	2.35	0.71	1	3	600	2.39	0.69	1	3	318	2.30	0.73	1	3	282	0.11
Education father	2.35	0.71	1	3	600	2.37	0.68	1	3	318	2.32	0.73	1	3	282	0.31
Siblings	1.87	1.44	0	10	600	1.86	1.47	0	10	318	1.87	1.41	0	10	282	0.99
Job preferences																
High occupational status	4.12	1.65	1	7	600	4.13	1.63	1	7	318	4.12	1.67	1	7	282	0.99
Cares about high salary	5.50	1.31	1	7	600	5.49	1.28	1	7	318	5.50	1.35	1	7	282	0.87
Avoids risk-taking	4.21	1.45	1	7	600	4.12	1.41	1	7	318	4.29	1.49	1	7	282	0.14
Value job stability	6.00	0.99	2	7	600	5.98	1.01	2	7	318	6.02	0.97	1	7	282	0.56
Confidence of future profession	4.40	1.78	1	7	600	4.44	1.8	1	7	318	4.36	1.76	1	7	282	0.55
Family life	5.09	1.69	1	7	600	5.10	1.65	1	7	318	5.09	1.74	1	7	282	0.94
Enjoy occupation	6.24	0.93	1	7	600	6.29	0.92	3	7	318	6.21	0.94	1	7	282	0.29
Flexibility in life	5.91	0.93	1	7	600	5.91	0.95	1	7	318	5.91	0.91	1	7	282	0.97
Belief about automation risk (%)																
Teacher	27	23	0	100	600	26	23	0	100	318	28	24	0	100	282	0.26
Economist	48	25	0	100	600	47	25	0	100	318	49	25	0	100	282	0.46
Office clerk	58	26	0	100	600	56	26	0	100	318	61	26	0	100	282	0.02
Registered Nurse	21	23	0	100	600	21	23	0	100	318	20	22	0	100	282	0.60

Notes: This table reports descriptive statistics and balance checks. The first three columns report descriptive statistics for the full sample, the control group, and the treatment group, respectively. The fourth column reports the p-value from a two-sample mean t-test between the control and treatment groups. Statistics regarding parental education stretch from 1 to 3, where 1 is mandatory school or lower, 2 is high school, and 3 is a bachelor's degree or higher. Statistics related to individual characteristics report numbers using a Likert scale of 1 to 7, where 1 is strongly disagree and 7 is strongly agree.

IV.B. Main results

I start by analyzing my pre-registered hypotheses and display the main results in Figure II. Panel (a) shows standardized OLS regression coefficients for occupational attractiveness with 95-percentage confidence intervals. I observe decreased occupational attractiveness for economists and office clerks. The effects for teachers and nurses are smaller and non-significant. Thus, I reject the first null hypothesis for economists and office clerks. Panel (b) plots standardized OLS regression coefficients for the expected probability of entering the occupation with 95-percentage confidence intervals. All coefficients, except those related to office clerks, are nearly zero. This finding indicates that the information treatment did not significantly impact the expected probability of entering most occupations. Thus, I reject the second null hypothesis only for office clerks.

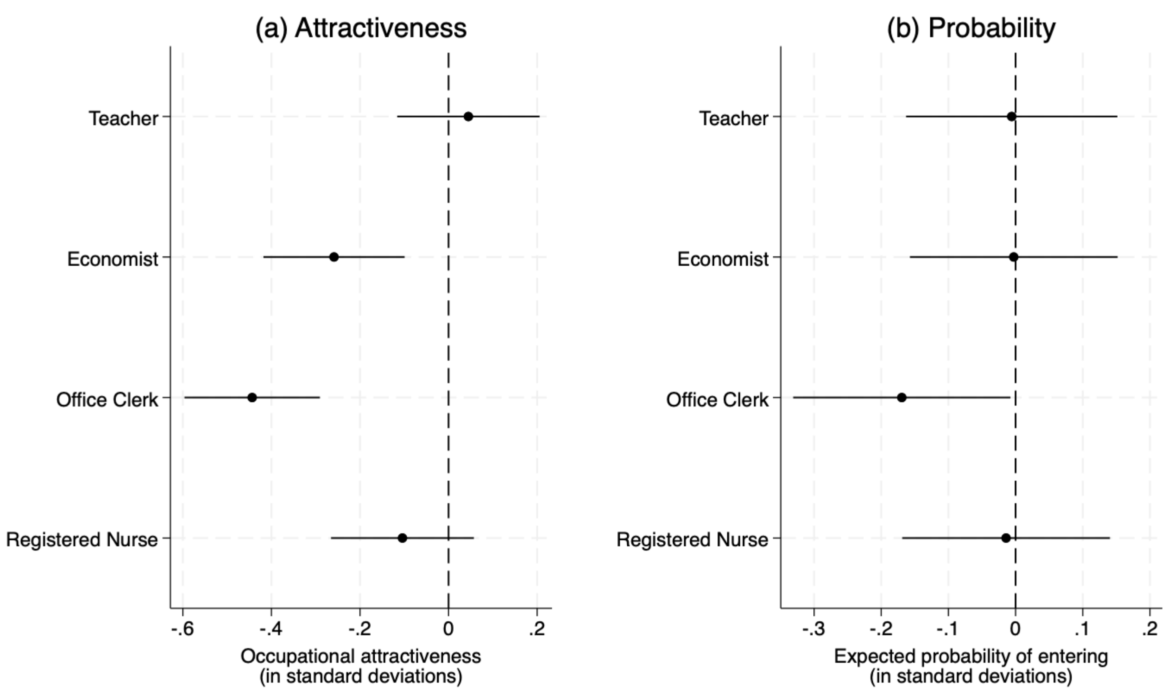

Figure II: Main results

Notes: This figure displays the treatment effect. Panel (a) shows the occupational attractiveness and how the treatment group differs from the control group. Panel (b) shows the expected probability of entering the occupation and how the treatment group differs from the control group. All plots control for background characteristics and individual job preferences. Both figures report standardized OLS regression coefficients and 95-percent confidence intervals.

Table II: Main results - Attractiveness and probability of entering the occupation

	Teacher			Economist			Office clerk			Reg. Nurse		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Panel A - Occupational attractiveness												
Treated	0.05	0.05	0.04	-0.26***	-0.25***	-0.26***	-0.45***	-0.42***	-0.44***	-0.14*	-0.09	-0.10
	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)
Mean control group		3.27			3.68			3.19			4.23	
Observations	600	600	600	599	599	599	598	598	598	600	600	600
R-squared	0.06	0.06	0.12	0.02	0.11	0.16	0.05	0.16	0.19	0.00	0.10	0.13
Panel B - Expected probability of entering the profession												
Treated	0.00	-0.00	-0.01	-0.03	0.02	-0.00	-0.14*	-0.14*	-0.17**	-0.01	0.01	-0.01
	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)
Mean control group		2.53			2.24			2.78			2.20	
Observations	600	600	600	600	600	600	600	600	600	600	600	600
R-squared	0.00	0.10	0.16	0.00	0.14	0.21	0.00	0.10	0.16	0.00	0.13	0.20
Controls		✓	✓		✓	✓		✓	✓		✓	✓
Job preferences			✓			✓			✓			✓

Notes: This table displays standardized OLS estimates for the main results. Panel (a) shows the occupational attractiveness and how the treatment group differs from the control group. Panel (b) shows the expected probability of entering the occupation. Controls include race, gender, parental education, income from the previous year, nationality, city size, employment, relationship status, and number of siblings. Job preferences include preferences for occupational social status, salary preferences, risk preferences, job stability, confidence in the future profession, family preferences, job flexibility, and enjoyment. Robust standard errors in parenthesis. *** p<0.01, ** p<0.05, * p<0.1.

I confirm the visual evidence with regression estimates in Table II. Panel A displays estimates for occupational attractiveness. All point estimates are robust when controlling for job preferences and background characteristics, indicating that the effects are driven by the information treatment rather than individual-specific traits. Notably, the addition of covariates does not affect the statistical precision. Using my preferred specification when controlling for background characteristics and job preferences, the occupational attractiveness for economists decreases by about 0.26 standard deviations ($p < 0.01$) compared to the control group. The effect is considered to be small (Cohen's d).[12] Next, the effect for office clerks is larger as the occupational attractiveness decreases with 0.44 standard deviations ($p < 0.01$). The findings for economists and office clerks are consistent with my predictions. Panel B displays results for the expected probability of entering the occupation. Respondents expect less to become an office clerk by 0.17 standard deviations ($p < 0.05$). The mechanisms from the model suggest that respondents have revised their beliefs in a way that negatively affects the view of economists and office clerks. Still, the shock did not change their perceptions about teachers and registered nurses. The negative effects may be due to the high automation risk, which my theoretical framework can explain. Due to incorrect beliefs, treated respondents revised their beliefs and answered conditionally to the information. It seems that the model only makes correct predictions when underestimating the automation risk. Still, it can also be due to the nature of the teaching and nursing occupations being different from other jobs. Thus, other factors may be more predictive of individuals sorting into these occupations.

IV.C. Mechanisms

Is the effect related to incorrect beliefs?

Turning to analyze how beliefs are affected by treatment. I started to analyze the impact of treatment if beliefs were initially correct. To do so, I ran regressions that only included respondents who guessed an automation risk in the interval ± 5 percentage points from the automation risk by Willrobotstakemyjob.com (2024). Figure A1 displays the results. No

[12] Cohen's d is a way to measure effect size. An effect of 0.2 standard deviations is considered to be a small effect. An effect of 0.5, respectively, and 0.8 standard deviations is considered medium and large.

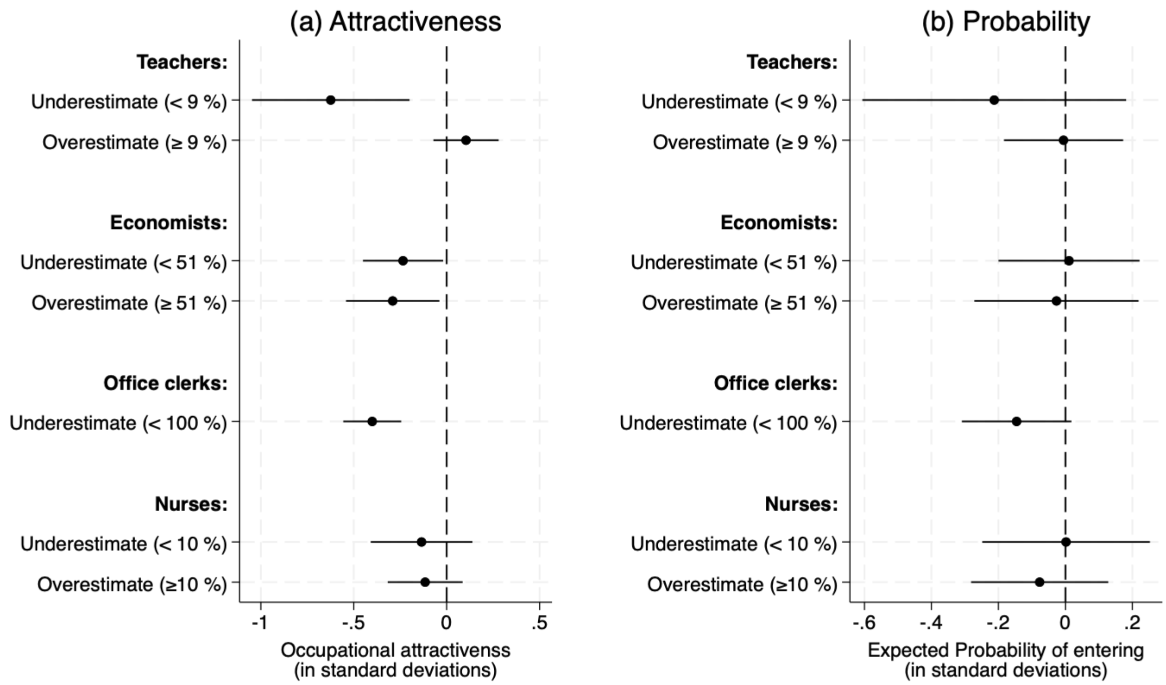

Figure III: Treatment effect if overestimate or underestimate the automation risk

Notes: This figure displays the treatment effect for respondents who overestimated and underestimated the automation risk. Panel (a) shows the occupational attractiveness and how the treatment group differs from the control group. Panel (b) shows the expected probability of entering the occupation and how the treatment group differs from the control group. All plots control for background characteristics and individual job preferences. Both figures report standardized OLS regression coefficients and 95-percent confidence intervals. Automation risk by Willrobotstakemyjob.com (2024) in parentheses.

effect on treated respondents was found on either attractiveness or the expected probability of entering the occupation, indicating that the treatment did not affect respondents with correct beliefs. The finding aligns with the model as respondents already had correct beliefs and should not change their beliefs of that occupation.

Next, I analyze how the effect differed depending on whether respondents overestimated or underestimated the automation risk for occupation and depict the results in Figure III. I did not analyze the effect for office clerks if respondents overestimated the automation risk as this was 100 percent. In panel (a), all coefficients point in a negative direction. Respondents who both underestimated and overestimated the automation risk for economists prescribe lower occupational attractiveness to economists. Interestingly, respondents who underestimated the automation risk view the teaching occupation as less attractive. No effect was found

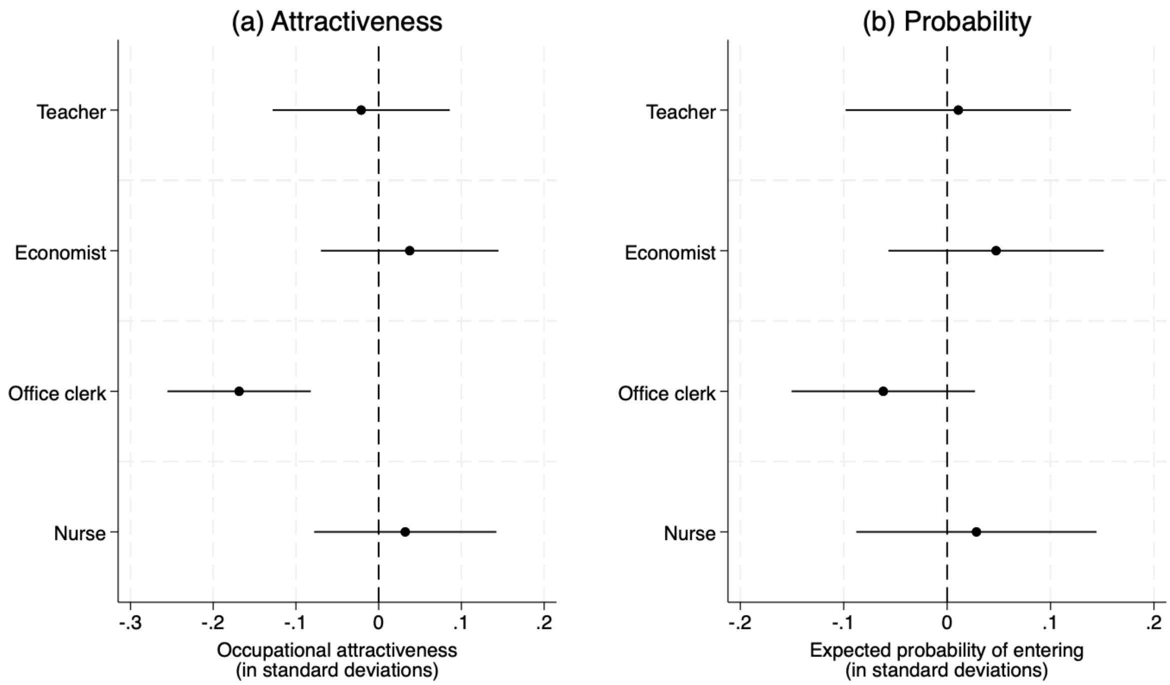

Figure IV: Surprise effect for main outcomes

Notes: This figures show standardized OLS regression coefficients using Specification 5. All plots control for background characteristics and individual job preferences. Panel (a) shows the occupational attractiveness and how the treatment group differs from the control group. Panel (b) shows the expected probability of entering the occupation and how the treatment group differs from the control group. Both figures report standardized OLS regression coefficients and 95-percent confidence intervals.

for nurses. Panel (b) shows less of an effect where respondents expect less to become office clerks. Corresponding estimates are presented in Table A1.

Next, I analyze how deviations in perceptions are affected by treatment. I modify the main specification by interacting the treatment variable and the difference in automation risk by Willrobotstakemyjob.com (2024) and perceived automation risk. I estimate the specification:

$$y_{ij} = \beta D_i \times (\overline{\text{AUTO-RISK}}_{ij} - \text{AUTO-RISK}_{ij}) + \alpha \text{AUTO-RISK}_{ij} + \delta' \mathbf{x}_i + \psi' \mathbf{z}_i + \varepsilon_{ij} \qquad (5)$$

where AUTO-RISK is respondents estimated automation risk and $\overline{\text{AUTO-RISK}}$ being the automation risk index by Willrobotstakemyjob.com (2024). The results are presented in Figure IV. The corresponding estimates are presented in Table A2. I find that occupational attractiveness for office clerks is additionally reduced by 0.17 standard deviation ($p < 0.01$) if they underestimate the automation risk. All other estimates in Table A2 are close to zero, indicating that larger deviations from the true automation risk did not affect occupational attractiveness and the expected probability of entering the occupation.

Are occupational-specific beliefs affected?

I pre-registered an analysis to examine perceptions of future occupational payment, social status, and job stability, but without specific hypotheses. These results are depicted in Table A3. In panel A, estimates for perceptions of future occupational payment are reported. There seems to be no effect on teachers but negative effects on economists and office clerks. Perceptions about future occupational payment in the treatment group decreased by 0.45 standard deviations ($p < 0.01$). Moreover, perceptions about future occupational payment for registered nurses increased by about 0.13 standard deviations ($p < 0.1$). Panel B depicts estimates for occupational social status. The treatment group prescribes lower social status for economists and office clerks, with 0.2 and 0.3 standard deviations, respectively. Teachers and nurses do not experience any changes in perceived social status. Panel C reports estimates for perceived job security. Teachers and nurses experienced improved job stability by 0.23 and 0.14 standard deviations. Next, I turn to analyze how deviations from the true automation risk relate to the findings in Table A3, using Specification 5. I find that larger deviations from the automation risk for office clerks negatively affect occupational-specific beliefs. However, there is no effect except for the teacher's perceived job security, which slightly decreases if the automation risk is underestimated. I provide the estimates in Table A4.

In sum, economists and office clerks experience negative effects on perceptions of their occupation. These results can be linked to the decreased occupational attractiveness for economists and office clerks in Table II. The findings are also consistent with the model since they show that the effect is pronounced by respondents who have incorrect beliefs. Finally, similar to the studies by Card et al. (2012), Coffman et al. (2017), Belot et al. (2019), and Jones and Kofoed (2020), I document that information provision can be used to manipulate occupational perceptions and labor market outcomes.

Respondents rank occupations differently

So far, the analysis has focused on the effect within occupations. I extend my analysis by investigating how respondents rank the four occupations. The results are reported in Figure A2. Teachers improve their ranking by about 0.2 standard deviations ($p < 0.01$). Next, office clerks were ranked lower in the treatment group by about 0.2 standard deviations ($p < 0.01$). No differences in the ranking are observed for economists and nurses. The reason behind the improved ranking of teachers can be the perceptions of improved job stability. For office clerks, the worse rankings probably result from the high automation risk. Finally, no statistically significant changes are displayed for economists and nurses. The findings in Figure A2 provide evidence for the decreased occupational attractiveness for office clerks. It seems that the information treatment affects preferences within and between occupations.

IV.D. Heterogeneity

Do the effects differ by gender?

I now turn to my pre-registered analysis of how my results differ by gender. To analyze gender differences, I run separate regressions for men and women and present visual results in Figure V. The figure displays decreased occupational attractiveness for economists and office clerks for both men and women. Moreover, men seem less likely to become office clerks. Corresponding estimates are provided in Table A5. Columns 1, 3, 5, and 7 show estimates for men, and columns 2, 4, 6, and 8 show estimates for women. Panel A shows estimates for occupational attractiveness. Columns 1 and 2 show estimates for teachers. Neither men nor women in the treatment group change perceptions about occupational attractiveness for the teaching occupation. Columns 3 and 4 show estimates for economists. Both men and women prescribe lower attractiveness to be an economist, where the magnitude is slightly larger for men. Columns 5 and 6 show estimates for office clerks. Both men and women find the occupation less attractive. The magnitude is larger for men, indicating that the effect in Figure II is driven by men. Finally, columns 7 and 8 show estimates for registered nurses. I find no effect on either men or women. The coefficients are fairly small, implying that the information treatment had little effect on the occupational attractiveness of being a nurse.

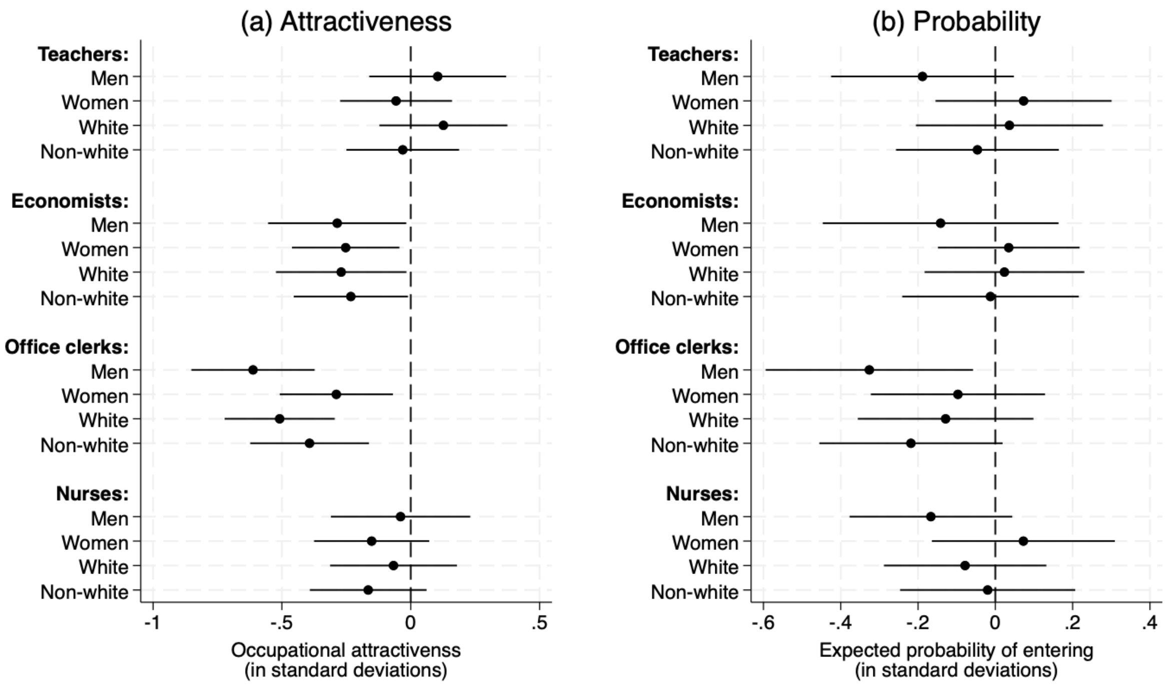

Figure V: Treatment effect by gender and race

Notes: This figure presents how the treatment effect differs by gender and race. All plots control for background characteristics and individual job preferences. Panel (a) shows the occupational attractiveness and how the treatment group differs from the control group. Panel (b) shows the expected probability of entering the occupation and how the treatment group differs from the control group. Both figures report standardized OLS regression coefficients and 95-percent confidence intervals.

Interestingly, only for nurses is the magnitude larger for women, which can be due to nursing being dominated by women. However, the coefficient in column 8 is fairly small, implying less of an effect.

Panel B displays estimates for the likelihood of entering the occupation. In columns 1 and 2, I find no effect on the expected probability of entering the occupation. In columns 3 and 4, I observed no effect on the expected probability of becoming an economist. In columns 5 and 6, I find that men are also less willing to become office clerks by 0.23 standard deviations compared to women, who experienced no change. The differences in perceptions of office clerks between men and women are statistically significant ($p < 0.1$). In the final columns, 7 and 8, I observe no effect on the likelihood of becoming a nurse. Despite non-statistically significant results, the magnitude for men is overall larger for men, indicating that men are more sensitive to automation risk than women. The effect is particularly pronounced for economists and office clerks.

Next, I relate my findings to the literature by Wiswall and Zafar (2018), who found that women are more sensitive to non-pecuniary outcomes. I re-estimate the effect on occupational-specific beliefs (from Table A3) for men and women separately and report the estimates in Table A6. Compared to Wiswall and Zafar (2018), I find no clear pattern that women are more sensitive to non-pecuniary outcomes. Instead, the disparities in effect across attributes and occupations suggest that automation risk does not have a homogeneous effect on occupational attributes.

Do the effects differ by race?

Next, in line with my pre-registered analysis, I compare white and non-white respondents in Figure V. The figure displays decreased occupational attractiveness for office clerks for both whites and non-whites and decreased expected probability of becoming an office clerk for non-whites. Table A7 provides corresponding estimates. Columns 1, 3, 5, and 7 show estimates for whites, and columns 2, 4, 6, and 8 show estimates for non-whites. Panel A reports estimates for occupational attractiveness. Columns 1 and 2 show that the information treatment does not affect the attractiveness of teachers for either whites or non-whites. In columns 3 and 4, I find that occupational attractiveness for economists is negatively affected for both whites and non-whites in the treatment group. The magnitude is slightly larger for whites. In columns 5 and 6, I find that occupational attractiveness is negatively affected for office clerks. The magnitude is larger for whites. In columns 7 and 8, I find no differences between whites and non-whites and their perceptions of attractiveness to become a nurse. Overall, the magnitude for whites is larger for all occupations except nurses. Thus, whites are more affected by the treatment of information when evaluating occupational attractiveness.

Panel B reports estimates for the likelihood of entering the occupation. I display no statistically significant effect for teachers in columns 1 and 2. The coefficients are close to zero, indicating that race does not matter for the expected probability of becoming a teacher. For economists in columns 3 and 4, the coefficients are close to zero for the probability of becoming an economist. Thus, the information treatment does not seem to affect the expected probability of becoming an economist. Columns 5 and 6 report estimates for office clerks. The subjective probability of becoming an office clerk decreases more for non-whites than whites, which is surprising as white respondents experienced a lower attractiveness to be an office clerk. The direction of effect is more ambiguous for the likelihood of entering the occupation. Moreover, the coefficients are near zero except for the self-reported probability of becoming an office clerk, indicating no effect from the information treatment. My heterogeneity analysis shows disparities between gender and race in how perceptions are affected, which sheds light on the findings by Manski (2004).

IV.E. Supplementary analysis

I pre-registered an analysis of several other outcome variables: Worry about labor future labor market outcomes, Additional years of study, Retirement age, Governmental redistribution of wealth, and Imposing regulation for AI. These variables are not connected to any occupation. I estimate the specification:

$$y_{ij} = \beta D_i + \alpha \sum^{j} \text{AUTO-RISK}_{ij} + \delta' \mathbf{x}_i + \psi' \mathbf{z}_i + \varepsilon_{ij} \tag{6}$$

where the only difference from the main specification 4, is the summation of AUTO-RISK_{ij} for all jobs which control for beliefs about automation risk that might influence all perceptions.

Table A8 depicts no effects for outcomes related to labor market outcomes, retirement, education, and political change. Hence, I choose to continue analyzing gender differences. Table A9 depicts estimates for men in uneven and women in even columns. In the first two columns, I found no effect on the worry of future labor market outcomes for men or women, which was surprising since men seemed more sensitive to automation risk. Columns 3 and 4 report estimates for additional years of study. Men expect to study 0.38 years more ($p < 0.1$). In contrast, women do not expect additional years of study. The expected increase in study years may be attributed to higher awareness of automation risk, but the effect is small. Consequently, men may feel compelled to pursue further education to improve their competitiveness in the labor market. Columns 5 to 8 report estimates if the respondent is expected to retire at age 63, respectively, 69 years old. The estimates suggest that the information treatment does not affect the retirement age expectations for any retirement age. Next, I turn to political views and how these are changed due to the information treatment. Columns 9 and 10 report whether the treatment group believes the government should redistribute wealth more. This question is important as AI targets middle-skilled jobs, and recent technological development has been a determinant for increases in wealth inequality. My estimates suggest that the information treatment does not affect opinions on the redistribution of wealth. The final columns, 11 and 12, depict whether the government should regulate technological development. The data shows a decrease for men by 0.24 standard deviations ($p < 0.1$). No effect is displayed for women. The earlier analysis in Section IV.C concluded that men seemed more sensible to the information treatment; it is thus surprising that men do not want to regulate the development of new technologies. Next, I analyze whether the effects differ depending on whether respondents underestimated or overestimated the effect and report the results in Table A10. However, the coefficients are imprecisely estimated. In sum, I find little or no effect from my information treatment on outcomes related to labor market outcomes, retirement, education, and political change. One explanation can be that the treatment content did not add any information related to these factors.

I relate my study to the previous literature that studied determinants of college majors by investigating how automation risk affects the likelihood of graduating in business and economics, engineering and computer science, humanities and other social sciences, and natural science and math. Results for men and women are presented in Table A11. All coefficients are small except for treated men choosing humanities and other social sciences, who are about 0.21 standard deviation less likely to choose that as their major. However, the effect is small and is only statistically significant at the 10-percent level. Overall, it seems that automation risk has little effect on the expected choice of college major. One potential explanation is that a college major does not imply having a specific occupation. A more suitable approach to studying the effect on college majors would have been constructing the information treatment to cover how the average graduate would have been affected by automation risk.

IV.F. Challenges to validity

Low attention among respondents may result in invalid estimates. Respondents' attention was not controlled due to the associated increased costs. However, the estimated time was 5 minutes and 50 seconds when pre-running the experiment, and the average respondent time was 5 minutes and 37 seconds. The difference is small and not statistically significant ($p = 0.18$), which mitigates this concern. Despite finding no big differences in the average duration time and the estimated time, I believe it is important to analyze whether inattentive respondents affect the results. To do so, I re-ran the main regressions, including respondents with a 4.5-minute or lower duration. Table A12 shows that my results seem robust when only including respondents with a duration time of 4.5 minutes or lower.

Next, I do not know how much respondents believed in the information provided and how reliable the risk indexes were. It is less likely to affect respondents' perceptions if they are unreliable. In addition, the treatment may have been interpreted as negative information, as it contained information that jobs may be computerized. This explanation may be why I found few positive effects, even if the respondent overestimated the automation risk. Another drawback of using survey data is the subjective answers using Likert scales. The distance between the answers does not need to be the same for all respondents. Moreover, non-parametric tests are helpful when the population distribution is unknown. I assess the robustness of my two main hypotheses using the Mann-Whitney test and report p-values in Table A13. The findings are consistent with my main results, which reject the first null hypothesis for economists and office clerks and reject the second null for office clerks. A final concern is that participants may be aware of being part of an experiment and respond to an answer that does not align with their beliefs.

V. CONCLUSION

This paper examines whether automation risk affects young adults' job preferences through a pre-registered online experiment focusing on teachers, economists, office clerks, and registered nurses. The results show a small to medium-sized decrease in occupational attractiveness for economists and office clerks, with no effect for teachers and registered nurses. The effect is more pronounced for men and whites. Next, I find no effect on the expected probability of becoming a teacher, economist, or registered nurse. On the other hand, I document a small negative effect on the expected probability of becoming an office clerk, which is pronounced for men and non-whites. My information treatment had little impact the occupational perceptions of teachers and nurses. The latter finding can be due to the nature of the teaching and nursing occupation, and they may be less sensitive to automation risk. The study highlights the economic importance of understanding how automation risk affects the labor supply for these occupations. My theoretical framework suggests respondents have revised their beliefs due to the information shock. I provide evidence for how automation risk influences individual beliefs. The treatment had no effect on respondents with accurate initial perceptions, and the effect differed for those underestimating or overestimating automation risk. Notably, respondents did not have more accurate beliefs about the automation risk for teachers and nurses compared to economists and office clerks, indicating other factors at play beyond automation risk perceptions. My model does not consider which occupation I selected. Instead, it treats all jobs the same, which is a drawback.

This study has several limitations. First, this study did not observe the actual outcome. Still, this concern is mitigated by the findings of Arcidiacono et al. (2020) that occupational probabilities are highly informative of the actual outcome. Second, some respondents may have started to study or already chosen a career path. The ideal sample would be 16-18, just about to enter the labor market. A final limitation is that the calculated automation risk is today's automation risk. No time frame was given by Willrobotstakemyjob.com (2024), which could have been meaningful to include in the treatment.

Despite these limitations, I believe the study has high internal validity as the results pass several robustness checks. The external validity is considered lower due to the smaller sample and the fact that respondents using prolific may differ from others in the same age group. What benefits my external validity is the use of two countries in my sample. Generalizing the results is challenging due to potential general equilibrium effects if the provided information were known to the entire population. Hence, other factors might have influenced the expected choice instead. As a result of low external validity, I encourage more research on how automation risk affects occupational choices across countries and age groups. For example, future studies could investigate how automation risk influences the decision to change occupations in response to this risk.

My results are important for policymakers to understand how automation risk influences occupational choice, especially for occupations with a global shortage, such as teachers and nurses. When addressing forthcoming occupation shortages, policymakers must be aware of the influence of automation risk on occupational preferences, particularly in light of the rapid pace of technological advancement.

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Appendix

A. Additional tables and figures

Table A1: Treatment effect if overestimate and underestimate the automation risk

	Teacher		Economist		Office clerk		Reg. Nurse	
	Under	Over	Under	Over	Under	Over	Under	Under
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A - Occupational attractiveness								
Treated	-0.62***	0.10	-0.23**	-0.29**	-0.40***		-0.14	-0.12
	(0.21)	(0.09)	(0.11)	(0.13)	(0.08)		(0.14)	(0.10)
Observations	124	469	345	253	570		223	370
Panel B - Expected probability of entering the profession								
Treated	-0.21	-0.01	0.01	-0.03	-0.15*		0.00	-0.08
	(0.20)	(0.09)	(0.11)	(0.12)	(0.08)		(0.13)	(0.10)
Observations	124	469	345	254	572		223	370
Background controls	✓	✓	✓	✓	✓		✓	✓
Job preferences	✓	✓	✓	✓	✓		✓	✓

Notes: This table displays standardized OLS estimates for occupational attractiveness and the probability of entering the occupation if underestimating or overestimating the automation risk. Estimates are not included for observations that guessed an automation risk of 100 for office clerks. Uneven columns depict estimates if underestimating the automation risk, and even columns depict estimates if overestimating the automation risk. Panel (a) shows the occupational attractiveness and how the treatment group differs from the control group. Panel (b) shows the expected probability of entering the occupation. Controls include race, gender, parental education, income from the previous year, nationality, city size, employment, relationship status, and number of siblings. Job preferences include preferences for occupational social status, salary preferences, risk preferences, job stability, confidence in the future profession, family preferences, job flexibility, and enjoyment. Robust standard errors in parenthesis. *** p<0.01, ** p<0.05, * p<0.1.

Table A2: Surprise effect - Attractiveness and probability of entering the occupation

	Teacher (1)	Economist (2)	Office clerk (3)	Reg. Nurse (4)
Panel A - Occupational attractiveness				
Treated × ($\overline{\text{AUTO-RISK}}$ − AUTO-RISK)	-0.02	0.04	-0.17***	0.003
	(0.05)	(0.05)	(0.04)	(0.06)
Observations	600	599	598	600
Panel B - Expected probability of entering the profession				
Treated × ($\overline{\text{AUTO-RISK}}$ − AUTO-RISK)	0.01	0.05	-0.06	-0.03
	(0.06)	(0.05)	(0.05)	(0.0)
Observations	600	600	600	600
Controls	✓	✓	✓	✓
Job preferences	✓	✓	✓	✓

Notes: This table displays standardized OLS estimates using Specification 5 for occupational attractiveness and the probability of entering the occupation. Moreover, the table accounts for correct beliefs and depicts estimates of whether the respondents initially had incorrect beliefs. Panel (a) shows the occupational attractiveness and how the treatment group differs from the control group. Panel (b) shows the expected probability of entering the occupation. Controls include race, gender, parental education, income from the previous year, nationality, city size, employment, relationship status, and number of siblings. Job preferences include preferences for occupational social status, salary preferences, risk preferences, job stability, confidence in the future profession, family preferences, job flexibility, and enjoyment. Robust standard errors in parenthesis. *** p<0.01, ** p<0.05, * p<0.1.

Table A3: Occupational specific beliefs

	Teacher (1)	Economist (2)	Office clerk (3)	Reg. Nurse (4)
Panel A - Will be well-paid in the future				
Treated	-0.00	-0.32***	-0.45***	0.13*
	(0.08)	(0.08)	(0.08)	(0.08)
Panel B - Occupational social status				
Treated	-0.00	-0.20**	-0.30***	0.06
	(0.08)	(0.08)	(0.08)	(0.08)
Panel C - Perceived job security				
Treated	0.23***	-0.32***	-0.56***	0.14*
	(0.08)	(0.08)	(0.08)	(0.08)
Observations	600	600	600	600
Controls	✓	✓	✓	✓
Job preferences	✓	✓	✓	✓

Notes: This table shows standardized OLS regressions estimates related to beliefs for all occupations. Panel A report estimates the questions of whether the occupation will be well-paid in the future. Panel B reports estimates about the perceived occupational social status. Panel C reports estimates for the perceived occupational job security. Controls include race, parental education, income the previous year, nationality, city size, employment, relationship status, and number of siblings. Robust standard errors in parenthesis. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table A4: Surprise effect on occupational specific beliefs

	Teacher (1)	Economist (2)	Office clerk (3)	Reg. Nurse (4)
Panel A - Will be well-paid in the future				
Treated × ($\overline{\text{AUTO-RISK}}$ − AUTO-RISK)	0.04	0.07	-0.19***	0.02
	(0.05)	(0.05)	(0.04)	(0.05)
Panel B - Occupational social status				
Treated × ($\overline{\text{AUTO-RISK}}$ − AUTO-RISK)	-0.02	0.04	-0.16***	-0.04
	(0.06)	(0.06)	(0.04)	(0.05)
Panel C - Perceived job security				
Treated × ($\overline{\text{AUTO-RISK}}$ − AUTO-RISK)	-0.19***	0.04	-0.18***	0.03
	(0.06)	(0.06)	(0.04)	(0.06)
Observations	600	600	600	600
Controls	✓	✓	✓	✓
Job preferences	✓	✓	✓	✓

Notes: This table shows standardized OLS regressions estimates related to beliefs for all occupations using Specification 5. Moreover, the table accounts for correct beliefs and estimates whether the respondents initially had incorrect beliefs. Panel A report estimates the questions of whether the occupation will be well-paid in the future. Panel B reports estimates about the perceived occupational social status. Panel C reports estimates for the perceived occupational job security. Controls include race, parental education, previous year's income, nationality, city size, employment, relationship status, and number of siblings. Robust standard errors in parenthesis. *** p<0.01, ** p<0.05, * p<0.1.

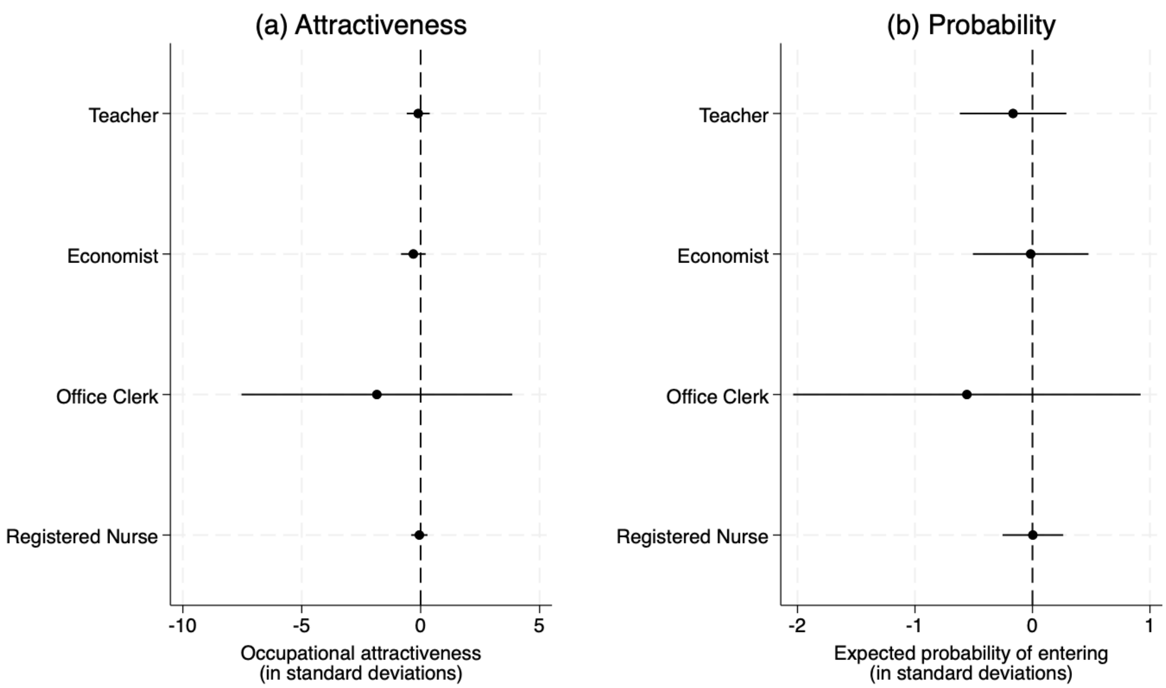

Figure A1: Effects ±5 percentage points from the true automation risk

Notes: This figure plots estimates where I only include respondents who guessed an automation risk in the interval ±5 percentage points from the true automation risk. All plots control for background characteristics and individual job preferences. Panel (a) shows the occupational attractiveness and how the treatment group differs from the control group. Panel (b) shows the expected probability of entering the occupation and how the treatment group differs from the control group. Both figures report standardized OLS regression coefficients and 95-percent confidence intervals.

Table A5: Heterogeneity - Gender

	Teacher		Economist		Office clerk		Reg. Nurse	
	Men	Women	Men	Women	Men	Women	Men	Women
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A - Occupational attractiveness								
Treated	0.10	-0.06	-0.29**	-0.25**	-0.61***	-0.29**	-0.04	-0.15
	(0.13)	(0.11)	(0.14)	(0.11)	(0.12)	(0.11)	(0.14)	(0.11)
Observations	244	325	244	324	243	324	244	325
R-squared	0.21	0.17	0.17	0.19	0.28	0.23	0.19	0.17
Panel B - Expected probability of entering the profession								
Treated	-0.19	0.07	-0.14	0.03	-0.33**	-0.10	-0.17	0.07
	(0.12)	(0.12)	(0.15)	(0.09)	(0.14)	(0.11)	(0.11)	(0.12)
Observations	244	325	244	325	244	325	244	325
R-squared	0.31	0.18	0.24	0.18	0.29	0.19	0.33	0.20
Background controls	✓	✓	✓	✓	✓	✓	✓	✓
Job preferences	✓	✓	✓	✓	✓	✓	✓	✓

Notes: This table displays standardized OLS estimates for occupational attractiveness and the probability of entering the occupation, separating men and women. Panel (a) shows the occupational attractiveness and how the treatment group differs from the control group. Panel (b) shows the expected probability of entering the occupation. Controls include race, parental education, income from the previous year, nationality, city size, employment, relationship status, and number of siblings. Job preferences include preferences for occupational social status, salary preferences, risk preferences, job stability, confidence in the future profession, family preferences, job flexibility, and enjoyment. Robust standard errors in parenthesis. *** p<0.01, ** p<0.05, * p<0.1.

Table A6: Occupational specific beliefs by gender

	Teacher		Economist		Office clerk		Reg. Nurse	
	Men	Women	Men	Women	Men	Women	Men	Women
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A - Will be well-paid in the future								
Treated	0.01	-0.06	-0.42***	-0.28**	-0.62***	-0.33***	0.19	0.08
	(0.13)	(0.12)	(0.13)	(0.11)	(0.14)	(0.10)	(0.12)	(0.11)
Observations	244	325	244	324	243	324	244	325
Panel B - Occupational social status								
Treated	0.07	-0.12	-0.22*	-0.18	-0.34**	-0.29***	0.09	0.02
	(0.13)	(0.11)	(0.13)	(0.11)	(0.14)	(0.10)	(0.13)	(0.11)
Observations	244	325	244	324	243	324	244	325
Panel C - Perceived job security								
Treated	0.18	0.28**	-0.13	-0.43***	-0.52***	-0.58***	0.18	0.17
	(0.13)	(0.11)	(0.13)	(0.11)	(0.12)	(0.10)	(0.14)	(0.11)
Observations	244	325	244	325	244	325	244	325
Background controls	✓	✓	✓	✓	✓	✓	✓	✓
Job preferences	✓	✓	✓	✓	✓	✓	✓	✓

Notes: This table displays standardized OLS estimates for occupational-specific questions, separating men and women. Panel A report estimates the questions of whether the occupation will be well-paid in the future. Panel B reports estimates about the perceived occupational social status. Panel C reports estimates for the perceived occupational job security. Controls include race, parental education, income from the previous year, nationality, city size, employment, relationship status, and number of siblings. Controls include race, parental education, income the previous year, nationality, city size, employment, relationship status, and number of siblings. Robust standard errors in parenthesis. *** p<0.01, ** p<0.05, * p<0.1.

Table A7: Heterogeneity - Race

	Teacher		Economist		Office clerk		Reg. Nurse	
	White	Non-white	White	Non-white	White	Non-white	White	Non-white
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A - Occupational attractiveness								
Treated	0.13	-0.03	-0.27**	-0.23**	-0.51***	-0.39***	-0.07	-0.17
	(0.13)	(0.11)	(0.13)	(0.11)	(0.11)	(0.12)	(0.12)	(0.12)
Observations	282	316	282	315	280	316	282	316
R-squared	0.24	0.18	0.19	0.20	0.30	0.23	0.15	0.16
Panel B - Expected probability of entering the profession								
Treated	0.04	-0.05	0.02	-0.01	-0.13	-0.22*	-0.08	-0.02
	(0.12)	(0.11)	(0.10)	(0.12)	(0.12)	(0.12)	(0.11)	(0.12)
Observations	282	316	282	316	282	316	282	316
R-squared	0.29	0.17	0.32	0.23	0.24	0.20	0.24	0.26
Background controls	✓	✓	✓	✓	✓	✓	✓	✓
Job preferences	✓	✓	✓	✓	✓	✓	✓	✓

Notes: This table displays standardized OLS estimates for occupational attractiveness and the probability of entering the occupation separated by whites and non-whites. Panel (a) shows the occupational attractiveness and how the treatment group differs from the control group. Panel (b) shows the expected probability of entering the occupation. Controls include gender, parental education, income from the previous year, nationality, city size, employment, relationship status, and number of siblings. Job preferences include preferences for occupational social status, salary preferences, risk preferences, job stability, confidence in the future profession, family preferences, job flexibility, and enjoyment. Robust standard errors in parenthesis. *** p<0.01, ** p<0.05, * p<0.1.

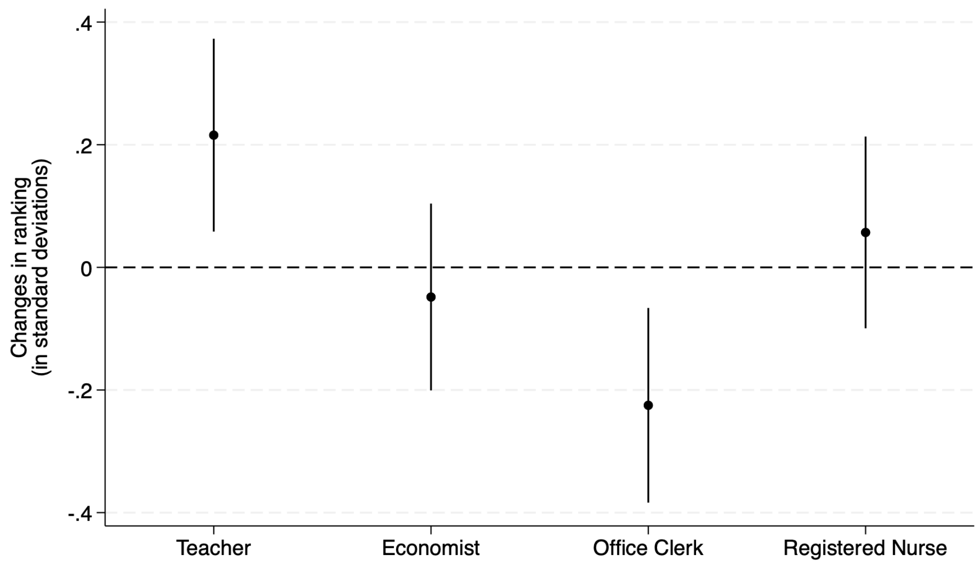

Figure A2: Changes in occupational ranking

Notes: This figure shows how rankings of occupations differ by the control and treatment group. All plots control for background characteristics and individual job preferences. The figure reports standardized OLS regression coefficients and 95-percent confidence intervals.

Table A8: Reactions to treatment

	Worry of labor outcomes	Additional study years	Retire - 63	Retire - 69	Redistribute wealth	Impose regulations
	(1)	(2)	(3)	(4)	(5)	(6)
Treated	-0.02	0.18	-0.04	0.11	0.01	-0.09
	(0.07)	(0.13)	(0.08)	(0.08)	(0.08)	(0.08)
Observations	600	600	600	600	600	600
R-squared	0.33	0.15	0.21	0.14	0.15	0.15
Background controls	✓	✓	✓	✓	✓	✓
Job preferences	✓	✓	✓	✓	✓	✓

Notes: This table shows estimates for the supplementary analysis analyzing perceptions of labor outcomes, education, retirement, and political preferences. All estimates use Specification 6. Controls include race, parental education, previous year's income, nationality, city size, employment, relationship status, and number of siblings. Job preferences include preferences for occupational social status, salary preferences, risk preferences, job stability, confidence in the future profession, family preferences, job flexibility, and enjoyment. Robust standard errors in parenthesis. *** p<0.01, ** p<0.05, * p<0.1.

Table A9: Reactions to treatment - Gender

	Worry about labor outcomes		Additional years of study		Retire - 63		Retire - 69		Redistribute wealth		Impose regulations	
	Men	Women	Men	Women	Men	Women	Men	Women	Men	Women	Men	Women
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Treated	-0.10	0.03	0.38*	-0.10	-0.06	0.05	0.13	0.14	0.05	-0.10	-0.24*	-0.04
	(0.11)	(0.10)	(0.14)	(0.11)	(0.13)	(0.11)	(0.13)	(0.11)	(0.13)	(0.11)	(0.14)	(0.11)
Observations	244	325	244	325	244	325	244	325	244	325	244	325
R-squared	0.42	0.37	0.24	0.26	0.28	0.27	0.26	0.23	0.25	0.20	0.24	0.22
Background controls	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Job preferences	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓

Notes: This table shows estimates for the supplementary analysis analyzing perceptions of labor outcomes, education, retirement, and political preferences for men and women separately. All estimates use Specification 6. Controls include race, parental education, previous year's income, nationality, city size, employment, relationship status, and number of siblings. Robust standard errors in parenthesis. *** p<0.01, ** p<0.05, * p<0.1.

Table A10: Reactions to treatment if overestimating or underestimating the aggregate automation risk

	Worry about labor outcomes		Additional years of study		Retire - 63		Retire - 69		Redistribute wealth		Impose regulations	
	Under	Over	Under	Over	Under	Over	Under	Under	Under	Over	Under	Over
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Treated	0.03	-0.05	0.20	0.27	-0.00	0.02	0.09	0.14	0.06	-0.09	-0.05	-0.11
	(0.10)	(0.12)	(0.18)	(0.19)	(0.11)	(0.12)	(0.11)	(0.13)	(0.11)	(0.13)	(0.11)	(0.13)
Observations	345	249	345	249	345	249	345	249	345	249	345	249
R-squared	0.40	0.34	0.20	0.21	0.22	0.32	0.20	0.24	0.22	0.23	0.19	0.23
Background controls	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Job preferences	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓

Notes: This table shows estimates for the supplementary analysis analyzing perceptions of labor outcomes, education, retirement, and political preferences for men and women separately if underestimating or overestimating the automation risk the aggregate automation risk. All estimates use Specification 6. Uneven columns depict estimates if underestimating the automation risk, and even columns depict estimates if overestimating the automation risk. All estimates use Specification 6. Controls include race, parental education, previous year's income, nationality, city size, employment, relationship status, and number of siblings. Robust standard errors in parenthesis. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table A11: College major

	Business		Engineering		Humanities		Science	
	Men	Women	Men	Women	Men	Women	Men	Women
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Treated	-0.04	0.02	0.04	0.10	-0.21*	0.09	-0.04	-0.04
	(0.14)	(0.10)	(0.15)	(0.10)	(0.11)	(0.13)	(0.13)	(0.12)
Observations	244	325	244	325	244	325	244	325
R-squared	0.21	0.28	0.19	0.25	0.31	0.10	0.24	0.16
Background controls	✓	✓	✓	✓	✓	✓	✓	✓
Job preferences	✓	✓	✓	✓	✓	✓	✓	✓

Notes: This table displays standardized OLS estimates for expected college majors, separating men and women. All estimates use Specification 6. Controls include race, parental education, previous year's income, nationality, city size, employment, relationship status, and number of siblings. Job preferences include preferences for occupational social status, salary preferences, risk preferences, job stability, confidence in the future profession, family preferences, job flexibility, and enjoyment. Robust standard errors in parenthesis. *** p<0.01, ** p<0.05, * p<0.1.

Table A12: Robustness check - Duration time 4.5 minutes

	Teacher (1)	Economist (2)	Office clerk (3)	Reg. Nurse (4)
Panel A - Occupational attractiveness				
Treated	-0.05	-0.29**	-0.48***	0.02
	(0.14)	(0.13)	(0.12)	(0.13)
Observations	262	262	262	262
Panel B - Expected probability of entering the profession				
Treated	-0.22*	-0.07	-0.29**	-0.14
	(0.13)	(0.13)	(0.13)	(0.12)
Observations	262	262	262	262
Controls	✓	✓	✓	✓
Job preferences	✓	✓	✓	✓

Notes: This table displays standardized OLS estimates for occupational attractiveness and the probability of entering the occupation only, including respondents with a duration time less than 4.5 minutes. Panel (a) shows the occupational attractiveness and how the treatment group differs from the control group. Panel (b) shows the expected probability of entering the occupation. Controls include race, gender, parental education, income from the previous year, nationality, city size, employment, relationship status, and number of siblings. Job preferences include preferences for occupational social status, salary preferences, risk preferences, job stability, confidence in the future profession, family preferences, job flexibility, and enjoyment. Robust standard errors in parenthesis. *** p<0.01, ** p<0.05, * p<0.1.

Table A13: Non-parametric tests - P-values

	Teacher (1)	Economist (2)	Office clerk (3)	Reg. Nurse (4)
Panel A - Occupational attractiveness				
Treated	0.51	0.00	0.00	0.09
Panel B - Expected probability of entering the profession				
Treated	0.79	0.55	0.07	0.83

Notes: This table displays p-values using the Mann-Whitney test comparing the treatment and control group.

B. Survey

LUND UNIVERSITY

Prolific ID

What is your Prolific ID?
Please note that this response should auto-fill with the correct ID.

${e://Field/PROLIFIC_PID}

Introduction

Information
Welcome to this survey, and thank you for taking part. I am a master's student from Lund University, researching young adults' job preferences. This study is focused on gathering insights from young adults aged 18-21 regarding job preferences.

Management of Data and Confidentially
This survey aims to capture your perspectives, and your input is highly valued. Rest assured, all information provided will remain strictly confidential and anonymous. The results of this study will be presented solely in aggregate form, ensuring that individual responses cannot be traced back to participants. Finally, the data collection process complies with the European regulations outlined in GDPR, and appropriate measures will be taken to safeguard your privacy.

Participation
All participation is voluntary; you can leave the survey at any stage. If you choose to leave the study, you do not need to mention why.

Responsible researcher
Marcus Rundström
Second-year Master's student
marcus.rundstrom@nek.lu.se
Department of Economics, Lund University, Sweden

If you give your consent to take part, click "Yes."

If you do not give your consent, please leave the survey.

- ◯ Yes

Background

Gender:

- ◯ Male
- ◯ Female
- ◯ Other
- ◯ Prefer not to say

Which year where you born in?

2002 2003 2004 2005 2006

Relationship status:

- ◯ Single
- ◯ Living apart
- ◯ In a relationship
- ◯ Married
- ◯ Other

Currently I am

- ◯ Working

- Study
- Unemployed
- Other

Birth country

- USA
- Foreign/Other
- UK

I live in a city with population size (inhabitants)

- 0-100 000
- 100 001 - 500 000
- 500 001 - 1 000 000
- 1 000 000 +

Total gross income last in 2023:

Note: If your total income was more than 100 000 dollars, then answer 100 000 dollar.

	0	20000	40000	60000	80000	100000
Dollar						

Highest academic degree obtained

- Mandatory school or lower
- High school
- Bachelor's degree or higher

Highest academic degree obtained by mother

- ○ Mandatory school or lower
- ○ High school
- ○ Bachelor's degree or higher

Highest academic degree obtained by father

- ○ Mandatory school or lower
- ○ High school
- ○ Bachelor's degree or higher

How many siblings do you have?

0 1 2 3 4 5 6 7 8 9 10

How many children do you have?

0 1 2 3 4 5 6 7 8 9 10

I am:

- ○ White/Caucasian
- ○ Black/African American
- ○ American Indian
- ○ Hispanic/Latino

- Asian/Pacific Islander
- Other

Individual preferences

These questions ask about your beliefs. Even if you do not know with certainty, please answer the question as best as possible.

How well do you agree with the statements?

	Strongly disagree	Disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Agree	Strongly agree
My future profession must have a high social status.	O	O	O	O	O	O	O
A high salary is important for me.	O	O	O	O	O	O	O
I value flexibility in my life.	O	O	O	O	O	O	O
Having the opportunity to work from a distance is important for me.	O	O	O	O	O	O	O
I want an occupation that I enjoy.	O	O	O	O	O	O	O
I care about building a family life.	O	O	O	O	O	O	O
Job stability is important to me.	O	O	O	O	O	O	O
I am confident of what my future profession will be.	O	O	O	O	O	O	O

	Strongly disagree	Disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Agree	Strongly agree
In comparison to others, I am willing to avoid any type of risk.	○	○	○	○	○	○	○

Below, you are asked to estimate the automation risk for three occupations. Automation risk is the probability that a job can be fully automatized.

What do you think is the automation risk for teachers?

When choosing your answer, please include all types of kindergarten, elementary, middle, and secondary school (high school) teachers.

0 25 50 75 100

Percent

What do you think is the automation risk for economists?

0 25 50 75 100

Percent

What do you think is the automation risk for office clerks?

0 25 50 75 100

Percent

What do you think is the automation risk for registered nurses?

0 25 50 75 100

Percent

Information

Please read the below information carefully. Thank you.

As you may be aware, there is a rising concern about robots, AI, and human labor market outcomes. Previous technological developments have substituted routine tasks. However, with the introduction of AI and ChatGPT, non-routine tasks could also be automated, and productivity could be enhanced. Moreover, the latest technology targets middle-skilled and high-skilled jobs as sophisticated algorithms have been developed to perform tasks that require greater cognitive abilities.

Below, you will find four occupations and the associated probability for automation.

- The automation risk for teachers (all types) is 9 percent.
- The automation risk for economists is 51 percent.
- The automation risk for office clerks is 100 percent.
- The automation risk for registered nurses is 10 percent.

The risk measure takes into account different attributes such as originality, thinking creatively, persuasion, social perceptiveness, assistance and caring for others, and coordination. Each attribute has two values: importance and level. Thus, the attributes' different levels and importance enable us to understand the automation risk for various occupations. Finally, the measures are based on 0*NET data from November 2022, and the calculations were performed in January 2023.

Source:

Frey, C. B., & Osborne, M. A. (2017). The future of employment: How susceptible are jobs to computerisation?. *Technological forecasting and social change*, 114, 254-280.

Noy, S., & Zhang, W. (2023). Experimental evidence on the productivity effects of generative artificial intelligence. Science, 381(6654), 187-192.

https://willrobotstakemyjob.com/

I have read the information above:

○ Yes

Final questions

These questions ask about your beliefs. Even if you do not know with certainty, please answer the question as best as possible.

How would you rate the attractiveness for making a career as

	Very low	Low	Slightly low	Neither	Slightly high	High	Very high
Teacher (all types)	○	○	○	○	○	○	○
Economist	○	○	○	○	○	○	○
Office clerk	○	○	○	○	○	○	○
Registered nurse	○	○	○	○	○	○	○

What is the likelihood that you will become a/an:

	Very unlikely	Unlikely	Slightly unlikely	Neither likely nor unlikely	Slightly likely	Likely	Very likely
Teacher (all types)	○	○	○	○	○	○	○
Economist	○	○	○	○	○	○	○
Office clerk	○	○	○	○	○	○	○
Registered nurse	○	○	○	○	○	○	○

How well do you agree with the statements?

When choosing your answer, please include all types of kindergarten, elementary, middle, and secondary school (high school) teachers.

	Strongly disagree	Disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Agree	Strongly agree
Teachers will be well-paid in the future	○	○	○	○	○	○	○
Teachers have a high social status	○	○	○	○	○	○	○
I believe the teaching profession has a high job security.	○	○	○	○	○	○	○

How well do you agree with the statements?

	Strongly disagree	Disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Agree	Strongly agree
Economists will be well-paid in the future	○	○	○	○	○	○	○
Economists have a high social status	○	○	○	○	○	○	○
I believe the economist profession has a high job security.	○	○	○	○	○	○	○

How well do you agree with the statements?

	Strongly disagree	Disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Agree	Strongly agree
Office clerks will be well-paid in the future	○	○	○	○	○	○	○
Office clerks have a high social status	○	○	○	○	○	○	○

	Strongly disagree	Disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Agree	Strongly agree
I believe the office clerks has a high job security.	○	○	○	○	○	○	○

How well do you agree with the statements?

	Strongly disagree	Disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Agree	Strongly agree
Registered nurses will be well-paid in the future	○	○	○	○	○	○	○
Registered nurses have a high social status	○	○	○	○	○	○	○
I believe the registered nurses has a high job security.	○	○	○	○	○	○	○

Please rank the professions such that your first choice is the occupation you find most attractive to enter:

Teacher (all types)

Economists

Office clerks

Registered nurses

What is the probability that you will be working full-time after you reach the age of ____

	0	25	50	75	100	
63 years						
69 years						

I am worried about my labor market outcomes due to the technological development.

Strongly disagree

Disagree

Somewhat disagree

Neither agree nor disagree

Somewhat agree

Agree

Strongly agree

If you plan to study/study, how many years do you expect to study from now on? If you do not plan to study, please choose zero.

	0	1	2	3	4	5	6	7	8	9	10	
Years												

What is the likelihood that you graduate in one of the following majors?

	Very unlikely	Unlikely	Slightly unlikely	Neither likely nor unlikely	Slightly likely	Likely	Very likely	I do not want to begin studying
Business and Economics	○	○	○	○	○	○	○	○
Engineering and Computer Science	○	○	○	○	○	○	○	○
Humanities and Other Social Sciences	○	○	○	○	○	○	○	○
Natural Sciences and Math	○	○	○	○	○	○	○	○

The government should take more responsibility to redistribute wealth.

Strongly disagree

○

Disagree

○

Somewhat disagree

○

Neither agree nor disagree

○

Somewhat agree

○

Agree

○

Strongly agree

○

Politicians should regulate the development of new technologies such as AI.

Strongly disagree

○

Disagree

○

Somewhat disagree

○

Neither agree nor disagree

○

Somewhat agree

○

Agree

○

Strongly agree

○