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ARE MORE AUTOMATABLE JOBS LESS SATISFYING?

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Are more automatable jobs less satisfying?

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Abstract

We investigate whether the characteristics which render a job more likely to disappear due to automation also make that job less satisfying. The literature on automation offers convincing reasons in favour of this hypothesis, but it has not been empirically tested before. We use a widely-established, occupation-level measure of automatability and find that more automatable jobs are indeed significantly less satisfying using data from the European Working Conditions Survey. The effect is sizeable and robust to controlling for a wide range of individual-level variables and job-context variables. Our finding suggests that more automatable occupations are less satisfying because of their inherent nature (i.e. the nature of the tasks required for the performance of that occupation). We conduct a mediation analysis and find that the smaller creative intelligence requirement related to automatable occupations is the most important reason for their lower job satisfaction. We discuss to what extent these economy-wide findings translate to the level of the individual worker, in the context of a labor market segmented by education level.

Keywords: Automation; Job Satisfaction; Occupational Task Content; European Working Conditions Survey

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Statements and Declarations

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1 Introduction and Motivation

There is a growing consensus in the academic literature that technical progress in the fields of computing, computer-assisted machines, robotics and artificial intelligence is likely to make certain occupations disappear (Arntz et al., 2016; Bresnahan, 1999; Brynjolfsson & McAfee, 2011; Frey & Osborne, 2017). In the leading economic conceptualization of automation — the task-based framework of Acemoglu and Restrepo (2018a; 2018b) —, automation takes the form of capital entirely displacing labor from the execution of a task. Other modelling approaches to automation do not adopt a task-based perspective, but still view automation as a potential process of job destruction: they focus on the relationship between "automation capital" and labor, which is dominated by substitutability rather than complementarity (Cords & Prettner, 2022; Eden & Gaggl, 2018; Jaimovich et al., 2021; Lankisch et al, 2019; Prettner & Strulik, 2020). The empirical literature finds convincing evidence indicating that automation displaces workers from tasks that they were previously performing (Acemoglu & Restrepo, 2020; Autor & Salomons, 2018; Gregory et al., 2022). The automation of a task also engenders productivity gains (Acemoglu & Restrepo, 2018a; 2018b) which has been found to raise labor demand and thus create jobs in the execution of non-automated tasks (Acemoglu et al., 2020; Acemoglu & Restrepo, 2020; Aghion et al., 2022; Gregory et al., 2022). In this study, we focus on the nature of the jobs which could be lost due to automation. In particular, we study whether the task content which makes an occupation automatable also make an occupation less satisfying.

There is variation in the automatability of occupations in the sense that not all tasks are equally easily automated. Autor et al. (2003) identified an important determinant of task automatability by making the now canonical distinction between routine and non-routine tasks. Put simply, routine tasks are tasks that can be readily executed by machines following simple rules. Non-routine tasks are tasks that require high levels of flexibility, creativity, generalized problem-solving and complex communications. They cannot easily be executed by machines because the rules required for their execution cannot be made explicit. In part, this is because humans executing these tasks only have a tacit understanding of the set of rules they follow to successfully perform the task (Autor, 2014). Empirical studies have systematically found that automation has been heavily biased towards routine tasks (Autor et al., 2003; Autor & Dorn, 2013; Goos et al., 2009). Increasingly, however, technologies have been developed which allow automation to overcome its difficulties in performing non-routine tasks (Frey & Osborne, 2017). With regard to non-routine tasks of a cognitive nature, the joint evolution of machine learning techniques and the availability of big data implies that machines can increasingly infer the rules which we apply — tacitly but not explicitly — to perform non-routine tasks (Autor, 2014; Brynjolfsson & McAfee, 2011). With regard to non-routine tasks of a manual nature, the rise of advanced robotics with increased intelligence and machine vision enables machines to execute more complex manual tasks (Manyika et al., 2013). In spite of the rapidly growing capabilities of automation technologies to perform tasks previously executed by labor, Frey and Osborne (2017) argue that some important engineering bottlenecks to the automation of all tasks remain. The authors identify tasks requiring a high level of manual dexterity, creative intelligence and social intelligence as the most important bottlenecks to the automation of occupations.

It can be argued based on the literature that — due to their inherent nature — automatable tasks are potentially less satisfying. Deschacht (2021) explicitly states that automation could be expected to improve job quality, since it is biased towards replacing humans from routine tasks. He cites, for instance, the use of robots to assist in the lifting of heavy objects as an area where automation would remove the need for unpleasant human work. Similarly, Sherwani et al. (2020) set out the opportunities of robot technology to relieve humans from performing the so-called '3D jobs' — dirty, dangerous or dull. In general, it is well-known that the specific set of tasks executed at the job is an important determinant of job satisfaction. For instance, Cornelißen (2009) finds that task diversity is an important determinant of job satisfaction in Germany. Green et al. (2016) likewise show that task variety and task discretion (which refers to decision-making participation at the level of workers' own jobs) affect job-related well-being. The task content of an occupation is thus an important determinant of both the automatability of that occupation and job satisfaction.

In particular, it could be argued that this common driver of task content results in a negative association between automatability and job satisfaction. This assumed relationship (that automatable tasks could be less satisfying) has important policy repercussions since the degree to which workers enjoyed the job they lost is important for the welfare effects of automation-driven job losses. The hypothesis is justifiable, but it has never been explicitly tested in spite of its direct importance in the evaluation of the labor market effects of automation.

Our main findings are as follows. We find that individuals employed in more automatable occupations indeed report significantly lower job satisfaction on average. The results are robust to controlling for a very wide range of individual-level socio-demographic controls and job-context controls, strengthening the hypothesis that automatable occupations are *fundamentally* less satisfying — meaning "less satisfying because of their task content". Our results thus suggest that taking into account the nature of the disappearing jobs could make the welfare implications of automation-driven job losses more positive. In subsequent mediation analyses, we find that the negative automatability-satisfaction relationship is entirely explained by the fact that occupations which require less creativity are both (1) more readily automatable and (2) less satisfying. Other bottlenecks to the automation of an occupation such as the need for manual dexterity and the need for social intelligence seem to play no significant role. When taking into account the fact that labor markets are segmented by educational requirements, we find evidence that, for lower-educated individuals, automation-driven job losses are concentrated among the less satisfying occupations. For higher-educated individuals, in contrast, automation is found to be biased towards making more satisfying occupations disappear.

The remainder of this text is structured as follows. In section 2, we explain which datasets and empirical strategy we use. In section 3, we set out our results regarding the link between occupation-level job satisfaction and automatability. We also do a mediation analysis to determine which characteristics of the content of a job explain the satisfaction-automatability relationship. In section 4, we discuss the implications of our findings for the welfare effect of automation. Section 5 concludes the paper.

2 Data and empirical approach

We make use of the sixth wave of the European Working Conditions Survey (EWCS), conducted by Eurofound (2016), to obtain our core dataset. The EWCS contains all information necessary for our empirical approach: job satisfaction data, information on individual-level and job-level drivers of job satisfaction (to be used as control variables), and 4-digit ISCO-08 codes identifying the occupation (to be used for the construction of our automatability indicator). The sixth-wave of the EWCS dataset is the result of face-to-face interviews with 43 850 people in employment, aged 15 or older. The average duration of the interview was 45 minutes and no proxy interview was allowed. The survey covers 35 European countries (the EU28, the five candidate countries for EU membership, Norway, and Switzerland) and all interviews were carried out in 2015. The sixth-wave of the EWCS dataset is regarded as a trustworthy data source and it is often used in recent scientific research (Borgmann et al., 2019; Gomez-Baya & Lucia-Casademunt, 2018; Nappo, 2019; Ollé-Espluga et al., 2021; Padrosa et al., 2021; Pita & Torregrosa, 2021; Williams & Horodnic, 2019). We follow Pita and Torregrosa (2021) by selecting Q88 of the survey as the best predictor of overall job satisfaction:

On the whole, are you very satisfied, satisfied, not very satisfied or not at all satisfied with working conditions in your main paid job?

Our indicator for job satisfaction is thus an ordinal variable measured on a four-point scale. Table 1 sets out the response distribution in the data.

Table 1: Frequencies for dependent variable Job Satisfaction.

Not at all satisfied (1)	Not very satisfied (2)	Satisfied (3)	Very satisfied (4)
1104	4713	21665	9205
3.0%	12.8%	59.1%	25.1%

For the construction of our occupation-level indicator of automatability, we make use of the work of Frey and Osborne (2017). Together with machine learning experts, the authors identified 70 occupations of which they could determine with high certainty whether or not they would be automated. They then selected nine objective variables from the O*NET database (describing the task content for each occupation) which correspond closely to the bottlenecks to automation (being manual dexterity, creative intelligence and social intelligence). The final result of the study is that for 702 occupations (defined by a six-digit SOC-2010 code) the authors obtain a probability estimate between 0 and 1 which represents the likelihood of an occupation being fully automated (Frey & Osborne, 2017). Since occupations are identified using 4-digit ISCO-08 codes in the EWCS, we make use of the correspondence table provided by the US Bureau of Labor Statistics to convert the automatability estimates of Frey and Osborne (2017) to the ISCO-08 format. When multiple SOC-codes are available for one ISCO-code, we make use of a weighted average with the weights defined as the total US dependent employment in that SOC-occupation in 2015 (Occupational Employment Survey). A similar approach is followed by Mihaylov and Tijdens (2019). Using this procedure, we obtain automatability estimates for 360 of the 439 existing 4-digit ISCO-08 codes. This procedure results in a valid automatability estimate for 84.1% of the full 2015 EWCS sample (36 883 individuals).

In Appendix A, we show how our occupation-level measure of automatability relates to age[1], education level and countries. The observation that younger workers are on average slightly more at risk of automation in our sample is in accordance with the findings of Battisti and Gravina (2021) for robotics technology and the model

[1]Note that our dataset contains information on workers aged 15 to 88. At the edges of the age range, the average automatability is not very informative due to the low number of respondents. Here we restricted ourselves to the ages with at least 150 respondents.

of Acemoglu and Restrepo (2022). In our sample, average automatability is for the most part monotonically decreasing in the education level of the respondents and this is in line with the empirical literature as well (Arntz et al., 2016; Frey & Osborne, 2017). Our cross-country differences in average automatability largely coincide with the mean automatability calculations by country of Arntz et al. (2016): the Pearson correlation coefficient is 76% when comparing for the seventeen countries which are both in their and our sample. In particular, Table A3 echoes the findings of Bowles (2014) and Arntz et al. (2016) that the so-called 'peripheral' countries of the EU are specialized in occupations more at risk of automation. Overall, the fact that the automatability estimates in our sample follow the regular patterns discovered in the empirical literature boosts the confidence in our automatability measure.

It is important to clarify that we interpret the potential automatability-satisfaction relationship as non-causal: the idea is that the task content which makes an occupation more automatable also makes it less satisfying. This contrasts with the approach of Nazareno and Schiff (2021) who use the same Frey and Osborne (2017) indicator of automatability, but they use it to study whether the increased use of automation technologies causes changes in the content and context of occupations and thus indirectly affects job satisfaction in a causal way. We believe that our non-causal interpretation is more in line with the original interpretation of the automatability measure by Frey and Osborne (2017):

> *Finally, we emphasise that since our probability estimates describe the likelihood of an occupation being fully automated, we do not capture any within-occupation variation resulting from the computerisation of tasks that simply free-up time for human labor to perform other tasks.* (p.268)

Since the authors explicitly aim to measure the "destruction effect of technology" (p. 258) and not the changes automation technologies might cause in the (task) content and context of occupations, the causal mechanisms for the automatability-satisfaction relationship highlighted by Nazareno and Schiff (2021) are not appropriate. While it is undeniable that the rise of automation technologies will also change jobs rather than only fully destroying them (for instance by more intensely surveilling workers or reducing the workload of routine tasks within an occupation), the Frey and Osborne (2017) measure is explicitly designed to only measure the destruction effect.[2]In section 3, the results of our mediation analysis also indicate that there is no significant effect of automatability on job satisfaction left once we control for the job content characteristics which function as bottlenecks to automation. This supports our interpretation that the link between automatability and job satisfaction is, statistically speaking, spurious and non-causal in the sense that it is entirely explained by the common driver of the content of an occupation.

Given that our main dependent variable of interest — job satisfaction — is measured on a four-point scale, we opt to use an ordered logit model for the estimation of our empirical model (Greene, 2003). The underlying latent variable model can be defined as in equation 1.

$$JobSatis_{ij} = \alpha_{ij} + \beta_1 automatability_i + \beta_2 X_{ij} + \epsilon_{ij} \tag{1}$$

In this formula i denotes the occupation dimension and j denotes the individual dimension within a given occupation. The term X_{ij} denotes a vector of control variables which include individual-level socio-demographic controls (e.g., age, country, education level ...) and job-context characteristics (e.g., hourly wage, employment duration, type of contract, sector ...) unrelated to the task content. For the validity of the ordinal logit model, the proportional odds assumption has to hold (O'Connell, 2006). Since the typical omnibus test for proportionality is very strongly anticonservative in a large sample like ours, the test will nearly always reject the null hypothesis of proportionality (Allison, 1999; Clogg & Shihadeh, 1994). As a solution, we make use of the graphical method proposed by Kim (2003) to assess the practical significance of the proportional odds assumption in our empirical model.

[2]Note that the potential of automation to fully replace occupations need not coincide with its potential to transform occupations: the weaving and stitching profession is identified by Frey and Osborne (2017) as a profession that is very likely to disappear due to automation, while the dentist profession is not very likely to disappear. But is the practice of stitching also far more likely to be transformed due to the rise of robotics and machine learning than the dentist task set is?

Note that since we are interested in the relationship between automatability and job satisfaction that is generated by the inherent task content of occupations, we do not add variables proxying for the content of a job as controls X_{ij} in our baseline specification. If we controlled for job content, we would eliminate the possibility of the statistically 'spurious' effect of automatability on job satisfaction which is our object of interest. In a second stage however, we want to identify which job content characteristics are responsible for the automatability-satisfaction link. We do this by executing a mediation analysis with three key job content characteristics which are plausible drivers of both automatability and job satisfaction according to the literature. The use of a mediation analysis to test for confounding is entirely in accordance with the work of MacKinnon et al. (2000) who indicate that "mediation and confounding are identical statistically and can be distinguished only on conceptual grounds" (p.173). Given that we make use of an ordered logit model, the mediation analysis requires making use of the KHB procedure to discern the impact of rescaling and actual confounding (Karlson et al., 2012).

3 Results

3.1 Are automatable occupations less satisfying?

Table 2 describes the results of the ordinal logistic regressions for Job Satisfaction.[3]In the model without any control variables (model 1), automatability is found to contribute negatively to job satisfaction. The odds ratio (obtained by exponentiating the coefficient) is 0.602, which implies that an increase in automatability by 100 percentage points (i.e., shifting from completely non-automatable to completely automatable) implies a 39.8% decrease in the odds of being "very satisfied" or "satisfied" versus being "not very satisfied" or "not at all satisfied".[4]Moving from the first to the fifth model, we progressively add more covariates to the model specification. Remember that we want to test whether more automatable occupations are fundamentally less satisfying. In other words, we want to test whether more automatable occupations are less satisfying because of the tasks required for the execution of those occupations. We only want to capture the effect of automatability on job satisfaction through the task content of the occupation. As a result, we want to avoid our analysis being confounded by effects of automatability through worker-specific or "work context"-related characteristics (e.g., more automatable occupations resulting in worse job satisfaction because of more insecure employment contracts used in more automatable occupations). We exclude these confounding effects by explicitly controlling for them. The coefficient of automatability shrinks gradually in absolute value as more control variables are added, but it remains highly significant. Note that the effect remains highly significant even if we follow the advice of Kristensen and Westergaard-Nielsen (2007) to require significance at the 1% level rather than at the 5% level when the dependent variable is a subjective job satisfaction measure.

These findings indicate that individuals working in more automatable jobs are less satisfied with their job, not only because of individual-specific reasons and job-context reasons, but also because of the fundamental nature of the occupation (i.e., the task content of the occupation). In the fifth model, we also control for the specific sector in which the respondent is employed, based on 3-digit NACE (Rev. 2). Since this sectoral decomposition distinguishes 272 industries, one could fear that, within one industry, insufficient variation in occupation (measured by ISCO-codes) remains such that the coefficient on automatability is imprecisely estimated. The variance inflation factor (VIF) of automatability indeed does increase somewhat (from 1.25 in model 4 to 1.57 in model 5), but it remains relatively low (Kennedy, 2008). In this fifth model, the automatability-job satisfaction relationship is still significant and it still has important implications. A fifty percentage point rise in automatability of an occupation has, ceteris paribus, the same negative effect on job satisfaction as fall in the net monthly work earnings by 287 euros (for an individual at the median net hourly wage and median monthly hours worked for Germany in 2015 in the sample).

Table 2: Ordinal logistic regression results with Job Satisfaction as dependent variable

	(1) Model 1	(2) Model 2	(3) Model 3	(4) Model 4	(5) Model 5
Automatability	-0.602***	-0.551***	-0.356***	-0.254***	-0.180***
	(0.096)	(0.085)	(0.079)	(0.077)	(0.060)
Observations	34541	34140	34043	26475	25416
McFadden R-Squared	0.6%	3.1%	3.6%	3.8%	4.6%

Cluster-robust standard errors between parentheses.
*** $p < 0.01$, ** $p < 0.05$, *** $p < 0.10$

[3]Following Abadie et al. (2022), we compute standard errors which are robust for clustering at the occupation-level because our explanatory variable of interest (which ultimately affects the outcome causally via job content characteristics) only varies at the level of the occupation.

[4]Because of the proportional odds assumption, the ordinal logistic regression implies the same effect of automatability regardless of the precise level of satisfaction (e.g., the odds of "very satisfied" versus the three lower categories are affected in the same way).

Model 1 does not include any control variables. Model 2 includes socio-demographic control variables on the level of the individual (country dummies, number of people in household, sex, age, and a dummy which is one when the respondents and both parents were born in the country). Model 3 includes the controls of model 2 and also controls for the educational attainment of the respondent (ISCED level). Model 4 includes the controls of model 3 and also controls for characteristics of the job which are unrelated to the task content of the occupation (dummy variable for self-employment vs. employee, type of employment contract, public vs. private sector indicator, duration of employment at current organisation, part-time vs. full-time dummy, hours worked per month, net hourly wage in euros[5], and the square of the net hourly wage in euros). Model 5 includes the controls of model 4 and 3-digit NACE (Rev. 2) dummies.

[5]The net hourly wage per euros is constructed based on $Q24$ (How many hours do you usually work per week in your main paid job?) and $Q104euro$ (Please can you tell us how much are your NET monthly earnings from your main paid job? Please refer to your average earnings in recent months.). For individuals who did not know their exact income, we made use of the middle of the indicated income band (if available). We made use of the euro exchange rate on the on the median date of fieldwork for each country, as done by the EWCS. We removed outliers using the boxplot method, proposed by Tukey (1977).

3.2 Which job content characteristics drive this automatability-satisfaction relationship?

In section 3.1, we have observed a statistically significant and robust negative relationship between automatability and job satisfaction. For reasons indicated in the introduction, we do not believe that this relationship can be interpreted causally. We proceed by examining which job content characteristics can explain the relationship. Since the purpose of our investigation here is to "determine whether a covariate explains an observed relationship", our hypothesis under study is of the confounding type and it is best tested using a mediation analysis (MacKinnon et al., 200, p.179). We select the three indicators of the task content of an occupation which act as bottlenecks to the automation of an occupation in the study of Frey and Osborne (2017) and consider these as potential mediators of the negative automatability-satisfaction relationship. The three bottlenecks to automation relate to 'Perception and Manipulation', 'Creative Intelligence', and 'Social Intelligence'. For robustness purposes, we conduct two parallel mediation analyses with the bottleneck intensity of occupations once measured based on objective O*NET criteria and once measured based on the average self-perceived characterisation of jobs in the EWCS data.

In the first approach, we construct an objective measure for the bottlenecks to automatability by mirroring the approach taken by Frey and Osborne (2017). The nine O*NET variables in Table 3 proxy for the three bottlenecks to the automation of an occupation. Following Frey and Osborne (2017), we make use of the level (not the importance) estimate for the different O*NET database variables. Since the O*NET database uses the 2019 O*NET SOC classification for occupations, the transformation to ISCO-08 codes is not straightforward.[6]

Table 3: Description of the Frey and Osborne (2017) bottlenecks to automation

Automation bottleneck	O*NET variable	O*NET description	Mean (and standard deviation) in our sample
Perception and manipulation	Finger dexterity	The ability to make precisely coordinated movements of the fingers of one or both hands to grasp, manipulate, or assemble very small objects.	34.2 (10.1)
	Manual dexterity	The ability to quickly move your hand, your hand together with your arm, or your two hands to grasp, manipulate, or assemble objects.	28.8 (15.4)
	Cramped workspace, awkward positions	How often does this job require working in cramped workspaces that requires getting into awkward positions?	21.7 (16.6)
Creative intelligence	Originality	The ability to come up with unusual or clever ideas about a given topic or situation, or to develop creative ways to solve a problem.	38.2 (10.0)
	Fine arts	Knowledge of theory and techniques required to compose, produce, and perform works of music, dance, visual arts, drama, and sculpture.	6.9 (10.1)
Social intelligence	Social perceptiveness	Being aware of others' reactions and understanding why they react as they do.	43.6 (8.9)
	Negotiation	Bringing others together and trying to reconcile differences.	37.6 (10.4)
	Persuasion	Persuading others to change their minds or behaviour.	39.5 (10.6)
	Assisting and caring for others	Providing personal assistance, medical attention, emotional support, or other personal care to others such as co-workers, customers, or patients.	42.8 (13.1)

Since the different proxies for 'Perception and manipulation' and 'Social intelligence' are strongly correlated, we construct overall measures by averaging over the different items. The 'Perception and manipulation' construct is the result of averaging over 'Finger dexterity', 'Manual dexterity' and 'Cramped workspace, awkward positions' (Cronbach's Alpha = 0.842). The 'Social intelligence' construct is the result of averaging over 'Social perceptiveness', 'Negotiation', 'Persuasion' and 'Assisting and caring for others' (Cronbach's Alpha = 0.794). The 'Creative intelligence' construct arguably has too little internal consistency (Cronbach's Alpha = 0.562), so 'Originality' and 'Fine arts' are kept as individual items.

The second approach to measuring the bottlenecks to automation is based on the self-perceived evaluation individuals attribute to their job in the EWCS data. The three questions which best proxy for the bottlenecks of Frey and Osborne (2017) are set out in Table 4. For each occupation, within-occupation averages for these indicators will serve as the mediators for the effect of automatability on job satisfaction in a subsequent phase. Compared to the objective measure of the bottlenecks, these self-perceived measures have the advantage of being based on European data directly relevant for the sample. Especially for 'Perception and Manipulation', the self-perceived measures are not perfect and probably only partially capture the bottlenecks to automation, however.

Table 4: Description of the self-perceived proxies for the bottlenecks to automation

Automation bottleneck	EWCS Question	Scale	Mean (and standard deviation)
Perception and Manipulation	Q30c. Does your main paid job involve carrying or moving heavy loads?	Seven-point scale	5.71 (0.93)
Creative Intelligence	Q61i. Select the response which best describes your work situation - You are able to apply your own ideas in your work?	Five-point scale	2.46 (0.53)
Social Intelligence	Q30f. Does your main paid job involve dealing directly with people who are not employees at your workplace such as customers, passengers, pupils, patients etc?	Seven-point scale	3.80 (1.36)

In Table 5, we summarize the results of two simple OLS regression for automatability. The results are fully in line with our expectations. In the first regression with objective measures for the automation bottlenecks, occupations which require more advanced skills in terms of Perception and Manipulation, Originality (here taken as the best proxy for Creative Intelligence) and Social Intelligence are less readily automatable. This is logical since both the dependent variable (the automatability estimates) and the explanatory variables of interest (the bottlenecks) directly originate from the Frey and Osborne (2017) study. In the second regression with self-perceived measures for the automation bottlenecks, we also find negative point estimates related to all regressors of interest. This confirms that what is measured by the self-perceived indicators still constitutes bottlenecks to automation. Based on the standardized coefficients, it is clear that both analyses find Creative Intelligence to be the most influential hurdle to the automatability of an occupation. The fact that, for 'Perception and Manipulation' and 'Social Intelligence', the standardized coefficients are considerably lower when using the self-perceived measures reaffirms that our self-perceived measures for these bottlenecks are somewhat narrow interpretation of the bottlenecks.

Table 5: OLS regression for automatability, including all controls of model 5

	Standardized coefficients (objective bottlenecks)	Standardized coefficients (self-perceived bottlenecks)
Perception and manipulation	-0.084***	-0.026
	(0.020)	(0.025)
Creative Intelligence	-0.167***	-0.192***
	(0.043)	(0.022)
Fine arts	-0.033	
	(0.022)	
Social intelligence	-0.109***	-0.062**
	(0.038)	(0.031)
Observations	24597	25416
Adjusted R-Squared	67.8%	54.5%

Cluster-robust standard errors between parentheses.
*** $p < 0.01$, ** $p < 0.05$, *** $p < 0.10$

In Table 6, the results of the mediation analysis are summarized. Since we are interested in the joint mediation of multiple job content characteristics, we use multiple mediation analysis (VanderWeele & Vansteelandt, 2014). We use the KHB approach such that we do not capture the effects of rescaling that is typical of comparing ordered logit coefficients across different models (Karlson et al., 2012). The mediation analysis allows us to dissect the total effect of automatability on job satisfaction (as found in section 3.1) into (1) the indirect effects of automatability through the mediators, and (2) the remaining direct effect of automatability (which is not explained by our mediators). We make use of the specification of the model with all control variables (Model 5). Note that for the purposes of the mediation analyses, all mediators were standardized such that their mean is zero and their standard deviation is 1.

In the reduced model for job satisfaction, we find the total effect of automatability on job satisfaction: we again observe the negative automatability-satisfaction relationship. The results are not completely identical to the Model 5 of the previous section because the regression here only includes data for which valid mediator data is available. After controlling for the task content characteristics in the complete model, we find that the negative automatability-satisfaction link completely disappears. This is the case regardless of whether the task content of an occupation is measured in an objective or self-perceived manner. In other words, we find that the automation bottlenecks related to the task content of occupations succeed at fully explaining the the negative effect of automatability on job satisfaction. In the 'Indirect Effects' column, the indirect effect of automatability on job satisfaction through the different bottlenecks is set out. The KHB procedure indicates that the indirect negative effect of automatability on job satisfaction through the decreased room for creativity fully explains the negative automatability-satisfaction relationship. More accurately phrased, it is the fact that occupations with less room for creativity are both more automatable and less satisfying which explains the apparently negative relationship observed in section 3.1. Regardless of the measure for the bottlenecks, the indirect effect of automatability through 'Perception and Manipulation' is not significant. Likewise, regardless of the measure for the bottlenecks, the indirect effect of automatability through social intelligence is insignificant.

[6] First, we transform the 2019 O*NET SOC codes to 2018 SOC codes (using the crosswalk available on the O*NET website). In a subsequent phase, we transform the 2018 SOC codes to 2010 SOC codes (using the relevant BLS crosswalk). As a third step, we transform the 2010 SOC codes to ISCO-08 codes, using the same procedure as for the automatability estimates (BLS crosswalk and weights based on the Occupational Employment Survey).

Table 6: Mediation analysis for automatability as a driver of job satisfaction (KHB approach), model 5

	Analysis based on objective measures for bottlenecks				Analysis based on self-perceived measures for bottlenecks			
	Reduced model (without mediators)	Complete model (with mediators)	Indirect effect through mediator	Confounding percentage	Reduced model (without mediators)	Complete model (with mediators)	Indirect effect through mediator	Confounding percentage
Automatability	-0.197*** (0.064)	0.002 (0.080)			-0.183*** (0.060)	0.074 (0.056)		
Perception and manipulation		-0.086*** (0.026)	-0.006 (0.018)	2.9%		-0.151*** (0.023)	-0.027 (0.022)	10.5%
Creative Intelligence		0.150*** (0.036)	-0.262*** (0.066)	131.2%		0.180*** (0.024)	-0.246*** (0.040)	94.3%
Fine arts		-0.027 (0.019)	0.017 (0.013)	-8.3%				
Social intelligence		-0.032 (0.031)	0.051 (0.049)	-25.7%		-0.021 (0.022)	0.013 (0.014)	-4.9%
McFadden R-Squared	4.6%	4.8%			4.6%	5.0%		

Cluster-robust standard errors between parentheses.
*** $p < 0.01$, ** $p < 0.05$, *** $p < 0.10$

4 In a labor market segmented by education level, is automation still biased towards less satisfying occupations?

We have found that automatable occupations are inherently less satisfying, because of the task content of the occupation. Does this imply that automation-based job losses are less problematic than 'average job losses' (caused by a hypothetical random process)? We argue that this conclusion can only be drawn from a simplified, aggregate labor market perspective where each individual qualifies for any job. In this reductive framework, automation-driven job losses are indeed to be preferred to randomly generated job losses, because the former are biased towards less satisfying jobs. More realistically speaking, however, individuals require certain skills to qualify for occupations such that not all jobs are equally available to all individuals. In other words, labor markets are in practice segmented by educational requirements. Ideally, we should look for every individual whether, within the set of jobs for which he or she qualifies, it is true that the more automatable jobs are less satisfying. If this is not the case, the conclusion that "the jobs lost due to automation were the less satisfying ones" does not materialize on the level of the individual.

In our analysis here, we assume that the education level is the only factor deciding whether you qualify for a job (i.e., labor markets are only segmented based on education level). We might find that automatability no longer contributes negatively to job satisfaction after controlling for the educational requirements of an occupation. In that case, we can conclude that the automatability-satisfaction relationship found in section 3 only reflects the fact that occupations requiring a higher level of education are both more satisfying and less automatable.

In Table 7, we explicitly control for the educational requirements of an occupation. We proxy these educational requirements by calculating for each occupation the average ISCED score of individuals executing that occupation. Figure 1 displays the histogram for our obtained educational requirements indicator. Table 7 summarizes the results of the ordered logit regression where this educational requirements indicator is added as a control: the effect of automatability on job satisfaction turns insignificant when controlling for educational requirements in the second column. Intuitively, this implies that, while more automatable occupations are intrinsically less satisfying on a macro level (as found in Section 3.1), this result is entirely driven by the fact that automation will mostly hit occupations with few educational requirements (see Fig. A2) and these are less satisfying jobs (column (2), Table 7). In other words, we found evidence for a bias towards the automation of less satisfying jobs on the macro level. However, for an individual with a given labor market specific to their educational attainment, the occupations disappearing due to automation are, *on average*, not less satisfying than those unaffected by automation.

Fig 1: Histogram of Average ISCED level of Occupation

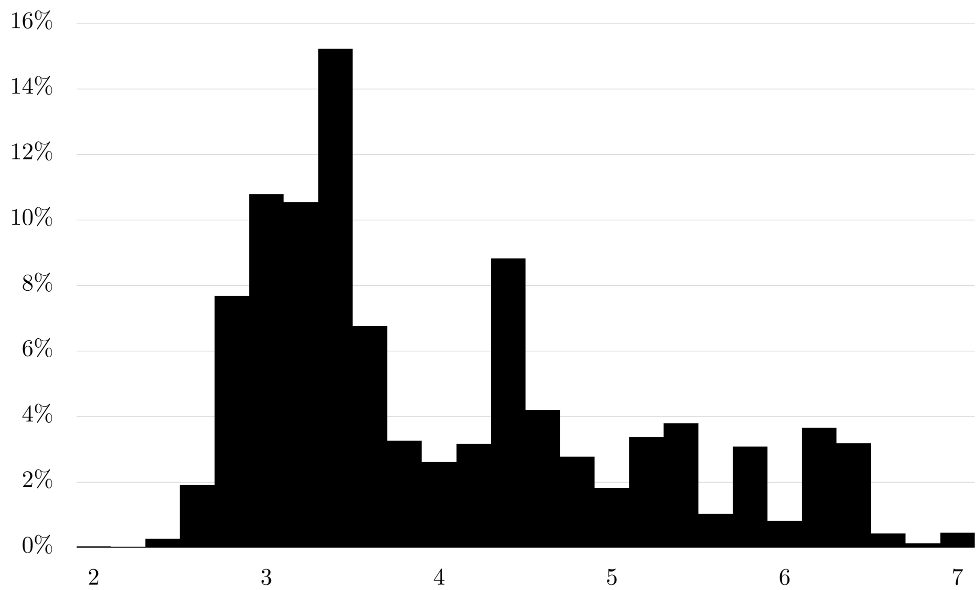


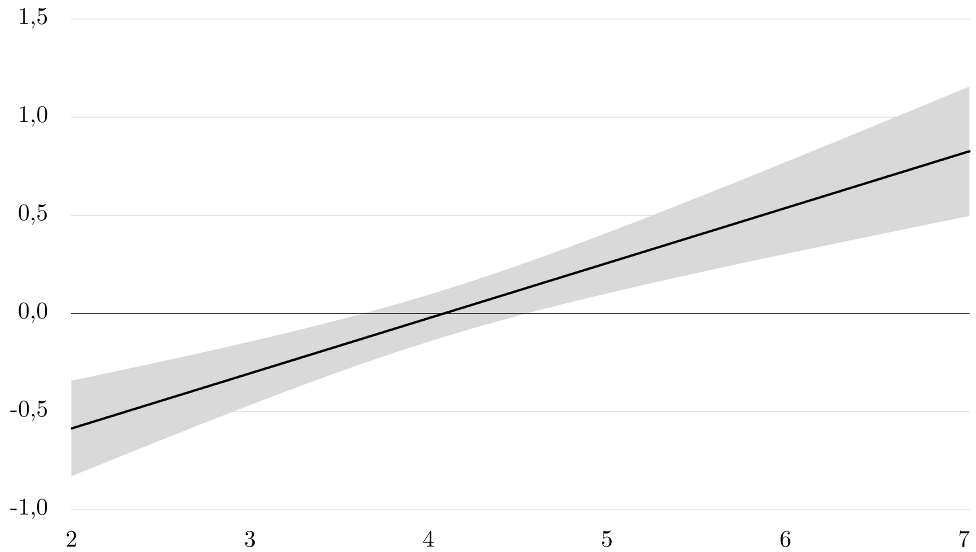
Table 7: Ordered logit model 5 and additional controls for educational requirements

	(1)	(2)	(3)
Automatability	-0.183*** (0.060)	-0.034 (0.061)	-1.148 (0.222)
Average education level of occupation (normalized)		0.177*** (0.029)	0.053 (0.032)
Av. ed. level (normalized)* Automatability			0.281*** (0.058)
Observations	25416	25416	25416
McFadden R-Squared	4.6%	4.8%	4.8%

Cluster-robust standard errors between parentheses.
*** p < 0.01, ** p < 0.05, *** p < 0.10

It is not because automation is not found to affect the job satisfaction of the average individual, that this holds for any individual, however. Column (3) of Table 7 indicates that there is heterogeneity in the effect of automatability: among occupations with a lower educational requirement, the effect of automatability is found to be more negative. Figure 2 shows the coefficient of 'Automatability' at different levels for 'Average education level'. It indicates that, while there is no significant effect of automation at the average ISCED score of 3.84, this does not hold for other educational requirements. At the median educational requirement of 3.35 (and thus, a fortiori, also for all less educationally demanding occupations), automatability has a negative effect on job satisfaction (p-value < 0.01). This indicates that for a large share of the working force, automation is likely going to be biased towards those occupations which are less satisfying. In contrast, for the 23% most educationally demanding jobs, there is evidence that automation will be biased towards more satisfying occupations. For them, the relevant automation-driven job losses might thus be concentrated among the *more* satisfying occupations.

Fig. 2: Effect of Automatability on Job Satisfaction
by Average ISCED level of Occupation



The grey-shaded area denotes the 95% confidence bounds.

Overall, the negative automatability-satisfaction relationship on the macro level thus seems to be mostly generated by the fact that occupations requiring a higher level of education are both more satisfying and less automatable. Automation-driven job losses will be concentrated among lower-educated individuals (cfr. Fig. A2). Automation will thus likely increase employment and wage inequality. For a large group of lower-educated individuals, there is some support for the consoling thought that, out of the pool of relevant occupations, it will at least be the less satisfying occupations which are set to disappear due to automation.

5 Conclusion & Discussion

In this work, we studied whether the probability of an occupation disappearing due to automation is linked with reported job satisfaction. Implicitly, it is sometimes assumed that the characteristics which make an occupation more automatable, also make it less satisfying. However, this assumption has never been explicitly tested in the literature before. For the purpose of our study, we analysed the well-developed literature studying which occupations are most at risk of automation and we selected the automatability estimates of Frey and Osborne (2017). Our core dataset is the 2015 wave of the European Working Conditions Survey.

Our main findings are as follows. We find that individuals employed in more automatable occupations indeed report significantly lower job satisfaction on average. The results are robust to controlling for a very wide range of individual-level socio-demographic controls and job-context controls, strengthening the hypothesis that automatable occupations are *fundamentally* less satisfying — meaning "less satisfying because of their task content". The negative job satisfaction effect of automatability we find is quite sizeable, implying that taking into account the nature of the disappearing jobs could truly make the welfare implications of automation-driven job losses more positive. In subsequent mediation analyses, we find that the negative automatability-satisfaction relationship is entirely explained by the fact that occupations which require less creativity are both (1) more readily automatable and (2) less satisfying. Other bottlenecks to the automation of an occupation such as the need for manual dexterity and the need for social intelligence seem to play no significant role. It is important to realize that these findings only imply that automation will *on average* make less satisfying occupations disappear. The negative automatability-satisfaction relationship on the macro level seems to be mostly explained by the fact that occupations requiring a higher level of education are both more satisfying and less automatable. When taking into account that labor markets are segmented by educational requirements, there is no evidence for the claim that jobs disappearing due to automation are, on average, less satisfying than those which are not automated. For lower-educated individuals in particular, however, there is some evidence that, within the pool of occupations for which they qualify, automation-driven job losses are concentrated among the less satisfying occupations. For higher-educated individuals, in contrast, automation is found to be biased towards the more satisfying occupations. For them, the relevant automation-driven job losses might be concentrated among the more satisfying occupations.

Our findings have important implications for how public policymakers should evaluate automation-driven job losses. On the level of the whole economy, there is robust evidence in favour of the hypothesis that automation is biased towards less satisfying jobs. Consequently, the quality of the remaining pool of jobs stands to improve because of automation. One should be cautious to interpret these findings too optimistically, however. To a large extent, the negative automatability-satisfaction relationship on the macro level is a reflection of the fact that lower-skilled occupations are typically less satisfying and more lower-skilled occupations will disappear due to automation (Acemoglu & Restrepo, 2020; Arntz et al., 2016; Frey & Osborne, 2017). In the absence of changes in the skill composition of the workforce, the first-order effect of automation will mostly pertain to the disappearance of low-quality jobs for individuals without a higher education degree. The consoling thought that "the lost jobs were, even among the group of lower-skilled jobs, the less satisfying jobs" may be little more than an afterthought if automation entails a shortage of jobs for the lower-skilled.

In this light, our study reinforces the calls for upskilling and retraining projects as a response to labor market automation (Illanes et al., 2018; Jaiswal et al., 2022). If such programs were to succeed at bridging the economy-wide skills gap, automation-driven unemployment could be avoided. Moreover, our study suggests that automation would increase the overall quality of jobs in such a best-case scenario. Fully attaining this best-case scenario could be overly ambitious, however, since studies are skeptical about the effectiveness of skills upgrading programs (Peter-Cookey & Janyam, 2017; Stenberg, 2011). In this light, the call for compensation for displaced workers (through universal basic income schemes or through reverse income taxation) remains very relevant (Brynjolfsson & McAfee, 2014; Ford, 2015; Hughes, 2014).

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Appendix A

Fig A1: Average automatability of occupations by age

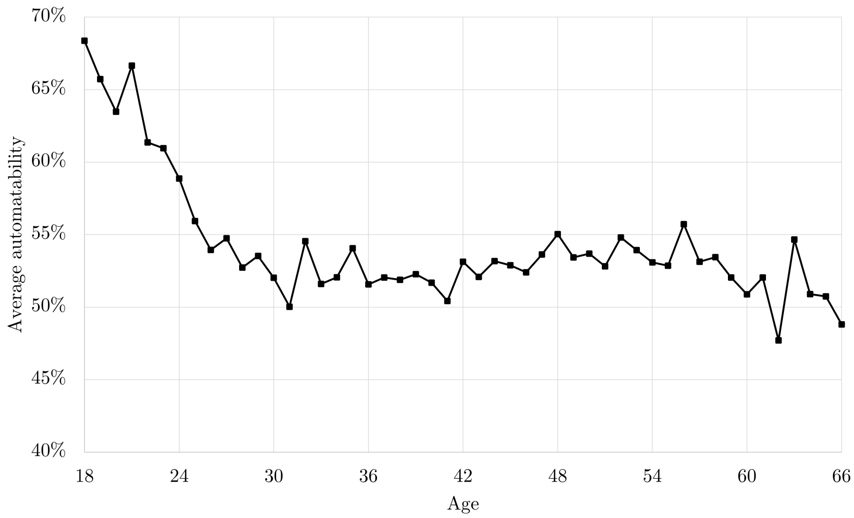

Fig A2: Average automatability of occupations by education level

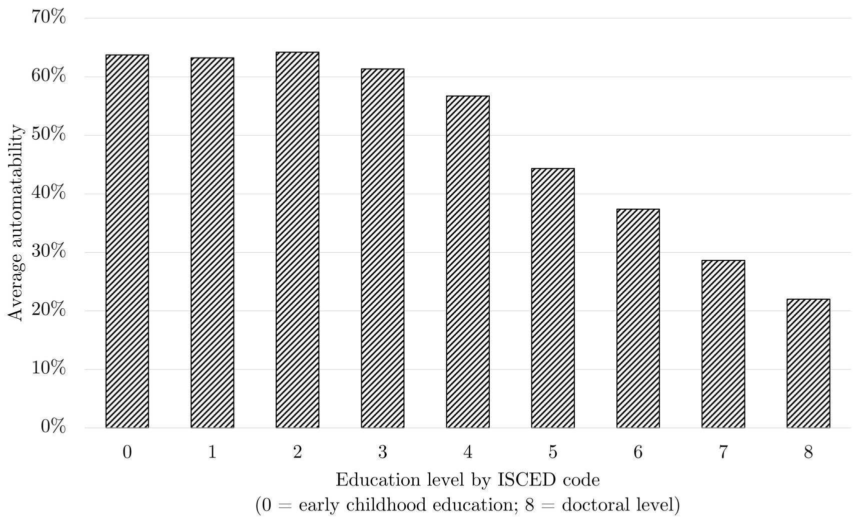

Fig. A3: Average automatability of occupations by country