Skill-related Job Preferences of University Students: Is there a Distaste to Using Digital Skills?

Renate Strobl and Conny Wunsch

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Abstract

Using a hypothetical choice approach, we elicit university students' preferences for jobs that differ in the skills they require. Focusing on skills increasingly demanded in the labour market, we find that higher importance of social skills in the job is positively valued by students overall and females in particular. Management skills are appreciated as well, but to a much lesser extent and only by men. In contrast, the intensive use of digital skills provides a large disutility to females, which they are willing to offset by accepting significant wage cuts. We also find evidence that perceived own skill endowment is a potential driver for student's skill-related job preferences. Our results suggest that promoting key skills could reduce costly avoidance behaviour and improve labour market outcomes, especially of women.

Keywords: Job preferences; digital, social and management skills; hypothetical choice game

Affiliations: All authors are affiliated with the Faculty of Business and Economics, University of Basel, Switzerland. Renate Strobl is also affiliated with the University of Lucerne, Conny Wunsch with CEPR, CESifo, DIW and IZA.

Address for correspondence: Conny Wunsch, Faculty of Business and Economics, University of Basel, Peter Merian Weg 6, PO Box, CH-4002 Basel, Switzerland. Email: conny.wunsch@unibas.ch.

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1 Introduction

Digitalisation is rapidly changing the world of work, including the types of skills required in the labour market. While the demand for skills associated with performing routine tasks is decelerating, as they can be relatively easily substituted by emerging technologies, skills that complement digital advancements are gaining paramount significance (e.g. Autor et al., 2003; Deloitte, 2017; Deming, 2017; Deming and Kahn, 2018). Besides IT skills, they also encompass non-cognitive skills such as communication, organisation and decision-making abilities, which are needed to manage growing task complexity. Studies conducted both in the US and Europe affirm the increasing rewards associated with IT skills (Falck et al., 2021), social skills (Deming, 2017; Edin et al., 2022) and leadership skills (Edin et al., 2022).

Given the fast transformation on the demand side of the labour market, it is crucial to gain knowledge of how the supply side responds to the shift in required skills. The goal of this paper is to generate evidence on this pressing issue by identifying labour supply preferences for skill requirements of jobs. Specifically, we aim to understand how individuals value jobs that demand a high level of proficiency in social, management and digital skills, which are key competencies in the digital age (e.g. Deloitte, 2017; OECD, 2019). We focus on university students as an increasingly important group of skilled labour market entrants. Moreover, it is important to inform policy makers and practitioners in education about how skill-related preferences drive graduates' job choices to counteract the potential risk of skill mismatch and inefficient labour market outcomes.

Inferring skill-related job preferences from actual job choices is challenging. First, labour market inefficiencies may force workers to choose jobs that deviate from their first best, rendering the derivation of preferences from observed choices misleading (Wiswall and Zafar, 2018). Second, the full set of actual job characteristics is typically unobserved by the researcher. Data limitations arise particularly with respect to skill-related job characteristics, given that actual tasks and use of skills tend to vary across workers even within the same observed occupation (e.g. Stinebrickner et al., 2018, 2019; Peto and Reizer, 2021). Overall, revealed-preference analyses based on observational data are prone to validity concerns due to unobserved heterogeneity and selection issues.

We use a stated-preference approach to avoid such issues. In a hypothetical choice game, we ask university students to choose between different jobs that exogenously vary in their job attributes. Besides basic attributes such as salary, working time and job stability, jobs are defined by the importance of social, management and digital skills needed to perform the job. Our experimental approach overcomes the above mentioned endogeneity problems and measures preferences in terms of economically interpretable willingness-to-pay estimates.

We conducted the hypothetical choice game as part of an online survey with 410 master and PhD students at the University of Basel, the oldest and fifth largest university in Switzerland. To elicit job preferences, we present all students with 16 hypothetical job scenarios. Each scenario consists of three different jobs that exogenously vary in four job attributes, while keeping all other job attributes constant. The first half of the scenarios elicit preferences about working hours and job security as standard job attributes. The second half focuses on preferences regarding the skills required in the jobs. All scenarios include annual gross earnings to be able to elicit students' willingness to pay for the non-monetary job attributes. For each of the 16 scenarios, we ask students to assign to each of the three job offers presented with which percentage probability they would choose it, with the stated probabilities adding up to 100. By comparing students' responses across the different scenarios, we can infer students' willingness to pay for the different job attributes. Because *all* students are presented with *all* scenarios, we can estimate the willingness to pay for each individual. By asking about hypothetical jobs in a within-subject design, we can vary job attributes across scenarios and abstract from individual (unobserved) differences across respondents.

Pooling all observations, we find that students appreciate jobs that require an above-average level of social and management skills. In contrast, intensive use of digital skills at the workplace is valued negatively and requires a large median compensation to make subjects willing to accept such a job. Distinguishing by gender reveals important heterogeneity in preferences. Females value jobs that require social skills more than males, which is consistent with evidence that women choose people-related professions more often than men (e.g. Blau and Kahn, 2017). Our results suggest that job preferences at least partly explain these patterns of occupational sorting. Second, we find that the distaste for using digital skills is fully driven by women's preferences. While men evaluate digitally oriented jobs rather positively (though their willingness to pay is not statistically significant), women exhibit a strong aversion to the intensive use of digital skills. With a median willingness to pay of 7%, they are willing to sacrifice a substantial proportion of their annual earnings to avoid this job feature.

Given that digital skills are increasingly demanded and highly rewarded, females' pronounced dislike of jobs that require such skills is likely to have negative consequences for their labour market outcomes. Moreover, persistent gender differences in these preferences have the potential of widening the gender wage gap when demand for digital skills increases. Our finding that skill-related job preferences are positively correlated with own skill endowment further suggests that promoting students', especially females', digital skills would improve their occupational choices and career outcomes by reducing potentially costly skill-related avoidance behaviour.

To the best of our knowledge, our study is the first to provide experimental evidence on skill-related job preferences of university students. Using choice experiments to elicit job preferences is still relatively novel in the literature. Existing studies have used this approach to study job preferences for standard job attributes, such as working time, job flexibility, job security and bonuses (Eriksson and Kristensen, 2014; Mas and Pallais, 2017; Wiswall and Zafar, 2018; Datta, 2019; Valet et al., 2021), as well as for fringe benefits (Eriksson and Kristensen, 2014) and gender diversity (Wiswall and Zafar, 2018; LaViers and Sandvik, 2022).

The experiment closest to ours is Gelblum (2020). This study takes a task-based approach and focuses on gender differences. It examines preferences over five gender-typical job tasks in a sample of US workers that have been recruited via Amazon Mechanical Turk. The paper finds that females prefer tasks involving caring for others and working with information, whereas males are more in favour of operating or repairing things. The author finds no preference hetereogeneity regarding working and communicating with others or decision-making and problem solving. In contrast to this study, we use a skill-based and gender neutral approach that allows for a broader picture of job preferences than evaluating tastes for single, gender-typical tasks. The three types of skills we study are relevant for a large number of different tasks and occupations. In particular, the skill categories we use are simultaneously relevant in many graduate occupations, regardless of field of study and gender. Moreover, in considering preferences for digital skills, we address a skill type which is especially important in the light of the current labour market transition. Another advantage of our study is that we collected data on self-assessed skills and are therefore able to evaluate how skill-related preferences are related to (perceived) own skill endowments.

We also contribute to recent literature that investigates whether gender differences in performed job tasks and used skills explain persistent gender segregation in the labour market and the gender pay gap. These studies use observational data on job applications, aspired occupations or realised job choices of various population groups (such as high school students, apprentices, college graduates or working-age subjects) and find significant gender disparities in performing object- vs. people-related tasks (Stinebrickner et al., 2018; Kuhn and Wolter, 2022) and in using cognitive and project management skills (Peto and Reizer, 2021; Chen and Luo, 2022). However, it remains unclear whether observed sorting on job content is driven by skill-related preferences or by other (unobserved) factors correlated with job choice. Our experimental approach allows for robust identification of preferences that are unbiased by unobserved heterogeneity and selection issues.

Lastly, by finding that females are reluctant to take up jobs oriented towards digital tasks, our study complements the vast literature on possible reasons for the gender STEM *(science, technology, engineering, and maths)* gap (see e.g. McNally, 2020, for a recent review). While digital skills can be seen as interdisciplinary skills which become increasingly important also in many non-STEM occupations, our work is well in line with studies considering gender differences in interest and preferences for the field as one underlying mechanism for women's underrepresentation in STEM professions (cf. Cheryan et al., 2017).

The remainder of this paper is structured as follows. Section 2 describes the theoretical background, the game design as well as the econometric approach to analyse the experimental data. Section 3 describes our data and study population. Section 4 presents and discusses the experimental results. The final section concludes. An appendix contains additional material.

2 Eliciting students' job preferences

2.1 A simple model of job preferences

We follow the literature (e.g. Blass et al., 2010; Wiswall and Zafar, 2018; Kosar et al., 2022) and assume that subjects choose the job that maximise their utility. There are $j = 1, .., J$ different job alternatives, each characterised by a K-dimensional vector of characteristics X_j, from which subject i draws utility

$$u_{ij} = \beta_i X_j + \varepsilon_{ij}, \tag{1}$$

where β_i is a vector measuring the subject's preferences for the K different job attributes, and ε_{ij} is an unobserved job-specific utility component. Assuming that $\varepsilon_{ij} = \varepsilon_{i1}...\varepsilon_{iJ}$ are i.i.d. conditional on X_j with the extreme value distribution, the subject's probability of choosing job j is

$$p_{ij} = \frac{\exp(X_j \beta_i)}{\sum_{j'=1}^{J} \exp(X_{j'} \beta_i)}. \tag{2}$$

Log-odds transforming equation (2) yields the following log-linear model for the difference in the probability of choosing job j over job j':

$$\ln\left(\frac{p_{ij}}{p_{ij'}}\right) = (X_j - X_{j'})\beta_i. \tag{3}$$

With appropriate data on the choice probabilities, this equation can be estimated directly using OLS to obtain estimates of the average preference parameters.

Willingness to pay (WTP). Since the β_i reflect utility differences that are difficult to interpret and compare across subjects, it is common to convert them into willingness-to-pay equivalents. The WTP with respect to job attribute X_k is defined as the monetary amount that establishes indifference between the change in X_k and compensating earnings equal to the WTP, keeping all other job attributes unchanged:

$$\begin{aligned} u_{ij}(Y_j, X_{jk}) &= u_{ij}(Y_j + WTP, X_{jk} + \Delta_j) \\ \beta_{iy}\ln(Y_j) + \beta_{ik}X_{jk} &= \beta_{iy}\ln(Y_j + WTP) + \beta_{ik}(X_{jk} + \Delta_j) \end{aligned}$$

where Y_j corresponds to the job attribute *annual earnings* associated with job j. This results in the following equation for the WTP:

$$WTP_{ik}(\Delta) = \left[\exp\left(\frac{-\beta_{ik}}{\beta_{iy}}\Delta_j\right) - 1\right] \times Y_j. \tag{4}$$

2.2 Hypothetical choice experiment

We use a hypothetical choice game to elicit students' job preferences that is based on the field-tested design of Wiswall and Zafar (2018). In the experiment, we present the participants with 16 hypothetical scenarios. Each scenario consists of three different jobs that differ in four job attributes. We instructed the respondents to assume that they were offered all three jobs presented within a scenario and, importantly, that the jobs were identical in all aspects apart from the given job characteristics. The game design allows eliminating several endogeneity and measurement issues that observational studies typically suffer from. First, asking the students about acceptance of job offers rather than applications for specific jobs ensures that decisions exclusively reflect worker preferences and are not distorted by employer preferences. Second and related, this approach additionally avoids selection bias in student's application decisions, for example due to anticipated discrimination or biased self-assessment. Third, exogenously manipulating attribute levels while holding all other undefined job attributes constant across jobs eliminates omitted variable bias arising from unobserved job aspects correlated with job choices.

Measurement of choice probabilities. Instead of asking the student to state which of the three offered jobs they would accept, we ask them for the percentage probability with which they would choose each job, with the stated probabilities adding up to 100. Eliciting choice probabilities is a recent innovation in stated-preferences experiments that has two important advantages over the traditional approach of asking for discrete choices. First, it provides richer information on preferences since it retrieves not only the respondents' most preferred alternative but implicitly the ranking of all options. Second, it allows the participant to express uncertainty about their choice given that, by design, the experimental scenarios provide less information than what would be available to the decision maker in real choice situations (Wiswall and Zafar, 2018; Blass et al., 2010).

Job attributes. In total, our experiment elicits preferences for seven different job attributes. All scenarios include (1) the annual gross salary for full-time employment five years after job take-up. This is essential for being able to translate the measured preferences into monetary equivalents, i.e. willingness-to-pay estimates. As standard job characteristics we include (2) the option for working part-time defined as work-time percentage below 90%[1], (3) the average number of weekly working hours for full-time work, and (4) positive job growth defined as an increase in vacancies in recent years. We included these attributes since the volume and flexibility of working time as well as job security are shown to be important drivers for career choices in the experimental and empirical literature (e.g. Wiswall and Zafar, 2018; Valet et al., 2021). Moreover, eliciting preferences for work time and job growth, though not of immediate interest for our study, provides an interesting benchmark to which we can compare the importance of skill-related job preferences. As second group of job characteristics we include three attributes reflecting the requirement of specific skills required for executing the job. In particular, we focus on the importance of (5) social skills, which we describe by the examples of communicating, working with others, networking, advising, negotiating and presenting information, (6) digital skills (e.g. using office software and communication tools, analysing digital data, using programming languages), and (7) management skills (e.g. developing objectives and

[1]This definition corresponds to that applied by the Swiss Federal Statistical Office.

strategies, making decisions, organising, planning, coordinating, leading and motivating people). As discussed earlier, these skills are increasingly demanded in the course of digitalisation and are thus crucial for labour market success.

Presentation of scenarios. To limit participants' cognitive burden, we follow Wiswall and Zafar (2018) and vary the job characteristics within two different blocks of eight scenarios each. In the first block, we present jobs that differ along standard characteristics, namely earnings, part-time option, working hours and job growth. The jobs in the second block vary along earnings and the three skill-related attributes. We randomise the order of scenarios within the two blocks. All participants complete all 16 scenarios, resulting in a within-subject design. The Appendix provides the game instructions, as presented to the participants at the beginning of the blocks A and B (Figure A1), as well as one example each for the block-specific scenarios (Figure A2).

Choice of job attribute values. To ensure that the values of the job attributes we present in the different scenarios reflect realistic and current labour market conditions, we rely on several sources of data. First, we build on the Swiss Labour Force Survey (SLFS) for the years years 2017 to 2021. The survey is conducted every quarter and it comprises around 32'000 individuals from the permanent resident population of Switzerland per quarter. It is the key source for measuring labour market indicators in Switzerland, including its internationally standardised unemployment rate. It contains rich information on labour market status, individual and job characteristics. Second, we use a very large and representative data set on open job vacancies in Switzerland for the years 2014 to 2019. The provider of these data, the Swiss company X28 AG, retrieves the characteristics of the advertised jobs via text mining and maps them to the ISCO-08 4-digit occupation codes. We use these data to measure changes in occupation-specific labour demand. Third, we use the ESCO classification[2] initiated by the European Commission, to measure occupation-specific skill requirements. Table 1 summarises the job attributes we use and their different levels.

[2] See `https://esco.ec.europa.eu/en/classification`

Table 1: Attributes and their levels

	Attributes	Attribute levels
1	Annual gross salary 5 years after job take-up (for full-time)	Various levels in the range of 73,000 - 160,000 CHF
2	Part-time option available	Yes / No
3	Work hours per week (on average, for full-time)	Various levels in the range of 38 - 53 hours
4	Positive job growth	Yes / No
5	Importance of social skills	Less important / Relatively important
6	Importance of digital skills	Less important / Relatively important
7	Importance of management skills	Less important / Relatively important

Notes: Table presents the job attributes and their levels used in the experimental scenarios.

The attribute values we use are based on the sample of employed individuals aged 30-45 with tertiary education observed in the SLSF, weighted by their sampling weights to mimic the actual distributions of job aspects in the relevant subpopulation of the Swiss labour force. We obtained the values for *annual gross earnings* and *weekly working hours* by randomly drawing percentiles in the 10th to 90th percentile range and retrieving the corresponding values from the observed wage and working hours distributions. Similarly, we determine the job-specific values of the other five (2-level) attributes via random draw based on the observed SLFS population share. For part-time work, we measure the share of part-time workers in the SLFS data and then randomly assign yes to a given job in a scenario according to this probability.

Since the SLFS lacks information on job vacancies and skill importance, we proceed in two steps for these attributes. We first use the X28 data to identify all occupations with rising demand. We define *positive job growth* as an increase in the share of vacancies in a specific ISCO 4-digit group among all vacancies between 2014 and 2019. For *skill importance*, we retrieve all single skills by ISCO 4-digit code that were classified as essential skills according to the ESCO classification. Then we measure the share of, respectively, social, management and digital skills among all essential skills required for a given occupation. We label the respective skill category as *relatively important* for a specific occupation in case of an above-average share, and as *less important* otherwise. In a second step, we merge the ISCO-specific information on job growth and skill importance to the SLFS data via the worker's occupation, compute the corresponding population shares and randomly assign values to the hypothetical jobs according to these proportions.

With this approach, we construct sequences of three jobs to build one scenario. From the scenarios obtained, we eliminate scenarios including a job that dominated the other two alternatives in all four attributes. Further, we exclude scenarios where the differences in annual earnings across the three jobs were higher than 30% in order to avoid quasi-dominant jobs. Moreover, to guarantee sufficient variation in attribute values, we discard scenarios where the drawn attribute levels are the same in two jobs in case of earnings or hours worked or in all three jobs in case of the dummy attributes.

2.3 Estimation

The hypothetical choice game results in 48 observations per individual (16 scenarios $\times$ 3 jobs). We use them to estimate the preference parameters and convert them into willingness-to-pay estimates for the 6 non-monetary job attributes for each individual. In the estimation, we account for the possibility that subjects state choice probabilities with error (e.g. by rounding to values ending with 5 or 10), and assume that we observe some $\tilde{p}_{ij}$ rather than p_{ij}. Moreover, we limit the impact of outliers by estimating the following linear median (instead of mean) regression model separately for each subject i using the least absolute deviations (LAD) estimator:

$$M\left[\ln\left(\frac{\tilde{p}_{ij}}{\tilde{p}_{ij'}}\right)|X_j X_{j'}\right] = (X_j - X_{j'})\beta_i. \tag{5}$$

This results in N individual estimates of the preference parameter for attribute X_k, β_{ik}= β_{1k},..,β_{Nk}, which can be aggregated to population measures such as the mean preferences $E(\beta_k)$ or median preferences $M(\beta_k)$. For inference on the population estimates, we employ a bootstrap procedure that resamples the individual estimates (with replacement) in 1000 replications (see Wiswall and Zafar, 2018, for details). The standard errors correspond to the standard deviation of the generated 1000 'pseudo' population estimates.

3 Data

We collected the data for this study as part of an ongoing online survey of Master's and doctoral students at the University of Basel, Switzerland, whose overarching goal is to gain insights into educational and occupational choices of university students in the light of the digital transformation. The target population of the survey consists of the full stock of master and PhD students enrolled in fall term 2021 as well as all newly enrolled master and PhD students in the three following semesters. Students in small study programs with less than 20 students are excluded from the survey to minimise the risk of identifying students from the data we collect. The survey is sent out by the central administration on our behalf. To us, the survey is anonymous because we do not know the identity of the respondents. To incentivise participation, respondents are offered the possibility to take part in a lottery of several online shop vouchers in the amount of 100, 200 or 500 CHF (1 CHF = 1.14 USD). The surveys were rolled out in the middle of the semester, well ahead of the exam period, to increase participation. Two reminders were sent one and two weeks after the initial invitation, respectively.

We included the hypothetical choice experiment in two consecutive survey waves in the fall semester 2022 and in the spring semester 2023. Our baseline sample consists of all students in the target population that participated in the survey in these two semesters. Our analysis sample consists of the 410 students that participated in our experiment in these two waves. Table 2 summarises the characteristics of this sample. It consists of 63% females and 62% study at the Master's level (column 1). The majority of participants is enrolled at the Faculties of Science (31%), Medicine (20%) as Humanities and Social Sciences (17%). Compared to the total Master's and PhD student population of the University of Basel in the fall semester 2022 (column 5), our sample includes a relatively higher (lower) proportion of students in the field of science (medicine), but is otherwise remarkably representative for the composition of the university's student body in terms of gender, study level and other study fields. In our analysis, we use survey weights to correct for imbalances in response rates across cells defined by field of study, gender, nationality and semester based on the aggregate student statistics.

Table 2: Sample characteristics

	Study participants				University of Basel
	All	Male	Female	Diff. (2)-(3)	All
	(1)	(2)	(3)	(4)	(5)
Demographic characteristics:					
Female	0.63				0.58
Age	27.94	28.69	27.47	1.22**	na
Nationality: Swiss	0.67	0.60	0.71	-0.11**	0.64
First language: German	0.75	0.71	0.78	-0.08*	na
Studies-related characteristics:					
High school grade: Very good/excellent	0.46	0.43	0.47	-0.04	na
Level of studies: PhD (vs. Master)	0.38	0.47	0.32	0.15***	0.42
Faculty of studies:					
Medicine	0.20	0.20	0.20	-0.00	0.31
Science	0.31	0.39	0.26	0.12***	0.24
Humanities & Social Sciences	0.17	0.08	0.22	-0.13***	0.19
Law	0.07	0.08	0.07	0.01	0.06
Business and Economics	0.09	0.16	0.05	0.12***	0.06
Psychology	0.09	0.05	0.11	-0.07**	0.08
Educational Sciences/Theology	0.04	0.03	0.05	-0.02	0.03
Inter-Faculty Study Programmes	0.04	0.02	0.05	-0.03	0.04
Observations	*410*	*153*	*257*		*7'040*

Notes: The table presents the mean characterictics of the study participants (for the whole sample and by gender) and of all Master's and PhD students enrolled at the University of Basel in fall semester 2022. ***/**/* indicates significant gender differences in characteristics on the 1/5/10% level based on two-sided t-tests.

Comparing male and female participants reveals significant gender differences with respect to age, nationality and first language (columns 2 to 4). Moreover, we observe typical patterns of gender segregation across fields of study. Females are underrepresented in science and economics majors and overrepresented in study programmes in the humanities, social sciences and psychology. We control for these gender-related differences when evaluating gender differences in job preferences.

4 Results

4.1 Willingness to pay

To obtain economically interpretable job preference measures, we estimate the beta parameters of the choice model and convert them into monetary measures of the willingness to pay, as shown in equation (4). Figure A3 in the Appendix depicts the distributions of estimated WTPs for the six different non-monetary job attributes. As often the case in choice experiments (cf. Kosar et al., 2022), the WTP distributions are highly skewed and contain large outliers. To minimise the sensitivity or our results to outliers, we concentrate our analyses on the median WTP rather than on the mean.

Table 3 shows the estimated median willingness to pay for the different job attributes. A negative estimate reflects the amount of annual earnings the median subject is willing to sacrifice to increase the attribute level by one unit and thus indicates that the subject appreciates the job feature. Correspondingly, a positive WTP represents the median compensation required to make the subject indifferent between obtaining that amount and accepting a one-unit increase in the value of the (disliked) attribute.

Table 3: Estimated willingness-to-pay

	CHF			Percentage of average earnings			
	All	Men	Women	All	Men	Women	Diff.
	CHF	CHF	CHF	%	%	%	*p-val.*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Part-time	-12717.10***	-8931.27***	-15798.61***	-11.16***	-7.84***	-13.87***	*0.002*
	(1601.22)	(1311.17)	(1823.18)	(1.41)	(1.21)	(1.51)	
Working hours	3349.32***	3378.47***	3234.55***	2.94***	2.97***	2.84***	*0.741*
	(214.95)	(309.99)	(304.53)	(0.19)	(0.26)	(0.28)	
Job growth	-4423.66***	-6147.37***	-2586.45**	-3.88***	-5.40***	-2.27**	*0.050*
	(882.83)	(1363.77)	(1190.52)	(0.77)	(1.19)	(1.02)	
Social skills	-6971.35***	-4059.00	-8891.78***	-6.12***	-3.56	-7.80***	*0.210*
	(1865.20)	(2682.18)	(2765.16)	(1.64)	(2.30)	(2.34)	
Digital skills	3912.89*	-3697.34	8084.23***	3.43*	-3.25	7.10***	*0.002*
	(2081.88)	(2775.45)	(2524.70)	(1.83)	(2.42)	(2.30)	
Management skills	-2003.46**	-1773.96*	-2161.30	-1.76**	-1.56**	-1.90	*0.833*
	(842.36)	(917.77)	(1586.60)	(0.74)	(0.75)	(1.42)	
Observations	*410*	*153*	*257*	*410*	*153*	*257*	

Notes: Median willingness to pay for job attributes for the whole sample and by gender. Bootstrapped standard errors (1000 replications) in parentheses. ***/**/* indicates significance on the 1/5/10% level based on bootstrapped standard errors. P-val. indicates significance of gender differences in median WTP.

Standard job attributes. Looking at the standard job dimensions first, we find that the median student is willing to give up nearly 11.2 % of their annual salary to to obtain a part-time rather than full-time job. Moreover, women have a much stronger preference for part-time work, exhibiting a willingness to pay that is nearly twice as high as that of men (13.8% vs. 7.8%). In addition to a lower work-time percentage, students also value a lower number of average full-time working hours. For one additional weekly hour of work, both women and men would have to be compensated by roughly 3% of their yearly earnings. Working in a job that exhibits growing demand is also an important job characteristic for the students, with male students placing a significantly higher value on this proxy for job security than females. Overall, these results are well in line with Wiswall and Zafar (2018) and Valet et al. (2021) who find significant preferences for part-time work, low working hours and job security, with large gender differences in the perceived importance of working part-time.

Social skills. Turning to the importance of different skills for executing particular jobs, we find that students highly appreciate jobs that require an above-average level of social skills. They are ready to forego around 6.1% of annual income for a job that requires more social skills. Both males and females value using interpersonal skills positively. The median WTP of women is 7.8% and statistically significant on the 1% level. For men it is less than half of this value with 3.6% but just short of statistical significance on conventional levels with a p-value of $p = .13$. Although the gender difference in WTP is not statistically significant, our finding is consistent with Lordan and Pischke (2022), who show that women are more satisfied than men in occupations with 'people'-related task contents. It is also in line with Gelblum (2020), who finds that females prefer tasks involving caring for others.

Management skills. The necessity of management skills at the workplace is also considered desirable, but to a much lesser extent than that of social skills. The estimated median WTP is similar for men and women, but it is only statistically significant for males. This is an interesting result in the light of the finding that men are more likely to hold management positions than women (e.g. Blau and Kahn, 2017). While traditional explanations for the gender leadership gap focus on discrimination or psychological aspects, such as lower competitiveness or higher risk aversion of women (see Eckel et al., 2021, for a review), our results suggest that one driver of this imbalance may be male's stronger preference for exercising management skills.

Digital skills. Our most striking finding is a significant willingness to pay to *avoid* jobs that require an important degree of digital skills. In contrast to the other two skill categories, the use of digital skills thus seems to be a "bad" for the median student. However, this finding hides important heterogeneity in preferences. The WTP estimate for men is negative (though insignificant), implying that males, if at all, favour IT-intensive jobs. In contrast, with a positive and significant willingness to pay of 7%, women are ready to sacrifice a substantial proportion of their annual salary to avoid jobs with strong focus on digital technologies. This elicited aversion to use digital skills is likely to have negative implications for women's labour market outcomes, given that digital skills are increasingly demanded and provide high returns to skill. Moreover, the contrasting preferences between men and women with respect to digital skill use have the potential to widen the gender wage gap given increasing demand for these skills.

Implied gender pay gap. Our data allow us to calculate the gender pay gap implied by the observed gender differences in job preferences. Table 4 shows the expected annual earnings according to the respondents' choices, calculated by weighting the job-specific earnings with the stated choice probability and averaging the expected values over all jobs and by gender. Panel I shows the results when including all jobs. The estimates in Panel II only include the jobs with the highest stated probability within a given scenario. The implied gender pay gap amounts to roughly 0.9% of average annual earnings, with little variation across blocks of job attributes. It reflects differences in earnings resulting solely from differences in job preferences and amounts to 6.6% of the raw gender pay gap of 13.6% observed for university graduates in Switzerland in 2020 (Kaiser and Möhr, 2023), which is quite substantial.

Table 4: Expected gender wage gap in the experiment

	Men	Women	Diff.		
	CHF	CHF	CHF	%	*p-val*
			(1)-(2)	(3)/(1)	(1)-(2)
	(1)	(2)	(3)	(4)	(5)
I. All jobs					
All scenarios	115594	114603	991**	0.86	*0.04*
Scenarios Block A	108696	107776	920	0.85	*0.15*
Scenarios Block B	122492	121430	1062	0.87	*0.11*
II. Jobs with highest choice probability					
All scenarios	116097	114999	1098**	0.95	*0.03*
Scenarios Block A	108452	107290	1162*	1.07	*0.09*
Scenarios Block B	123806	122842	964	0.78	*0.16*

Notes: Expected annual earnings according to the job choices in the hypothetical choice game. Expected earnings are calculated by weighting the job-specific earnings with the stated choice probabilities, basing on all jobs (Panel I) or only jobs with the highest probability within a scenario (Panel II). ***/**/* indicates significance on the 1/5/10% level based on two-sided t-tests.

4.2 Heterogeneity in job preferences

In Table 5 we further explore heterogeneity in job preferences across students with different characteristics. It reports the results of median regressions of the estimated individual WTPs on demographic and study-related variables. For every job attribute, we exclude estimated WTPs below the 1st and above the 99th percentile of all estimates to improve the precision of the estimates given that bootstrap standard errors are sensitive to outlier WTPs in relatively small samples like ours. Note that the medians themselves are unaffected by this choice.

We find that the gender differences in preferences for job growth and digital skill importance remain even after controlling for gender imbalances with respect to age, PhD level and field of study, as discovered in Table 2. The gender coefficient regarding the WTP for part-time work is just short of statistical significance with a p-value of $p = .11$). It is particularly noteworthy that the gender difference for digital skills increases to 10.1% when controlling for field of study. This implies that in addition to the observed gender segregation in field of study (and consequently, in field-specific jobs), there occurs further gender sorting into jobs according to skill preferences *conditional on the field of study.*

Table 5: Correlation of WTP estimates and basic characteristics

	Estimated WTP (as percentage of average earnings)					
	Part-time	Hours worked	Job growth	Social skills	Digital skills	Management skills
	(1)	(2)	(3)	(4)	(5)	(6)
Female	-4.28	0.07	4.12**	-3.28	10.14**	-0.15
	(2.71)	(0.48)	(2.02)	(4.66)	(4.42)	(2.23)
Age	-0.62*	0.01	-0.11	0.47	-0.00	-0.18
	(0.35)	(0.05)	(0.20)	(0.62)	(0.48)	(0.25)
First language: German	0.46	1.23**	8.30***	-9.72	-5.48	-0.67
	(4.29)	(0.60)	(3.05)	(6.17)	(6.53)	(2.48)
Nationality: Swiss	-4.44	0.05	-0.41	-6.58	-0.93	-0.63
	(3.80)	(0.49)	(2.20)	(5.01)	(6.29)	(2.53)
PhD student	-2.20	0.65	-3.14	-6.62	-10.09*	1.37
	(3.43)	(0.54)	(2.26)	(5.06)	(5.28)	(2.64)
High school grade: Very good/excellent	-1.86	0.54	-1.72	-4.83	-1.71	-3.55
	(3.57)	(0.47)	(2.09)	(5.15)	(4.90)	(2.46)
Faculty (Reference = Medicine):						
Psychology	0.56	-0.27	0.75	10.04	-0.84	2.83
	(4.85)	(0.98)	(3.80)	(9.34)	(7.55)	(4.52)
Law	-1.04	-0.17	0.04	13.24	1.03	-3.76
	(5.90)	(0.82)	(3.06)	(9.03)	(8.39)	(5.09)
Humanities and Social Sciences	-3.81	0.39	2.05	2.51	-7.26	-0.31
	(4.73)	(0.68)	(3.59)	(9.19)	(7.15)	(3.93)
Science	-0.83	1.03	4.97*	12.21	-11.83**	3.31
	(4.09)	(0.68)	(2.70)	(8.05)	(5.74)	(3.34)
Educational Sciences/Theology	-11.70	-0.84	-2.57	-7.76	-8.79	-4.88
	(16.55)	(1.53)	(6.97)	(23.87)	(15.63)	(28.76)
Inter-Faculty Study Programmes	-5.12	0.60	-3.72	-6.82	-4.45	-2.90
	(11.93)	(1.05)	(6.63)	(20.05)	(12.01)	(10.02)
Business and Economics	0.74	0.16	2.00	9.25	-5.75	-1.36
	(4.65)	(0.82)	(2.62)	(8.86)	(6.77)	(3.49)
Observations	*385*	*393*	*391*	*392*	*396*	*393*

Notes: Median regression. Dependent variable: Estimated willingness to pay for a unit change of the respective job attribute. Includes indicators for missing values in the covariates. Number of observations vary since we exclude outliers (i.e. 1st and 99th percentile) in the respective WTP distribution. Bootstrapped standard errors (1000 replications) in parentheses. ***/**/* indicates significance on the 1/5/10% level based on bootstrapped standard errors.

Table 5 shows that doctoral students are significantly more in favour of job that require digital skills, likely because they are more exposed to digital technologies as part of their research activities, such as data analyses and programming. The same holds for students enrolled in the Faculty of Science compared to the Faculty of Medicine as reference group. This is consistent with the fact that these study programmes include computer science and therefore represent a selection of students highly interested in digital technologies.

We find no WTP heterogeneity with respect to very good high school grades as a proxy for cognitive skills.

4.3 The role of own skills

One potential explanation for different job preferences regarding required skills are differences in students' skill sets. Students may dislike certain skill-related job characteristics because they feel not sufficiently endowed with the relevant skill to perform the job. Alternatively, they may simply have a distaste for using the skill even though having it. Distinguishing these channels is important for practitioners in education and policy makers. In the first case, the promotion of skill acquisition would be a promising solution, e.g. by adjusting university curricula with additional (compulsory) courses that provide digital skills. The second case could be addressed by increasing students' interest in applying their digital skills, e.g. via information campaigns.

To investigate whether skill-related preferences are influenced by the subject's skill portfolio, we regress the individual WTP estimates for skill importance on a self-reported measure of own skill endowment that we collect in the survey. We ask the students to self-assess their levels of social, digital and management skills. Specifically, we ask where they think they are positioned in a normal skill distribution considering students on their level of studies (Master or PhD) and in the same field of study.[3] While objectively measuring respondents' skills was not feasible within the scope of our survey, we argue that self-assessed skills are even more relevant since it is typically *perceived* own skill endowment (which is potentially subject to biased self-assessment) that drives choice behaviour.

Table 6 shows the results of median regressions. We find that one's perceived competency in a specific domain is strongly, exclusively, negatively and significantly associated with the estimated WTP for the same type of skill. This pattern applies to all three skill categories. It means that feeling less equipped with a specific skill increases the willingness to avoid jobs where this competence is important, even at the cost of lower earnings. This

[3] The skill levels included the ranges "very poor", "below average", "average", "above average" and "excellent" and were illustrated in a sketch of a normal distribution, as shown in Figure A4 in the appendix.

finding suggests that improving graduates' skills in dimensions that are important for the labour market would improve their job choices and labour market outcomes by potentially reducing costly avoidance behaviour. However, in the light of evidence that women tend to underestimate their abilities (e.g. Blau and Kahn, 2017), skill promotion interventions should take such psychological factors into account to effectively reduce barriers for females to take-up high-paying, (digital) skill intensive jobs.

Table 6: Correlation of WTP estimates and self-assessed skills

	Estimated WTP (as % of average earnings)		
	Social skills	Digital skills	Management skills
	(5)	(4)	(6)
Self-assessed social skills	**-9.16*****	3.69	-1.83
	(3.28)	(2.58)	(1.47)
Self-assessed digital skills	3.72	**-11.36*****	2.74
	(3.84)	(3.20)	(2.00)
Self-assessed management skills	-0.40	2.21	**-5.53*****
	(3.41)	(2.58)	(1.67)
Controls	Yes	Yes	Yes
Observations	*392*	*396*	*393*

Notes: Median regression. Dependent variable: Estimated willingness to pay for a unit change in respective job attribute. Independent variables: Self-assessed skill endowment (1=very poor, 2=below average, 3=average, 4=above average, 5=excellent). Controls: female, age, first language: German, PhD student, faculty, high school grade: very good/excellent, dummies if the respective covariate is missing. Number of observations vary since we exclude WTP outliers (i.e. 1st and 99th percentile of the respective WTP distribution). Bootstrapped standard errors (1000 replications) in parentheses. ***/**/* indicates significance on the 1/5/10% level based on bootstrapped standard errors.

4.4 Validation of WTP estimates

To gain assurance that our experimental results reflect students' actual job preferences and are not an artefact of our experimental design, we relate the WTP estimates to survey responses on preferred job characteristics. We ask students to state on a 5-point-Likert-scale how important they perceive various aspects of jobs, including those considered in the game. The answers provide simple non-monetary measures of job preferences that should be consistent with our WTP estimates. The survey questions were asked *before* the hypothetical choice game to rule out that responses are influenced by the game.

Table A1 in the Appendix provides an overview of the stated preferences both for the full sample and by gender. Attributes that are addressed in the experiment are highlighted in bold. We find that students do not necessarily place the highest weight on financial dimensions, but consider aspects of job security, work-life balance and qualification to be more important. Interestingly, the least important attribute for women is applying digital skills at the workplace, which confirms our experimental results. In total, observed gender differences in stated job preferences are consistent with existing literature, where women are shown to place higher importance on the possibility to work part-time and to reconcile work and family (e.g. Blau and Kahn, 2017).

Table 7: Job preferences: Correlation between experimental and survey measures

	Estimated WTP (as percentage of annual earnings)					
	Part-time	Hours worked	Job growth	Social skills	Digital skills	Management skills
Survey responses: Importance of ..	(1)	(2)	(3)	(4)	(5)	(6)
Option to work part-time	**-3.84****	-0.25	0.98	-1.96	-0.76	0.99
	(1.53)	(0.28)	(1.22)	(2.43)	(2.39)	(1.40)
Low contractual hours per week	-1.70	0.17	-1.70	0.87	1.01	-0.25
	(1.39)	(0.30)	(1.13)	(2.50)	(2.04)	(1.19)
Positive job growth	-1.38	-0.08	**-2.55****	-2.64	-0.81	1.05
	(1.48)	(0.26)	(1.02)	(2.75)	(2.63)	(1.49)
Use of my social skills	0.65	-0.40	-0.39	**-5.65***	5.22**	-0.57
	(1.63)	(0.24)	(1.10)	(2.96)	(2.50)	(1.39)
Use of my digital skills	0.46	0.03	-1.12	2.28	**-6.24*****	1.78
	(1.39)	(0.22)	(0.98)	(2.83)	(2.05)	(1.42)
Use of my management skills	-0.96	0.18	-1.10	-2.57	1.21	**-6.64*****
	(1.83)	(0.33)	(1.35)	(2.92)	(2.35)	(1.85)
High salary	4.11**	-0.07	1.37	0.23	2.11	0.20
	(1.89)	(0.31)	(1.28)	(3.09)	(2.44)	(2.02)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	*385*	*393*	*391*	*392*	*396*	*393*

Notes: Median regression. Dependent variable: Estimated willingness to pay for unit change in respective job attribute. Independent variables: Stated importance of job criteria in the survey (1=not important to 5=very important). Controls: female, age, first language: German, PhD student, faculty, high school grade: very good/excellent, dummies if the respective covariate is missing. Number of observations vary since we exclude outliers (i.e. 1st and 99th percentile) of each WTP outcome. Bootstrapped standard errors (1000 replications) in parentheses. ***/**/* indicates significance on the 1/5/10% level based on bootstrapped standard errors.

Table 7 shows the results when regressing the WTP estimates on the relevant survey responses. Reassuringly, all direct survey measures except the one related to working hours are significantly correlated with precisely the corresponding experimental WTP measures. For example, subjects rating the possibility to apply social skills as an important job criterion consistently have a lower WTP to avoid this attribute. For hours worked, there is a difference between measurement in the experiment, which refers to actual hours worked in a full-time job, and the survey question, which refers to contractual full-time hours, that could explain the absence of any correlation. Overall, these results make us confident about the validity of our experimental preference measure.

5 Conclusion

Against the background of the rapid technology-driven change in skill demand, this study measures preferences of university students regarding the use of different types of skills at the workplace. We conducted a hypothetical choice experiment that exogenously manipulates job attributes and allows for robust identification of job preferences.

We find that an above-average need for social skills in the job is positively valued by students overall and females in particular. Management skills are appreciated as well, but to a much lesser extent and only by men. In contrast, the intensive use of digital skills provides a large disutility to females which they are willing to offset by accepting significant wage cuts. Male students appreciate the use of digital skills on the job but their willingness to pay is not statistically significant. Finally, we find suggestive evidence that perceived own skill endowment acts as a driver for student's skill-related job preferences.

Women's reluctance to choose digitally oriented jobs may have negative effects on labour market outcomes at the aggregate and individual level, for example in the form of skill shortages and increased gender inequalities in employment prospects, job stability and earnings. Though we cannot interpret the measured relationship between perceived skill portfolio and skill-related preferences as causal, our results plausibly suggest that promoting key skills would be highly effective, as it could improve labour market outcomes not only by improving employability (i.e. via better matching the skill demand), but also at an earlier stage by adjusting graduates' preferences and thus broadening the variety of occupations they consider as possible careers. Since this second channel assumes that students correctly assess their aquired skills, skill-promoting interventions should additionally address psychological factors such as biased self-beliefs and lacking self-confidence, so that they can fully unfold their welfare-increasing potential.

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A Appendix

Figure A1: Game instructions

INSTRUCTIONS

Part A

In the following we will present you with 8 different scenarios. Each of the scenarios contains **3 different hypothetical job offers**. Each of the job offers is characterised by the following job characteristics:

1. Gross annual salary 5 years after starting the job (in CHF, when working full-time).
2. Possibility to work part-time (i.e. a work-time percentage below 90% is an option)
3. Hours worked per week (on average, in full-time)
4. Positive job growth (i.e. there has been an increase in vacancies in the job over the last few years)

Your task:
In each scenario, please imagine that you have **received each of these 3 job offers** and now have to decide which one to accept. In each scenario we will ask you for the **percentage probability** of you **choosing each of the 3 alternatives**. The probability of each alternative should be a **number between 0 and 100**, and the probabilities of the three alternatives should **add up to 100**.

IMPORTANT: Please assume that the jobs available for choice are **otherwise identical in all other aspects**.

Part B

In the following we will present 8 **more scenarios**, each with 3 hypothetical job offers. Each of the job offers is characterised this time by the following job characteristics:

1. **Gross annual salary** 5 years after starting the job (in CHF, when working full-time).
2. **Importance of social skills** for the exercise of the job
   Examples: Communicating, working with others, networking, advising, negotiating, presenting
3. **Importance of digital skills** for the exercise of the job
   Examples: Using office software and communication tools, analysing digital data, using programming languages
4. **Importance of management skills** for the exercise of the job
   Examples: Developing goals and strategies, making decisions, organising, planning and coordinating, guiding and motivating people

Again, in each scenario, please assume that you have **received each of these 3 job offers** and now have to decide which one to accept. We will again ask you for the **percentage probability** of you choosing **each of the 3 alternatives.**

IMPORTANT: Please assume that the jobs available for choice are **otherwise identical in all other aspects**.

Figure A2: Examples of job scenarios

(a) Block A

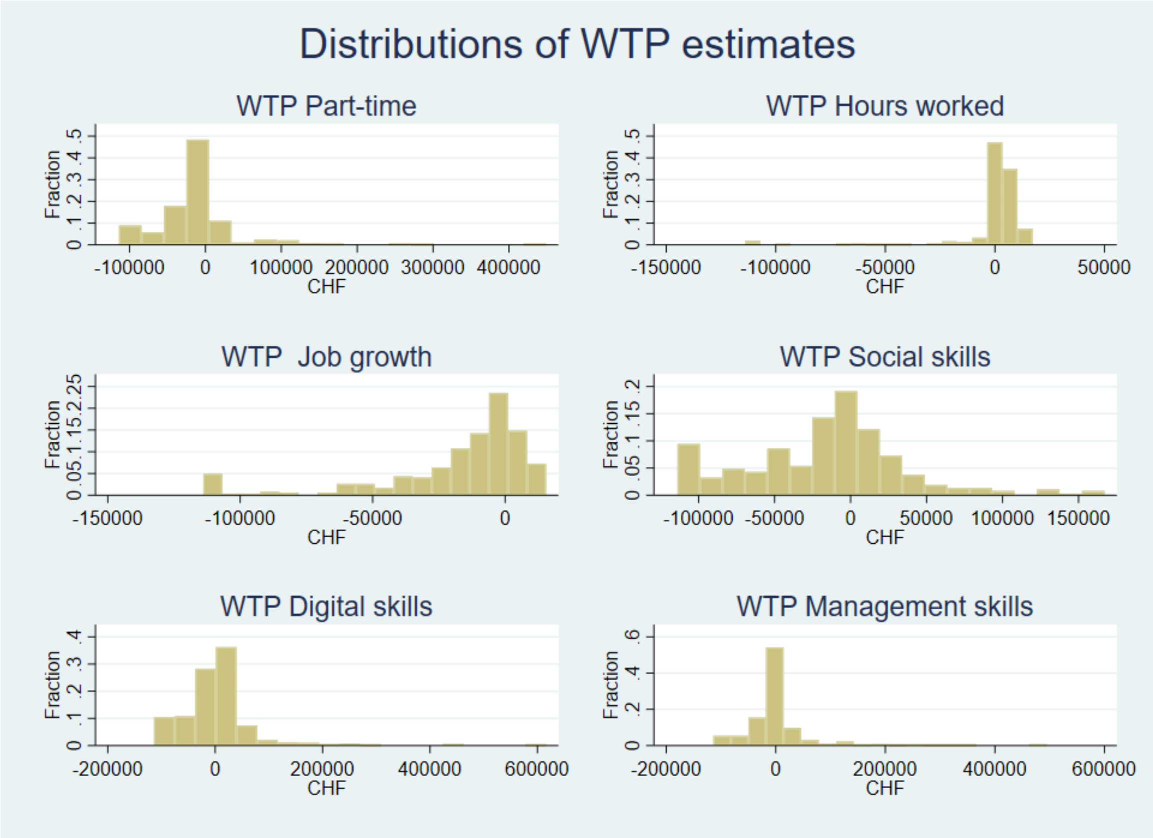
	JOB 1	JOB 2	JOB 3
Annual gross salary 5 years after job take-up (if working full time)	94'000 CHF	73'000 CHF	85'000 CHF
Part-time work is possible i.e. a work-time percentage below 90% is an option	No	Yes	Yes
Work hours per week on average, for full-time	47	40	50
Positive job growth i.e. an increase in vacancies in the job in recent years	Yes	Yes	No

(b) Block B

	JOB 1	JOB 2	JOB 3
Annual gross salary 5 years after job take-up (if working full time)	106'000 CHF	100'000 CHF	97'000 CHF
Importance of Social skills for the exercise of the job *Examples:* Communicating, working with others, networking, advising, negotiating, presenting information	Relatively important	Relatively important	Less important
Importance of Digital skills for the exercise of the job *Examples:* Using office software and communication tools, analysing digital data, using programming languages	Relatively important	Less important	Relatively important
Importance of Management skills for the exercise of the job *Examples:* Developing objectives & strategies, making decisions, organising, planning, coordinating, leading and motivating people	Less important	Relatively important	Less important

Notes: The figure shows two examplary screenshots of job scenarios presented to the participants in (a) block A and (b) block B of the hypothetical choice experiment.

Figure A3: Distributions of WTP



Notes: The graphs show the distributions of WTP estimates (1st to 95th percentile) of the six different job attributes.

Table A1: Importance of job aspects (survey responses)

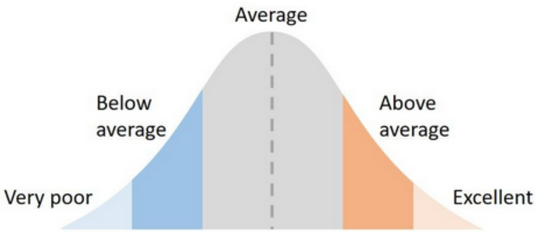
	All subjects	By gender		
	Means	Means		Diff.
	All	Male	Female	
Job aspects:	(1)	(2)	(3)	(2)-(3)
Salary and job stability:				
High salary	3.47	3.58	3.41	*0.17***
Permanent position	3.99	4.05	3.95	*0.09*
Good career prospects	3.82	3.87	3.79	*0.08*
Positive job growth	**3.53**	**3.50**	**3.54**	***-0.04***
Secure job	4.14	4.10	4.17	*-0.07*
Work-life balance:				
Option to work part-time	**3.51**	**3.28**	**3.65**	***-0.37******
Low contractual hours per week	**2.87**	**2.77**	**2.93**	***-0.15***
Flexible hours/homeoffice	3.72	3.70	3.74	*-0.04*
Reconcile work & family	4.08	3.96	4.15	*-0.19**
Meaningful job	4.53	4.44	4.58	*-0.15***
Skill-related aspects:				
Match with own academic level	4.06	4.04	4.07	*-0.03*
Use of own personal qualifications	4.24	4.23	4.25	*-0.02*
Use of own social skills	**3.78**	**3.59**	**3.89**	***-0.31******
Use of own digital skills	**3.05**	**3.25**	**2.92**	***0.33******
Use of own management skills	**3.39**	**3.29**	**3.44**	***-0.15***
Observations	*410*	*153*	*257*	

Notes: Table shows the students' answers to the survey question: "How important are the following aspects of jobs to you?", with the following answer options: 1="Not at all important" 2="Rather less important" 3="Moderately important" 4="Rather important" 5= "Very important". ***/**/* indicates significance on the 1/5/10% level based on two-sided t-tests.

Figure A4: Instructions for self-assessment of skills

Self-assessment of your interdisciplinary skills

All master students have skills, but inherently, they are differently developed for each individual. The following normal distribution aims to illustrate this:



The graph shows in a simplified way that skill levels within a population of master students are typically normally distributed, i.e.:

- the largest proportion of students have average skills *(grey range)*
- a smaller proportion have below- or above-average skills *(blue or orange range)*
- a very small proportion have very low or excellent skills *(light blue or light orange range)*.

In the following, please assess your personal skills using the ranges of this normal distribution as a reference.