Employers' preferences for IT-retrainees: evidence from a discrete choice experiment

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Abstract

Purpose – The purpose of this paper is to present the results of a discrete choice experiment (DCE) on the competencies of potential information technology (IT)-retrainees. The results give insights in the monetary value and relative returns to both soft and hard skills.
Design/methodology/approach – The authors apply a DCE in which the authors propose seven pairs of hypothetical candidates to employers based in the municipality of Amsterdam, the Netherlands. These hypothetical candidates differ on six observable skill attributes and have different starting wages. The authors use the inference from the DCE to calculate the marginal rates of substitution (MRS). The MRS gives an indication of the monetary value of each skill attribute.
Findings – Employers prefer a candidate who possesses a degree in an exact field over a similar candidate from another discipline. Programming experience from previous jobs is the most highly valued characteristic for an IT-retrainee. Employers would pay a candidate with basic programming experience a 53 percent higher starting wage. The most high-valued soft skill is listening skills, for which employers are willing to pay a 46 percent higher wage. The results of this paper show that both hard and soft skills are important, but not all soft skills are equally important.
Originality/value – The results on the returns to skills provide guidelines to tailor IT training and retraining programs to the needs of the business environment. A key strength of this paper is that the authors have information on the preference orderings for different skills and kinds of experience.
Keywords Skills, Information technology, Soft skills, Discrete choice experiment, Monetary valuation
Paper type Research paper

1. Introduction

The information technology (IT) sector takes up a fair share of the gross domestic product (GDP) in most developed countries. In 2015, roughly six percent of total value added in the OECD could be attributed to the IT sector (OECD, 2015). In the Netherlands, the demand for professionally educated IT specialists exceeds the supply from formal educational institutions. In 2016, there were on average 10800 vacancies in the IT sector in 2016, on a total of 365,000 people with an ICT-related job (CBS, 2017). Hence, employers are having trouble to fill in their IT vacancies (ROA, 2017). Labor market policy aimed at solving this

shortage by retraining graduates from other fields than IT can help dealing with this issue. Furthermore, these retraining programs could contribute to reducing youth unemployment. Still, such retraining programs are costly so it is important to get the most out of the investment in retraining. Aligning the selection of participants with employer demands could help optimizing the return on these training programs. However, it can be challenging to find the right candidates to retrain into the field of IT, when the preferences of employers are unknown. To recruit the most suitable candidates it is crucial to know which competencies and skills, such as previous experience, educational attainment or teamworking skills, are valued the most by employers in the IT sector.

In this light it is important to know to which degree cognitive skills are important, and to what degree non-cognitive skills play a role. There is rising evidence that non-cognitive skills play a role in predicting academic and economic success (Almlund *et al.*, 2011; Borghans *et al.*, 2008). However, in their study of the various cognitive achievement tests applied by US college admission committees, Heckman and Kautz (2012) highlight that these generic achievement tests do not capture non-cognitive skills, also known as "soft" skills. These soft skills, such as teamworking and verbal communication skills, predict success in many facets of later life and career (Heckman and Kautz, 2012). In the human resources literature, the emphasis is increasingly shifting toward "soft," non-cognitive skills in addition to "hard," cognitive skills (Andrews and Higson, 2008). Being an important predictor of success, these soft skills must be valued highly by employers, in addition to technical hard skills. Therefore, it is important to find out the role of soft skills in a technical field such as IT, and to which degree these soft skills complement hard skills.

Various studies on the employer preferences in the field of IT and the corresponding academic curriculum have highlighted the importance of soft skills (Dodson and Giorcelli, 2008; Johnson, 2015; McMurtrey *et al.*, 2008; Merhout *et al.*, 2009; Peslak and Davis, 2009; Radermacher and Walia, 2013; Thurner and Böttcher, 2012). However, all of these studies are descriptive. When one asks employers how they value a specific skill, the answer is not always reliable. Because specific skills can be associated with other skills and characteristics, selection effects may bias the results. To improve on what we know about the preferences of employers in the IT sector, experimental evidence is a necessity. This paper adds to the existing descriptive literature by providing the results of a controlled field experiment.

We present the results of a discrete choice experiment (DCE), also known as a vignette experiment, to identify both the cognitive and non-cognitive competencies that IT employers seek in potential retrainees. These potential retrainees include but do not necessarily have to be recent graduates from other fields. However, in the survey we describe previous experience as experience from student jobs and hobbies, so the type of candidate who we describe is either a recent graduate, or someone that just started working in a different field. We express the relative importance of these competencies by the marginal rate of substitution (MRS), using a technique from the field of health economics (Van de Schoot *et al.*, 2015). The marginal effects presented in this study reflect the increase in the hiring probability that is associated with a specific skill. We estimate the MRS for each skill in monetary terms. This allows us to express the employer preferences in terms of additional starting wage employers are willing to offer a candidate who possesses such a skill. It also gives an indication of the returns to soft skills relative to the returns to hard skills and educational attainment. This adds to the limited evidence available on the returns to soft skills and competencies.

While many studies have been conducted on the returns to education (such as Hout, 2012; Jensen, 2010; Psacharopoulos and Patrinos, 2004; Verhaest *et al.*, 2018), most of these studies only assess the value of a college degree instead of the specific skills acquired from education. Also, in relation to economic growth, Hanushek *et al.* (2017) show that specific

cognitive skills promote economic growth much more than mere years of educational attainment. On the contrary, Deming (2017) focuses on the growth in soft skill demand in the US labor market. Other work on hard vs soft skills includes Pinto and Ramalheira (2017), Deming (2017), Baert and Verhaest (2018) and Albandea and Giret (2018). In an increasingly polarizing labor market, the returns to skills is an important topic. Complementing the existing literature on the returns to college degrees and years of schooling, this paper gives insights in the monetary value and relative returns to soft and hard skills. Furthermore, no experimental work on selection into retraining has been done before, as far as we know. This paper gives novel experimental inference on selection into retraining, using a unique survey data set that has been designed specifically for this study.

We find that both soft and hard skills are valued by IT employers. Employers value computer programming experience the most. After programming experience, employers value listening skills the highest. Listening skills are defined as the ability to listen to others, such as team members, project managers and customers. Employers are willing to offer 53 percent additional starting wage for a candidate who has previous experience with computer programming. The level of education of the candidate is also valued highly: candidates with a master's degree are 27.2 percent more likely to be selected than candidates with a bachelor's degree. Candidates who possess a degree in an exact field are 33.7 percent more likely to get selected than candidates who possess a degree in other disciplines. As a comparison, graduates with a master's degree from a research university earn 13 percent more than graduates with a bachelor's degree from a university of applied sciences, one and a half year after graduation (Vereniging Hogescholen, 2015; VSNU, 2015). In monetary terms, the difference between average and poor teamworking skills is valued about equal to having a master's degree instead of a bachelor's degree. Different levels of verbal communication skills are the least important in the selection of a candidate.

In the next section, we summarize the literature on skills in the IT sector. In Section 3 we explain the design of our experiment and our methodology. In Section 5, we present our results. Finally, we present a conclusion and a discussion of our results in Section 6.

2. Skills in the IT sector

In the literature, some insights have already been gathered on the specific skills that are demanded by employers in the IT industry. This literature about the employer preferences in the IT sector mainly consists of surveys in which employers are asked to rank their preferences of skills ordinally. This literature points at skills that employers frequently report as important. In a survey of IT professionals in the Pittsburgh area in the USA, Peslak and Davis (2009) ask the respondents for the relative importance of general cognitive skills, specific cognitive skills and non-cognitive skills. They find that general, technical cognitive skills are the most important expertise according to the IT professional community. The authors find that general cognitive skills are valued higher than specific cognitive skills. Also, general non-cognitive skills are valued higher than specific cognitive skills. From an inquiry of IT professionals in the mid-Southern USA, McMurtrey et al. (2008) find that for entry-level employees, the most important skills are non-cognitive, specifically problem solving, critical thinking and team skills. On the other hand, the authors also find that cognitive skills, such as the knowledge of programming languages, are essential. Other US-based surveys by Bailey and Mitchell (2006) and Turley and Bieman (1995) also show that, according to IT employers, both cognitive and non-cognitive skills are important competencies.

A different methodological approach has been employed by Kovacs and Davis (2008). The authors analyze the keywords in digital job postings in the Pittsburgh area to find out what skill sets and competencies are demanded the most. Next to cognitive computer programming skills, the authors find that there is a high demand for communication skills.

This again highlights the importance of non-cognitive skills in the field of IT. To assess whether in general, not specifically in the field of IT, cognitive or non-cognitive skills are more valued or the other, Heijke *et al.* (2003) use data of the labor market situation of Dutch higher education graduates to estimate which competencies increase the hiring probability. They find that both vocational and generic competencies increase the hiring probability, but specifically that vocational, or technical, cognitive competencies seem to be increasing the chance of being matched to an employer within the respective field.

In the past, several resume audit experiments have been conducted that study the effect of educational attainment and experience on the probability of a positive response or an interview invitation response from a prospective employer (Deming *et al.*, 2016; Eriksson and Rooth, 2014; Farber *et al.*, 2017; Kroft *et al.*, 2013; Lahey and Beasley, 2018; Nunley *et al.*, 2016, 2017). This method has been applied frequently in Belgium, a neighbor country of the Netherlands (Baert and Verhaest, 2019, among others). In these resume audit experiments, researchers design and randomly send out fictitious job applications to employers. Eriksson and Rooth (2014) and Kroft *et al.* (2013) have differing levels of education in their samples, respectively. Nunley *et al.* (2016) show a three-month in-field internship helps generate interviews several years after graduation, whereas the specific college majors do not have an effect on employment outcomes.

A key strength of this paper is that we have information on the preference orderings for different skills and kinds of experience. This is key because resume audits generally only observe the very beginning of the hiring process and do not observe the full pool of applicants.

Econometric studies that utilize survey data on wages suffer from selection bias, and the wages we observe for workers do not represent the full distribution of wage offers. Altogether, the image from the existing literature is not clear. An answer to the question which skills are more important, and to what extent, is still difficult to get considering the problems that arise with previously applied methods. Therefore, we conduct a DC experiment to shed new light on this matter.

3. Methodology
The methodology that we apply in this paper is based on rational choice theory. DCEs are based on the random utility model, which assumes that economic agents maximize utility:

$$U^B - U^A > 0 \Leftrightarrow, \tag{1}$$

$$\Delta U^{B,A} > 0. \tag{2}$$

Equations (1) and (2) imply that if the utility of option B is higher than the utility of alternative A, the respondent will choose alternative B. If this is not the case, the respondent will choose alternative A. The key advantage is that the choices depend on the difference between the two levels of utilities. As a result, it is not required to know the cardinal levels of utility for each of the alternatives to estimate the model. A necessary assumption for this approach is that the difference in utility has to be greater than zero. This implies that the respondents are forced to make a choice between alternative A or alternative B.

An application of DCEs to the valuation of skills, like we provide in this paper, has been applied in different contexts before. Humburg and Van der Velden (2015) use a DCE approach to simulate the hiring decisions when recruiting university candidates based on CVs and observable skills. Their results show that employers attach high value to occupation-specific skills. However, their sample consists of employers from different fields. Also, Humburg and Van der Velden (2015) do not investigate the valuation of soft skills, but only whether the field of study is a match to the job, work experience, average grade and study characteristics. In the field of public health for instance, Biesma *et al.* (2007) study the employer preferences for

academic medical graduates. The authors investigate the differences between the demand for generic and field-specific competencies. They find that employers value generic competencies higher than specific competencies.

In this paper, we present the results of a DCE that gives insights in employer preferences for IT-retrainees. The main advantage of conducting DCEs is that they allow for the estimation of the relative strength of preferences. In this paper, the respondents are faced with a series of trade-offs between two hypothetical candidates, differing on various attributes. This way, we resolve the shortcoming of traditional ranking methods by exposing the trade-offs between the different skills.

3.1 Attributes and levels

DCEs assess the trade-off between a number of attributes that have certain levels. An attribute is a characteristic, in this study a (non)-cognitive skill, and a level is a value that a characteristic can take. One concern with these experiments is that they only measure the effects of the attributes that have been included *a priori* – they do not give inference on other factors that are not included in the questionnaire. This feature is a potential weakness of DCEs. The results only show the relative importance of the attributes that have been included, anything overlooked and omitted in the beginning will not show up in the results. Given this potential weakness, it is important to make well-informed decisions on which attributes to include. To provide guidance in choosing and defining the attributes and to avoid potential misconceptions, we base the attributes on the current literature. In addition, we held open interviews with IT employers in October 2016. On the basis of both the literature and the responses to these employer interviews, we have defined the following attributes.

From both the literature (see Section 2) and our interviews, the level of education came out as a factor employers value highly (Hewitt and Levine, 2006). We decided to include this attribute with two levels based on the higher educational system in the Netherlands: bachelor's and master's degrees. Employers explicitly stated that they consider a bachelor's degree a minimum requirement for the field of IT. Also, the level of education is a proxy for intelligence. In the Netherlands, higher education is divided into a more vocationally orientated track (hbo), and a more academically orientated track (wo). Both tracks lead to a bachelor's degree, but only the academic track gives access to an academic master's program in the corresponding field. In that sense, the term wo refers to a master's degree in the Netherlands, and the term hbo refers to a bachelor's degree from the vocational track. Therefore, we correspondingly label the attributes hbo and wo in the survey. In this paper, we use the term bachelor's to refer the hbo bachelor's degree, and the term master's to refer to the wo master's degree.

In addition to the level of education, we also include an attribute for whether the candidate has completed a degree in an exact field or not. In the survey questions, we define exact fields of study as any program containing multiple mathematical courses. These include, among others, the fields of mathematics, physics, chemistry, engineering, econometrics and economics. This can be seen as indicators of the quantitative and analytic skills that are useful in the field of IT. The importance of this characteristic was also pointed out by several employers during the interviews. Many employers also highlighted that their optimal candidate profile should show a specific interest in computer programming and the field of IT (McMurtrey *et al.*, 2008; Peslak and Davis, 2009). To measure this, we further include a variable for generic programming experience, which we describe in our survey as any experience with computer programming from previous jobs or hobbies. In the survey questions, we exemplify this as previously taken courses in secondary or higher education, or experience from a previous job or student job.

With respect to soft skills, the employers stated numerous different attributes they found important. To make a selection from the vast amount of soft skills they mentioned, we base the soft skills in our analysis primarily on the larger-scale surveys in the literature. From the literature, it seems that listening, verbal communication and teamworking skills are valued most by employers in the IT sector (Johnson, 2015; Thurner and Böttcher, 2012; Woodward *et al.*, 2010), so we include these three attributes. In the survey, we describe listening skills as the ability to listen to others, such as team members, project managers and customers. Verbal communication skills are defined as the ability to clearly express oneself both in written text and orally. Teamworking skills are defined as the ability to work together with other people in a team or group. The final attribute we include is a starting wage, based on the average starting wages in the IT sector: €2,400 vs €2,700 gross per month for bachelor's and master's graduates, respectively (Elsevier/SEO, 2016; Loonwijzer, 2017). This allows us to express the trade-offs from the DC experiment in monetary terms, under the assumption of a linear utility function. Table I lists the attributes and levels, as well as the order of appearance of the choice sets, which is explained below.

For all attributes, we only include two different levels. If we include more than two levels per attribute, the number of survey questions would increase rapidly, and this would likely have a negative effect on the response rate. For each of the skill attributes, we label the levels corresponding to "average" or "basic" and "none" or "poor." We prefer these labels over values such as "good" or "above average," because then the relative differences in the levels are not straightforward. We strive to make all participants uniformly interpret the labels and levels. A trade-off between something that is present and something that is non-existent is more straightforward than a situation in which participants have to value something labeled "good," which is more open to interpretation by the respondent (Johnston *et al.*, 2017, p. 327, Recommendation 1).

3.2 Efficient designs

With these attributes and levels, the next step is to set up the choice sets: sets of alternatives. Each question in the questionnaire consists of a pair of fictional candidates, differing in their attribute levels. With seven attributes each consisting of two levels, there are $2^7 = 128$ possible alternative possible candidates to be made. To make sure the survey is

| | (ii) Choice sets and alternatives (Candidates A and B) | | | | | | | | | | | | |
| | 1 | | 2 | | 3 | | 4 | | 5 | | 6 | | 7 | |
(i) Attributes	A	B	A	B	A	B	A	B	A	B	A	B	A	B
1. Level of education	1	0	1	0	0	1	1	0	1	0	0	1	1	0
0: bachelor's; 1: master's														
2. Exact field	0	1	0	1	0	1	1	0	0	0	1	0	1	0
0: no; 1: yes														
3. Programming experience	1	0	1	0	0	1	1	0	0	1	1	0	0	1
0: none; 1: basic														
4. Listening skills	0	1	0	1	0	1	1	0	1	1	0	1	0	1
0: poor; 1: average														
5. Verbal communication	0	1	1	0	1	1	1	1	1	0	1	0	0	1
0: poor; 1: average														
6. Teamworking	1	0	0	1	0	1	0	1	1	0	1	0	0	1
0: poor; 1: average														
7. Starting wage	1	0	0	1	1	0	1	0	1	0	1	0	0	1
0: €2,400; 1: €2,700														

Table I.
Attribute levels and their order appearance in the survey

Notes: The columns under (ii) depict the seven choice sets in the survey, where participants have to choose between Candidate A or B. The meaning of the 1s and 0s is displayed under (i)

manageable, we use the D-optimal design with the minimum number of choice sets to identify all the necessary parameters. A D-optimal design ensures that all possible trade-offs are reflected in the survey with minimal overlap, while the probability that a choice set with the same levels for an attribute occurs is minimized, and the probability of choosing each alternative is fairly even, with no obviously dominant choices.

This leaves us with the optimal set of choice sets out of the 128 possible choice sets, providing that we want to minimize the number of choice sets. This has resulted in seven choice sets of two alternatives. These choice sets are presented in Table I. The attributes are shown in the rows, together with a description of their levels, abbreviated by 1s and 0s. Then, the seven paired choice sets are reflected in the columns. As an example, the first question from the survey has been included in Table II, where the employer or recruitment officer has to make a choice between one of the two described candidates.

4. Data

4.1 Data collection

The objective of the DC experiment is to give insight in the employer preferences for IT-retrainees. Our sample is taken from the registers of the Amsterdam Chamber of Commerce. In the Netherlands, business owners are legally required to register with the Chamber of Commerce. Without this registration, it is not possible to hire any employees. Since we only look at firms that hire employees, their records give a representative image of the business environment that we are interested in. We made a selection of companies that are registered in SBI-2008 industry code 61, entailing "services in the area of IT," as defined by Statistics Netherlands. Our selection only includes companies that comprise at least one employee, to filter out the self-employed. This left us with the addresses of 1,901 entities based in the municipality of Amsterdam.
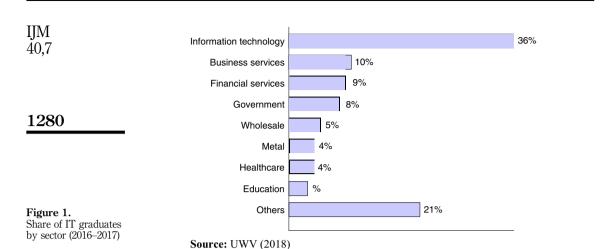
Figure 1 shows the distribution of IT graduates by sector in 2016/2017. The IT sector employs around 36 percent of the total number of IT graduates in the Netherlands. While we specifically target IT companies in our survey, IT professionals also work directly for companies in other sectors. Still, the IT sector employs the majority of IT graduates, so it makes sense to assume that this sector is experiencing the biggest difficulties from the shortage of graduates. Also, for other sectors it is easier to outsource IT, whereas for IT companies this is more difficult, as they would not outsource to their competitors.

We sent out the survey by mail to each of the 1,901 mail addresses of IT firms registered in the database of the Chamber of Commerce. The participants could return the completed survey by either mail or by e-mail. In addition to the paper-based survey, we hosted a web-based version of the survey. This web-based version was compatible on both computers and tablets, as well as on smartphones. A URL to the survey could be found in the cover letter.

Which candidate would you select for retraining to software engineer for your company?			
Candidate A		**Candidate B**	
Level of education	master's	Level of education	bachelor's
Exact field	no	Exact field	yes
Programming experience	basic	Programming experience	none
Listening skills	poor	Listening skills	average
Verbal communication skills	poor	Verbal communication skills	average
Teamworking skills	average	Teamworking skills	poor
Starting wage	€2,700	Starting wage	€2,400
Please select your preferred candidate			

Table II.
Example survey
question

Figure 1.
Share of IT graduates
by sector (2016–2017)

Information technology — 36%
Business services — 10%
Financial services — 9%
Government — 8%
Wholesale — 5%
Metal — 4%
Healthcare — 4%
Education — %
Others — 21%

Source: UWV (2018)

We sent a survey to each entity, and directed each letter to the recruiting department. Most firms consist of multiple entities, but we do not know beforehand which entity and which address hosts the recruiting department. For this reason, some firms ended up receiving multiple copies of the survey, and as a consequence returned just one. This explains why we only got 111 responses out of 1,901 addresses. Also, firms that turned out to be operating in different sectors than IT received our survey. This can partly be explained by the fact that firms can be classified in different sectors upon registration with the Chamber of Commerce, which makes the group of firms that is registered as an IT firm larger than the actual group.

4.2 Sample characteristics
Table III gives an overview of the main characteristics of the 111 out of 1,901 firms that completed the questionnaire. Most firms have a wider scope than just the region of their headquarters – most of them operate on a national or international level. This is interesting, since roughly 80 percent of firms employ 50 or less employees, where 50 percent employs only 10 or less. A possible explanation for the low numbers of employees in contrast to the (inter)national scope of their operations might be that most companies in the sample are start-up firms, still recruiting and increasing their number of employees. From the number of programmers hired in the previous year, we see that most firms are indeed hiring new personnel, bearing in mind the current size of their personnel file. In our survey, we also ask the respondent for their position within the individual firm. In most cases, the firm representative is either the chief executive officer or the chief human resources officer. In a few cases, the survey is filled in by the head of recruitment of the respective firm. This can be explained by the fact that of the firms in our sample, the majority employ less than 11 employees. Those firms are usually too small to justify an individual human resources officer, and only very few firms in our sample are large enough to justify an internal recruitment department. Even so, it is likely that the surveys are filled in by a representative that has the discretion about the firms hiring decision.

4.3 Attribute rankings
Before the main part of the survey, participants were asked to state their relative rankings of the six key attributes, excluding the wage attribute. This allows us to compare the results from the DCE with the type of results that are frequently reported in the literature. The rankings are displayed in Table IV. From this, it seems that employers value programming

	No.	%
Geographic area		
Municipality	6	5.4
Province	1	0.9
National	41	36.9
International	63	56.8
Total	111	100.0
Number of employees (full-time)		
1–10	58	52.3
11–50	31	27.9
51–250	17	15.3
> 250	5	4.5
Total	111	100.0
Number of programmers hired per year		
None	11	9.9
1–2	53	47.7
3–5	25	22.5
> 5	22	19.8
Total	111	100.0
Headquarters in Amsterdam		
Yes	93	83.8
No	18	16.2
Total	111	100.0

Table III.
Characteristics of the
firms in our sample

1st stated preference	1 No. (%)	2 No. (%)	3 No. (%)	4 No. (%)	5 No. (%)	6 No. (%)
Level of education	9 (9.3)	34 (35.1)	15 (15.5)	9 (9.3)	18 (18.8)	11 (11.5)
Exact field	21 (21.6)	7 (7.2)	6 (6.2)	8 (8.2)	14 (14.6)	40 (41.7)
Programming experience	51 (52.6)	11 (11.3)	11 (11.3)	8 (8.2)	9 (9.4)	7 (7.3)
Listening	4 (4.1)	6 (6.2)	20 (20.6)	23 (23.7)	26 (27.1)	18 (18.8)
Verbal communication	3 (3.1)	16 (16.5)	20 (20.6)	25 (25.8)	16 (16.7)	17 (17.7)
Teamworking	9 (9.3)	23 (23.7)	25 (25.8)	24 (24.7)	13 (13.5)	3 (3.1)
Total	97 (100.0)	97 (100.0)	97 (100.0)	97 (100.0)	97 (100.0)	97 (100.0)

Table IV.
Attribute rankings

experience the most, followed by the possession of a degree in an exact field. The level of education, i.e. holding a master's degree instead of a bachelor's degree, has most frequently been stated as the second-most important attribute. From the third-most important attribute onwards the pattern is unclear, but it is predominantly the soft skills that are mentioned here. To make this more clear, we estimate random effects probit models on the choice data from our survey in the next section.

5. Analysis and results
5.1 Random effects probit models of the hiring decision
The results from the random effects probit models are shown in Table V. We present the regression coefficient next to the marginal effect, which is calculated at the means of covariates. The marginal effect is the increase in the probability that a candidate is hired if the corresponding attribute changes from the worst level of the attribute to the best level (see Table I). In Column 1, we present our baseline specification. In Column 2, we add

	1 Full sample		2 Full sample		3 Large + International	
	Coefficient effect	Marginal effect	Coefficient effect	Marginal effect	Coefficient effect	Marginal effect
Level of education	0.681*** (0.091)	0.272*** (0.037)	0.681*** (0.091)	0.272*** (0.037)	0.760*** (0.178)	0.303*** (0.072)
Exact field	0.844*** (0.089)	0.337*** (0.036)	0.844*** (0.089)	0.337*** (0.036)	0.916*** (0.174)	0.365*** (0.071)
Programming experience	1.305*** (0.089)	0.520*** (0.037)	1.305*** (0.087)	0.520*** (0.036)	1.489*** (0.171)	0.594*** (0.071)
Listening skills	1.131*** (0.089)	0.451*** (0.030)	1.131*** (0.089)	0.451*** (0.030)	1.185*** (0.176)	0.473*** (0.072)
Verbal communication	0.199*** (0.076)	0.079*** (0.034)	0.199*** (0.076)	0.079*** (0.030)	0.273** (0.139)	0.109* (0.056)
Teamworking skills	0.663*** (0.085)	0.264*** (0.034)	0.663*** (0.085)	0.264*** (0.034)	0.781*** (0.161)	0.312*** (0.065)
Starting wage (×€1,000)	−0.961*** (0.131)	−0.383*** (0.027)	−0.961*** (0.068)	−0.383*** (0.028)	−1.070*** (0.130)	−0.429*** (0.055)
Larger firm (> 10 employees)	–	–	−0.008 (0.124)	–	–	–
International firm			0.011 (0.125)	–	–	–
Observations	1,554	–	1,554	–	476	–
Respondents	111	–	111	–	34	–
Log likelihood	−782.0	–	−782.0	–	−229.8	–
χ^2	303.3	–	303.3	–	95.0	–

Notes: Standard errors in parentheses. Column 1 shows the results of our baseline specification. In Column 2, we add dummy variables for larger firms (> 10 employees) and international firms. In Column 3, we perform a sub-analysis for large international firms. Interactions between skill attributes has been investigated, yet all are zero. The number of observations is derived by multiplying the number of respondents by 14, because the survey contains seven pairs of choices for each respondent.
*$p < 0.10$; **$p < 0.05$; ***$p < 0.01$

Table V.
Results random effects probit models for the hiring decision

dummy variables for larger firms (> 10 employees) and international firms, since about half of the employers in our sample employ 10 or less employees. Adding these control variables does not alter the regression coefficients, and the coefficients of these control variables are also statistically insignificant. Then, in Column 3, we perform a sub-analysis for large and international firms. Since the results seem to be robust after controlling for different subsamples, Column 1 is our preferred specification.

From the coefficients in Column 1, we see that programming experience is valued the highest by employers. The marginal effect is close to 0.5, which means that earlier programming experience improves the probability that the candidate is hired by almost 50 percent. The second-most high-valued attribute is listening skills. Average instead of poor listening skills increase the hiring probability by 45 percent. Interestingly both these hard and soft skills are valued more or less equally by employers, which also relates to earlier findings in the literature (see Section 2). Closely behind these attributes are the completion of an exact field, and the completion of university education (master's degree), followed by teamworking skills. The marginal effect of verbal communication skills is close to zero. The coefficient is also statistically insignificant for small, domestic firms. This suggests that IT employers do not value verbal communication skills highly, contrary to earlier findings (e.g. Bailey and Mitchell, 2006).

The only statistically significant interaction effect is the interaction of teamworking skills with the control dummy for large firms. This means that larger firms value teamworking skills higher than smaller firms. This can be explained by the fact that in larger firms, it is more likely that the candidate would have to work in teams. In larger firms, it is also more likely that the composition of these teams changes over time. The employees would need to adjust to this, and hence larger firms value teamworking skills higher.

In addition, we have investigated a specification including the interaction terms of the six attribute variables. It is possible that there are increasing or decreasing returns when a candidate possesses a combination of skills. For instance, a candidate who has listening skills in combination with programming experience. However, these coefficients are very small, and none of these coefficients are statistically significant. We therefore do not report the results of this specification in Table V, but these are available upon request.

5.2 Marginal rates of substitution
We use the coefficients from Column 1 of Table V to calculate the MRS for each skill attribute. The MRSs are displayed in Table VI. The MRS of a skill attribute with respect to the starting wage is calculated by dividing the coefficient by the coefficient of the wage attribute, multiplied by −1. The MRS assesses the relative importance employers attach to the specific characteristics. More specifically, the MRS measures how much more starting wage an employer is willing to offer a candidate who possesses a specific skill level, compared to a similar candidate who does not possess this skill. For instance, an employer would offer a candidate who holds a master's degree a 27.06 percent (€689.91) higher starting wage than an otherwise comparable candidate with a bachelor's degree.

6. Discussion and conclusion
DCEs have several advantages. When employers are explicitly asked to order their preferences in a questionnaire, it is difficult to assess the relative importance of the

	1 Experience	2 Listening	3 Exact	4 Education	5 Teamworking	6 Verbal	
Euros	1,357.96	1,176.90	878.25	708.64	689.91	207.08	**Table VI.** Marginal rates of substitution, small domestic firms
% of €2,550 (i.e. average starting wage)	53.25	46.15	34.44	27.79	27.06	8.12	

individual skills. The results from DCEs are proven different from traditional rating scale exercises (Wijnen *et al.*, 2015). Traditional ranking methods do not capture the strength of preference of one skill level to another. In the DCE presented in this paper, the respondents are faced with a series of trade-offs between two hypothetical candidates, differing on a couple of attributes. The participant has to choose the most suitable candidate for his or her enterprise. Doing so, DCEs resolve the shortcoming of traditional ranking methods by exposing the trade-offs between the different skills, and provide quantifiable data of the relative importance of the different skills. Furthermore, this allows for the estimation of the effect of possessing a particular skill on the success rates, or hiring probabilities. These models further allow for the assignment of monetary values to the individual skills (Ryan *et al.*, 2008).

While DCEs can be helpful in revealing the preferences of IT companies for potential retrainees, DCEs also have some potential weaknesses. One weakness is that DCEs are based on stated preferences, instead of revealed preferences (Coast *et al.*, 2012; Johnston *et al.*, 2017). Vossler *et al.* (2012) develop a game-theoretic model designed to test for the internal validity of stated preference methods. Supplemented with a framed field experiment, their results show that truthful preference revelation under a stated preference method is possible. In an experiment to externally validate the results of stated preferences methods, Vossler and Watson (2013) show that these results are indeed incentive compatible. In our survey, the trade-offs that recruitment officials are faced with closely resemble real-life trade-offs. Recruitment officials regularly cope with selection decisions based on resum´es, closely resembling the presentation of the choice sets in our survey. Therefore, the stated preferences from our survey are expected to closely resemble the actual preferences.

6.1 Concluding remarks

The goal of this paper is to give insight in the way employers value the competencies of potential IT-retrainees. To do this, we designed and conducted a DCE among IT companies in Amsterdam, the Netherlands. The results show that previously acquired programming experience is valued the highest: at 53.25 percent (€1,357.96) of additional monthly starting wage. Average listening skills are another highly valued competency. Employers value this skill at 46.15 percent (€1,176.90) of additional starting wage. Comparatively, according to large-scale surveys wo graduates earn 13 percent more than hbo graduates one and a half year after graduation (Vereniging Hogescholen, 2015; VSNU, 2015). In line with the literature on IT job skills, we find that a combination of soft skills and hard skills makes up the ideal IT retraining candidate. However, we do not find that hard and soft skills complement each other: the interaction effects are not significant.

The fact that employers value programming experience that has been acquired before the whole retraining trajectory started questions the value added in the formation of technical skills in IT retraining programs. When employers already seem to have a strong preference for candidates with prior knowledge of computer programming, these programs "retrain" candidates who already possess programming skills, perhaps yet without official qualification. The same holds for the level of education and candidates who possess a degree in an exact field. An interesting result is also that employers seem to value listening skills relatively high.

Employers value this skill only €181 lower than programming experience, which is the most high-valued competency for IT-retrainees. Furthermore, employers are willing to offer candidates with average teamworking skills a monthly wage premium of €689.91 over candidates with poor teamworking skills. Given the results from the experiment presented in this paper, it seems worthwhile to consider the focus on the formation of soft skills in IT retraining programs in addition to the formation of technical skills, since employers would

already select candidates with strong prior knowledge of computer programming into such programs. Alternatively, one can select candidates on highly valued non-cognitive skills such as listening and team skills *a priori*. The IT curriculum can then focus on the formation of cognitive, technical skills. However, since soft skills may be more difficult to teach than hard skills, a selection on soft skills may be the most efficient.

In the context of this paper, the information during the hiring process might differ from the information presented in the survey. In the end, the information that employers have on the applicants depends a lot on the questions asked during the job interviews and on the way these interviews are organized. This very likely differs among firms, where in the survey we provide all firms with the same information. Still, DCEs solve some of the shortcomings from resume audits that suffer from the problem that they only observe the beginning of the hiring process. The results presented in this paper go beyond the first stage of the hiring process by simulating the entire hiring process.

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