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IZA DP No. 14511

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ABSTRACT

Skill Demand and Wages. Evidence from Linked Vacancy Data*

This study provides new evidence on skill requirements in the labor market and shows to what extent skill demand is associated with wages and vacancy duration. Using more than 1.5 million job postings administered by the Austrian public employment service, I identify the most common skill requirements mentioned in job descriptions. Because employers in Austria are legally required to state the minimum remuneration for advertised positions, it is possible to relate the skill content of jobs to wage postings. Moreover, I estimate skill associations with starting wages for a subset of vacancies which can be matched to administrative data on employment spells of eventual hires. Accounting for education, work experience, and firm and occupation fixed-effects, there exists a robust association between the number of skill requirements and wages. In particular, jobs with many skill requirements pay substantially higher wages. While I estimate large effects for managerial and analytical skills, associations with most soft skills are small. Employers also need longer to fill vacancies with many skill requirements. Robustness tests show that measurement error is unlikely to explain these results and that the estimates can be replicated using vacancy postings from another job board.

JEL Classification: J23, J24, J31

Keywords: job advertisements, job boards, skills, wage differentials, vacancy duration

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* I thank Matthew Gibson, Andrea Ichino and Dan Hamermesh as well as workshop and conference participants in Vienna (Arbeitsmarktworkshop 2018), Austin (IZA Junior-Senior Symposium 2019), Graz (NOeG 2019), Manchester (EEA 2019) and Uppsala (EALE 2019) who provided valuable comments and suggestions. An earlier version of this paper was circulated under the title "*Skill Demand and Wages. Evidence from Online Job Ads in Austria*".

1 Introduction

Due to technological progress, labor markets have been facing substantial changes in the demand for skills and their associated returns. A popular approach to measure skill demand is to quantify the skill content of occupations (see, for example, Autor et al., 2003). While datasets of occupation profiles can provide a comprehensive and detailed summary of required skills, they only measure the average skill content of each occupation. In the analysis of labor market outcomes, it is thus not feasible to account for unobserved differences between occupations.

This study follows an alternative approach and exploits linked vacancy-worker data to analyze the recent demand for skills. Using more than 1.5 million job posts administered by the public employment service in Austria, I identify the 14 most common skill requirements mentioned in ad texts and estimate associations with wage postings, starting wages and vacancy duration. Because employers are legally required to specify the minimum remuneration for each advertised vacancy in Austria, I can exploit ad-level variation to relate skill requirements to prospective pay. Moreover, it is possible to match a subset of vacancy posts to future employment spells. The matched vacancy-worker data allow to connect skill requirements to starting wages of hired workers. Finally, I analyze whether the skill content of vacancies is related to the time employers need to find suitable hires.

This paper is also a methodological contribution as I discuss the opportunities and limitations of job ads as a measure for skill demand in the labor market. More specifically, I examine what kind of information job postings comprise, how measured effects should be interpreted and to what extent measurement error can bias these estimates.

A rising number of papers exploits job-board data to study the labor market, ranging from gender discrimination (Kuhn and Shen, 2012) to the effects of unemployment insurance programs (Marinescu, 2017). Two recent studies analyze data on vacancies from the Austrian public employment service. Lalive et al. (2015) use the job listings to study market externalities of unemployment insurance programs, and Mueller et al. (2020) examine the impact of vacancy duration on starting wages.[1] Job advertisements are also increasingly used to derive skill measures and analyze the impact of skill differences in the labor market (Deming and Kahn, 2018; Atalay et al., 2020; Deming and Noray, 2020; Modestino et al., 2020). While most of the existing literature on skill

[1]Compared to the data that I analyze in this paper, the two studies focus on vacancies which cover an earlier period and do not contain detailed information on skill requirements.

returns uses common supply-side measures of cognitive and non-cognitive skills such as standardized test scores, these studies focus on the demand side of skills.[2]

Most closely related to my paper is the study by Deming and Kahn (2018), which shows strong associations between skill requirements and average pay. Because I follow a data-driven approach to identify the most frequent skill requirements mentioned in job ads, the skill dimensions analyzed in my study differ somewhat from the ten general skill groups defined in Deming and Kahn (2018). Another key difference concerns the measure of earnings. Since potential earnings are usually not reported in vacancy posts in the United States, they supplement the sample of job ads with external earnings data and calculate average pay by occupations and metropolitan statistical areas. Using linked vacancy data instead, I am able to exploit ad-level variation in posted wages and also observe differences in starting wages of eventual hires, which allows to account for unobserved fixed-effects of firms, occupations and geographical regions.

In the first part of the analysis, I identify the most common keywords that describe the skill content of vacancies and group these into 14 different skill types. Despite a relatively short average text length of 160 words, I measure, on average, 1-2 skills per job ad. Vacancy posts for high-educated workers report more than twice as many skills than those for low educated. Whereas soft skills such as reliableness and teamwork competence are in high demand among employers who look for workers with a vocational degree or less, language and analytical skills are often frequented in posts for university graduates.

The second part of the analysis relates the skill measures to wage postings, starting wages and vacancy duration. Accounting for education requirements, prior work experience, and firm and occupation fixed-effects, I find that one additional skill increases posted wages, on average, by 0.6 percent. Especially jobs with many skill requirements are associated with substantially higher wages. Moreover, I estimate significant differences by individual skill types. Entrepreneurial and leadership skills show the largest impact, increasing wages by about 6 percent. Whereas analytical skills and other hard skills also have positive returns, many soft skills such as stress tolerance and reliableness are not associated with higher pay. Although the estimated returns to communication skills are relatively small, I find evidence for substantial interaction effects with analytical skills. This is in line with recent empirical evidence for the US which suggests that the labor market is increasingly characterized by strong complementarities between

[2]See, for example, Heckman et al. (2006); Lindqvist and Vestman (2011); Autor and Handel (2013); Hanushek et al. (2015) for previous evidence on the returns to skills.

social skills and cognitive skills (Deming and Kahn, 2018; Weinberger, 2014).

Examining starting wages of workers who eventually filled the vacancies, I find that the observed skill associations with wage postings translate into actual wage differences. Corresponding estimates are similar for both the number of skills and the requirement of specific skills. Next to these wage differentials, I also estimate that employers need more time to fill vacancies with many skill requirements. This suggests that there exists a positive correlation between labor market tightness and the skill content of jobs.

To investigate potential biases due to measurement error, I compute hypothetical effect sizes for different levels of under- and over-detection of skills and show that the underlying measurement error would have to be unrealistically large to explain the observed differences in skill returns. As an additional robustness check, I replicate my analysis using job ads from a large commercial online job board in Austria. Estimated wage effects are similar to those obtained for the main sample, showing that the observed impact is not specific to the pool of ads on the job board of the public employment service.

The remainder of this paper proceeds as follows: In the next section, I provide information on the wage setting process and regulations for job postings in Austria. Section 3 outlines the setup of Austria's major online job board and describes the dataset. In particular, I explain how skills are inferred from job ads, and I provide the corresponding statistics. The main estimation results are presented in Section 4. Section 5 discusses the findings and provides additional robustness checks with regard to measurement error and representativeness. Finally, Section 6 concludes.

2 Institutional framework

Nearly 98 percent of workers in the Austrian labor market are covered by collective bargaining agreements (CBAs).[3] While most agreements are negotiated on the industry level, there also exist some firm-level CBAs which are often complementary to industry agreements and specify better conditions for workers. The negotiated pay scale differs by occupation and often increases with education, age and experience. Wages specified in these agreements are legally binding and cannot be undercut, but firms are free to offer higher wages. In that sense, CBA wages should be interpreted as a lower bound for actual wages. Firms often claim that the degree of overpay depends on both

[3]See report by OECD (2012).

qualification and experience. A national minimum wage does not exist in Austria. Next to the pay structure, CBAs also regulate the extent of working hours and other working conditions.

A unique feature of the Austrian labor market is that, as of March 2011, employers are required to specify the respective CBA gross starting wage in job postings. Since August 2013, a similar regulation also applies to the few sectors that are not covered by collective bargaining agreements. Here, the posted wage should be at least the lower bound of the typical pay for an offered vacancy. Posted wages should exclude bonuses or other extra payments, and the unit of time has to be reported (hour, month or year). Employers who do not comply with these rules may be fined for violation by local authorities. Whereas the posted wage cannot be below the CBA figure, employers can post higher wages. If firms want to attract qualified applications and are able to overpay, it can be advantageous to post a higher wage. It is thus likely that some wage postings exceed the wage of the respective collective bargaining agreement. When I control for firm and occupation fixed-effects in the empirical analysis, most of the residual variation in posted wages should result from these ads.

Little empirical evidence exists on the wedge between collective bargaining wages and actual wages. While final wages are observed in the Austrian social security records, it is in many cases hard to figure out which bargaining agreement applies to a specific spell. A policy report by Leoni and Pollan (2011) estimates a gap of around 20 percent for the industrial sector. This is similar to wage differences estimated for vacancies that can be matched to social security records. As will be discussed in the subsequent section, I find that starting wages of matched full-time hires are, on average, 24 percent higher than posted wages.

3 Data

3.1 Vacancy data

To examine skill demand, I use job postings from the vacancy database of the public employment administration (AMS) in Austria. Employers can report their vacancies to the AMS, which publishes them on its online job board *e-Jobroom* and also actively mediates job seekers to firms. Contrary to many commercial competitors, the employment office does not charge companies for job postings. Users of the online job board can either use the open search mask or filter ads by several characteristics such as location or occupation. It is also possible to register for free and set up an application profile, which enables firms to get in contact with registered job searchers. Unemployed benefit recipients, who are automatically registered at the employment office, might be referred to suitable vacancies.

According to a representative quarterly survey among establishments conducted by Statistics Austria, the AMS covered about 50-60 percent of all open vacancies in recent years. Having about 80,000 active postings at a time in 2019, the *AMS e-Jobroom* also offers by far the biggest pool of vacancies in Austria.[4] A comparison to a large commercial competitor is provided in Section 5.3. Another advantage of the AMS database is that the vacancies are actively managed by caseworkers. Daily checks for activity by AMS employees greatly reduce the number of inactive vacancies, which are common on online job boards (Cheron and Decreuse, 2016).

The vacancy database contains detailed information on job characteristics, which are reported for all vacancies and often correspond to the data shown online. These data include vacancy entry and removal date, firm identifiers, location, occupation, required education, extent of work and wage postings. Education requirements are grouped into four levels, ranging from compulsory schooling to university education. The AMS uses a detailed 6-digit occupation classification scheme, which distinguishes about 3,000 different occupations. All wage postings are converted to monthly pay.[5] Next to these structured characteristics, an open text section allows employers to provide additional information about the vacancy and specify the desired profile of applicants. Using text pattern matching, I exploit this information to measure the skill requirements of job postings and whether the job requires prior work experience.

The estimation sample is composed of all vacancies for regular permanent employment that were posted in the years 2014 to 2019.[6] I restrict the sample to vacancies which contain data on all described characteristics and provide an ad text of at least 10 words. This reduces the sample size by 8 percent to about 1.5 million job ads.

Table 1 provides descriptive statistics for the main vacancy characteristics. It shows

[4]Austrian employers can also choose to directly enter job posts on the job board without the assistance of AMS caseworkers. These advertisements are not reported in the vacancy database. According to a recent comparison from January 2020, about 10% of the total stock of vacancies on the job board are not administered by AMS.

[5]In a few cases where wage ranges are reported, I use the lower bound as posted wage. Unreasonably low values (below 500 euros) and high values (above $10,000$ euros) are dropped from the sample to minimize measurement error.

[6]This excludes vacancies for temporary work, vocational training or minor employment, which together amount to 16.5% of the database.

that an average ad consists of approximately 160 words. Firms post a gross wage of, on average, 2,000 euros per month and the mean vacancy duration is about two months. Figure A.1, which is provided in the appendix, plots the share of remaining vacancies by week after entry. It shows that two third of entries exit in the first 2 months and less than 5 percent remain for more than 6 months. While most job ads are for full-time positions, I find substantial heterogeneity in the level of required education. Contrary to many other online job boards, the e-Jobroom lists numerous vacancies for lower to medium educated workers with basic school education or vocational training. Only 15 percent of ads require a higher secondary degree or university education. According to the Austrian labor force survey in 2017, approximately 30 percent of workers fall into the latter category. Although the reported levels are *minimum* requirements and should therefore understate the average education of successful applicants, the large difference to the composition of the current workforce suggests that jobs for lower educated workers are overrepresented on the job board. Another worker characteristic frequently mentioned in job ads is prior work experience. In my sample, the majority of postings mentions that applicants need to have at least some prior experience. 16 percent explicitly ask for applicants with substantial experience.[7] To account for firm fixed effects in the subsequent analysis, I need to observe multiple job ads per firm. The last two rows of Table 1 report the distribution of job ads across firms, showing that most employers post more than one job ad during the period of observation.

3.2 Skill requirements

To identify the most common skill requirements, I split up the ad texts into words and rank them according to their overall frequency. Next, I filter out all words that describe skill requirements.[8] These can either be general skills such as being communicative or specific skills like a programming language. Finally, I group the terms into skill categories. Table 2 provides an overview of this classification procedure. Column 2 and 3 show the 14 identified skills along with an excerpt of used keywords for each skill. To reduce the dimensionality of the skill set, I further aggregate these skills into five major skill groups. From the list of skills in Table 2, it becomes apparent that the job

[7]Because the AMS does not group postings by required level of experience, I infer experience requirements from word matches in the ad text. Experience is classified as *substantial* if employers explicitly state it or if they ask for multiple years of experience.

[8]In some cases, I have to rely on multiword expressions to avoid over-detection caused by expressions that do not necessarily refer to the skill profile.

Table 1: Job ad characteristics

	Mean	Std. Dev.	Min	Max
Posted monthly wage (2019 Euros)	2,018.11	624.73	500	10,000
Vacancy duration (in days)	57.39	56.75	0	365
# words	163.38	83.21	10	868
Urban area	0.34	0.47	0	1
Extent of work:				
- Full-time	0.71	0.45	0	1
- Part-time	0.20	0.40	0	1
- Full- or part-time	0.09	0.28	0	1
Education:				
- Compulsory schooling	0.33	0.47	0	1
- Vocational training	0.51	0.50	0	1
- Higher voc.-techn. schools/gymnasium	0.10	0.30	0	1
- (Applied) university	0.05	0.22	0	1
Prior experience:				
- Some experience	0.47	0.50	0	1
- Substantial experience	0.16	0.36	0	1

# ads per firm	1	2-5	6-10	11-100	>100
Firms (N=136,040)	36,512	51,872	20,695	25,201	1,760

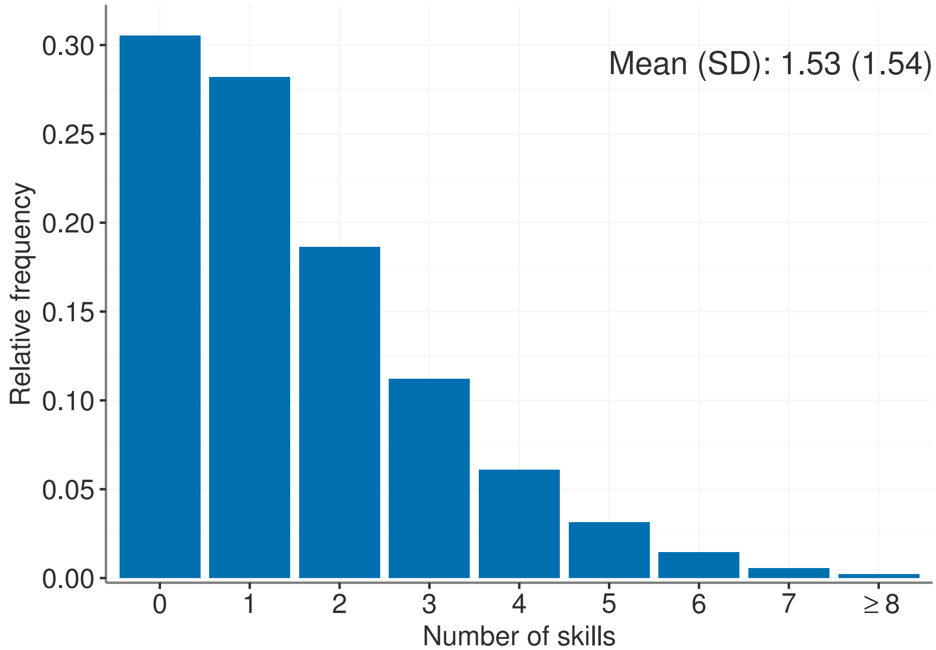
NOTE: N=1,569,760. A vacancy is classified as *urban* if the job is located in a district of the six largest Austrian cities (Vienna, Graz, Linz, Salzburg, Innsbruck and Klagenfurt).

posts mainly describe skill requirements of higher skilled occupations, which are often characterized by a higher complexity of tasks. Also, the skill set of university graduates might be more diverse than that of workers with lower schooling levels.[9]

The short profile descriptions in job postings cannot provide a full characterization of a worker's profile. Compared to occupational dictionaries, ad texts contain a shorter, more superficial summary of the required skill set. Furthermore, it is more difficult to describe the relative importance of skills. For this reason, firms might put more emphasis on major skill requirements, while minor skills are more likely to be omitted. In contrast to continuous skill measures, estimated effects should thus be interpreted as the impact of prioritized skills for a given job. It is also possible that these skill requirements are only observed with some degree of measurement error because of

[9] Note that Austria has a well-developed apprenticeship system with national standards and centralized examination, which helps employers to better assess the skills of applicants with vocational training.

Figure 1: Distribution of skills per job ad



over- or under-detection of described skill attributes. Potential sources of measurement error and its consequences will be discussed in Section 5.2.

As depicted in Figure 1, I observe on average 1.5 skills per job ad. Whereas 30 percent of posts do not list any of the skill types, around 5 percent request more than 4 skills. Table 3 shows the relative frequency of all skill types separately for low- and high-educated workers. As expected, there exists a strong correlation between skill content and levels of education. Job ads that require higher education specify, on average, more than twice as many skill requirements. Whereas social skills like communication and teamwork competency are frequent in both groups, cognitive skills such as analytical and programming skills are rarely asked of lower educated workers.

When examining the joint demand for skills within job ads, I find evidence for substantial correlations between many skill requirements (see Table A.1 in the appendix). To better understand these associations, I conduct a principal component analysis, which estimates variance-maximizing orthogonal linear combinations of the skill indicators. This allows to visualize the co-movement of skills in job postings.[10] Figure 2 shows the first two principal components of all 14 skill types. While I observe simi-

[10]To account for large differences in skill shares, I normalize the standard deviation of each skill indicator to 1.

Table 2: Classification of skills

Skill group	**Specific skill**	**Examples (translated from German)**
Analytical skills	Analytical skills	Problem solving skills, analytical thinking
Communication skills	Communication skills	Communication skills, communicative
Managerial skills	Entrepreneurial skills	Entrepreneurial spirit/mindset
	Leadership skills	Leadership strength, leadership
Other hard skills	Programming	Programmer, Programming, Python, SQL
	MS-Office skills	Microsoft Office, MS Word, MS Excel
	Foreign language	English, French, Spanish
Other soft skills	Teamwork	Teamwork, likes to work in teams, teamplayer
	Organizational skills	Organizational talent, organizational skills
	Self-reliance	Own initiative, self-reliant
	Assertiveness	Assertiveness, ability to assert oneself
	Creativity	Creativity, creative
	Stress tolerance	Personal resilience, stress resistance, stress
	Reliableness	Reliableness, reliable

lar principal components for most soft skills, those of hard skills are more scattered. This suggests that soft skills more often refer to a similar skill profile. Programming knowledge and reliableness stick out as these skills are often mentioned in isolation. Entrepreneurial skills are very centrally located in the graph of Figure 2. This is consistent with the view that entrepreneurs need to possess a variety of skills (Lazear, 2004).

The skill content of vacancies varies substantially between geographic regions. Figure A.2 in the appendix shows the average number of skill requirements by political district in Austria. Whereas job ads from the six largest cities and their surrounding districts list, on average, between 1.5 and 2 requirements, skill demand in rural areas is often much lower. This is in line with evidence from previous studies which show that demand for human capital is more concentrated in urban areas because of a higher supply of skilled workers and a greater potential for human capital spillovers (see, for example, Moretti, 2004).

3.3 Matched hires sample

If a vacancy was successfully mediated by the public employment service, the database also contains information on hired workers. In these cases, it is possible to match the

Table 3: Skill shares by education

Low educated		High educated	
Skill	Share	Skill	Share
Reliable	0.30	Language	0.48
Teamwork	0.23	Communicative	0.42
Communicative	0.15	Teamwork	0.37
Stress-tolerant	0.15	Self-reliant	0.27
Self-reliant	0.10	Analytical	0.26
Language	0.08	MS-Office skills	0.25
Leadership	0.06	Reliable	0.18
MS-Office skills	0.06	Leadership	0.16
Creative	0.04	Stress-tolerant	0.15
Organized	0.03	Programming	0.14
Analytical	0.03	Organized	0.10
Programming	0.02	Creative	0.08
Assertive	0.01	Assertive	0.07
Entrepreneurial	0.01	Entrepreneurial	0.04
Mean skills: 1.27		Mean skills: 2.97	
N=1,327,621		N=242,139	

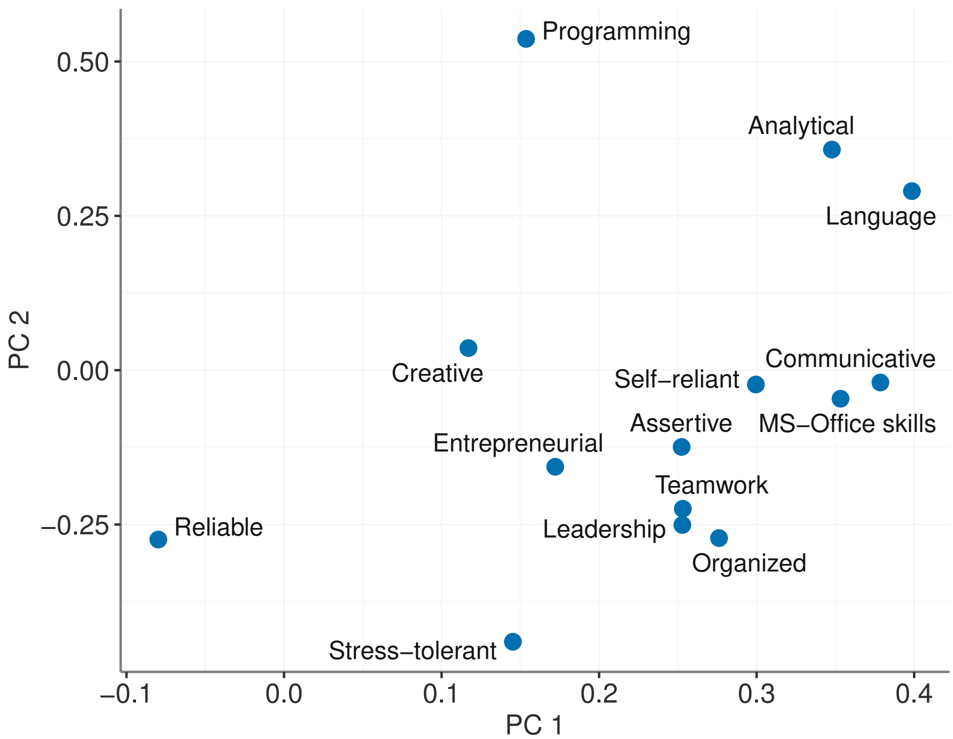
NOTE: **Low education**: Compulsory schooling and vocational training. **High education**: Higher voc.-techn. schools/gymnasium and (applied) university.

vacancy to Austrian social security records, which include data on employment and earnings for all work relations that are subject to social insurance.

Overall, 12.7 percent of vacancies in the estimation sample are filled by the public employment office. To find the corresponding employment relations in the social security records, I match work spells based on worker identifiers, and if available, on firm identifiers.[11] As work spell of a vacancy, I assign the worker's employment relation with the closest start date in a 60-day interval around the vacancy filling date. For the vacancies that allow a firm linkage as well, I choose the closest work spell at the respective firm in this interval. Some vacancies are filled by more than one job seeker, which results in multiple observations per vacancy. Following this procedure, I can match work spells to 90 percent of all mediated vacancies. This suggests that not all matches

[11] While a worker identifier is always provided for mediated job seekers, not all firms can be uniquely matched between the vacancy database and social security records.

Figure 2: Principal components of skills



recorded by AMS eventually resulted in an employment relation. It might also be the case that some of the mediated jobs were not subject to social security contributions and are thus not observed in the social security data.

The successful matches allow to estimate associations between skill requirements and realized earnings of hires who eventually filled the vacancy. Unfortunately, the social security records do not contain information on working hours, which may vary with skill requirements. To avoid such confounding effects, I additionally restrict the sample to full-time vacancies. As measure of starting wages, I compute average monthly earnings in the first year of employment. Approximately 140,000 hires can be matched to full-time vacancies in the estimation sample. Hired workers earn, on average, about 2,400 Euros per month, which is 24 percent higher than the posted wages of these vacancies.

Because the public employment service only mediates a subset of vacancies and mainly targets unemployed workers, mediated vacancies may be different from those in the overall sample. As a result, also skill estimates can differ between the full sample and the sample of matched hires due to sample selection. To permit a better comparison between the effects on posted and realized wages, I will also report associations between skills and posted wages for the subsample of matched hires. Table A.2 in the appendix compares selected characteristics of vacancies in both samples. It shows that posted wages are about 10 percent lower in the restricted sample. Similarly, education requirements of mediated vacancies are substantially lower. Almost half of the job postings require compulsory schooling and only 6 percent are for higher educated applicants. This difference is also reflected in the skill requirements. The number of skills is by a quarter lower in the sample of hired workers. Only soft skills are mentioned to a similar extent in both samples.

4 Analysis

4.1 Estimation strategy

To analyze the impact of skill demand on wages and vacancy duration, I estimate the following regression equation

$$y_{ijkl} = \alpha_j^F + \alpha_k^O + \alpha_l^E + S_{ijkl}^{'}\beta + X_{ijkl}^{'}\gamma + u_{ijkl}$$

where y_{ijkl} refers to the outcome and S_{ijkl} denotes the skill measure of ad i posted by firm j for occupation k in education group l. As skill measures, I use (i) the number of skills ($\#$ *skills*), and (ii) a vector of skill type indicators. Vector X_{ijkl} contains other job characteristics, including indicators for district, required work experience and the month in which the vacancy was posted. Finally, α_j^F, α_k^O and α_l^E denote firm, occupation and education group fixed effects, respectively. The identification assumption for the marginal effect of skills (β) is that, conditional on all included characteristics and fixed effects, stated skill requirements are not correlated with unobserved factors that explain differences in wages and vacancy duration.

Standard wage determination models predict that wages are determined by both productivity and bargaining power.[12] To measure returns to productivity, it is thus important to account for differences in bargaining power. As mentioned earlier, most collective bargaining agreements in Austria are industry-wide, with a few firm-level exceptions. Controlling for firm fixed effects removes any confounding effects on firm- or

[12] See Cahuc et al. (2006) for a theoretical framework.

industry-level which are constant across vacancy posts.[13] Furthermore, this specification allows to take out differences in the wage policy of firms, which might be correlated with skill requirements. Empirical studies that estimate firm-specific wage premiums often find evidence for substantial firm heterogeneity (Abowd et al. 1999; Card et al. 2013).

Although job descriptions in vacancy postings cannot provide a full characterization of the desired worker profile, the occupation itself contains information on skill requirements. It should be known to applicants which skills are necessary to complete the tasks of a specific occupation. Adding occupation indicators to the regressions allows a within-occupation comparison of skill types. This removes potential biases due to unreported occupation-specific skill requirements that are correlated with the observed skill measures. A drawback of this approach is that only returns to skills which vary within occupations can be identified. For completeness, I report all main regression results with and without occupation fixed effects.

4.2 Posted wages

I first examine the impact of skills on log posted wages. Estimation results for five different specifications are given in Table 4, where all estimates are scaled by factor 100 for better readability. The upper row reports point estimates for the number of skills. When including only the basic set of controls, I observe that posted wages increase by 4 percent per additional skill requirement. This effect is, to a large extent, driven by differences between occupations. Controlling for occupation fixed effects, the point estimate drops to about 1 percent. Differences between firms and varying education requirements also lead to smaller skill associations but their relative contribution is small. When I additionally account for these factors, the skill estimate decreases to about 0.6 percent.

As shown in Section 3.2, there exists substantial heterogeneity across job ads in the number of listed skills. It is possible that also wage effects change with increasing skill requirements. Using the full set of controls, I estimate log wage differences between each skill count and job postings that do not mention any of the described skills. Figure 3 shows that the wage effect sharply increases with the number of skill requirements. For

[13] Here, I assume that firms operate in one industry, which applies to the vast majority of Austrian firms. Even though individual bargaining power also influences final wages, this channel cannot affect the skill returns to posted wages.

vacancies with more than 7 skill requirements, I estimate almost 8 percent higher wage postings. The graph also demonstrates that the overall effect is not driven by changes at the extensive margin. In fact, the wage estimate for job ads with just a single skill requirement is much smaller than the average marginal impact.

The lower panel of Table 4 reports results for separate skill groups. I first focus on analytical skills and communication skills, which are among the most frequent requirements from higher educated workers. Moreover, they can be regarded as proxy for cognitive and non-cognitive abilities. Including only the basic controls, I estimate that recruiters of jobs requiring analytical skills post almost 20 percent higher wages. The coefficient declines substantially when I additionally account for firm and occupation fixed effects. Again, the decrease can be explained by the underlying correlation with occupations. In the last specification, I estimate a wage difference of 2.4 percent. Point estimates for communication skills are much smaller but correlated differences by firms, occupations and required levels of education are similar. Controlling for these confounding factors, I estimate that posted wages are 0.7 percent higher in jobs which require communications kills.

Table 4: Posted-wage regressions

	(1)	(2)	(3)	(4)	(5)
# skills	3.827	1.750	0.809	0.730	0.642
	(0.012)	(0.011)	(0.010)	(0.010)	(0.010)
Analytical skills	19.340	8.019	4.514	2.827	2.404
	(0.076)	(0.058)	(0.057)	(0.050)	(0.049)
Communication skills	2.357	1.300	1.179	0.818	0.685
	(0.046)	(0.039)	(0.033)	(0.033)	(0.032)
Managerial skills	9.064	10.050	5.103	5.811	5.614
	(0.063)	(0.050)	(0.049)	(0.045)	(0.045)
Other hard skills	10.879	3.720	2.852	1.394	1.103
	(0.047)	(0.041)	(0.040)	(0.038)	(0.037)
Other soft skills	-0.113	-0.749	-0.490	-0.264	-0.248
	(0.036)	(0.033)	(0.025)	(0.027)	(0.027)
Firm FE		✓		✓	✓
Occupation FE			✓	✓	✓
Education FE					✓

NOTE: N=1,569,760. All estimates are scaled by 100. Standard errors are reported in parantheses. All regressions control for entry month, district, experience and extent of work. See Table 2 for skill group classification.

By far the strongest conditional wage effect can be observed for managerial skills. In the full specification, the point estimate still amounts to about 6 percent. The last two rows of Table 4 report estimates for other hard skills and other soft skills. While the remaining soft skills have a negligible joint effect, employers that require additional hard skills post somewhat higher wages.

To distinguish the impact of specific skills, I regress log posted wages on indicators of all 14 skill types. Figure 4 plots the corresponding estimates from the regression that includes the complete set of controls. The results indicate substantial heterogeneity in the impact of hard skills. For language skills, I estimate a relatively large effect similar in size to the coefficient on analytical skills. The impact of programming skills is much smaller, and MS-Office skills are even associated with lower wages. This might be due to the fact that returns to profession-specific skills are absorbed by the occupation fixed effects. Indeed, I observe that, also conditional on education and experience, job ads for programmers offer relatively high wages. When I exclude occupation fixed effects from the wage regression, the point estimate on programming skills increases to 3 percent. Also for soft skills, I observe strong heterogeneity in wage estimates. Whereas assertiveness has a relatively strong effect of 4 percent, I estimate small negative coefficients on stress-tolerance, teamwork ability and reliableness.

To examine complementarities between hard and soft skills, I estimate additional wage regressions which include interaction terms of analytical and communication skills. As shown in Table A.3 in the appendix, I find in all specifications evidence for strong positive interaction effects. This difference is especially pronounced for communication skills. When both requirements are mentioned, the impact of communication skills is 3-4 times larger, while the effect size of analytical skills increases by about 70 percent.

Figure 3: Posted-wage effect by number of skills

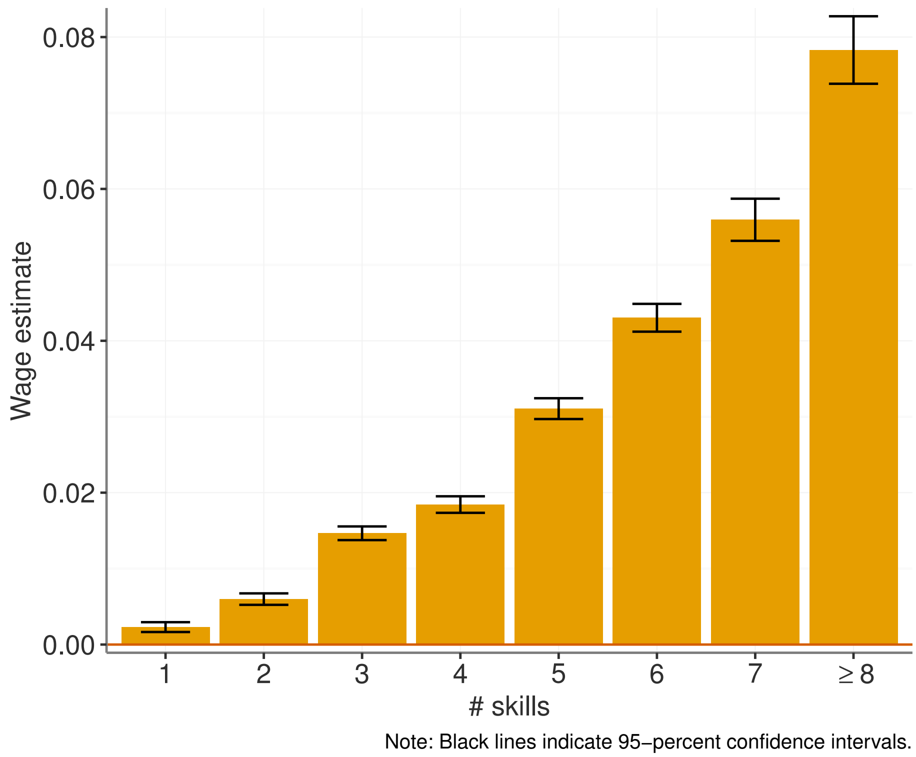
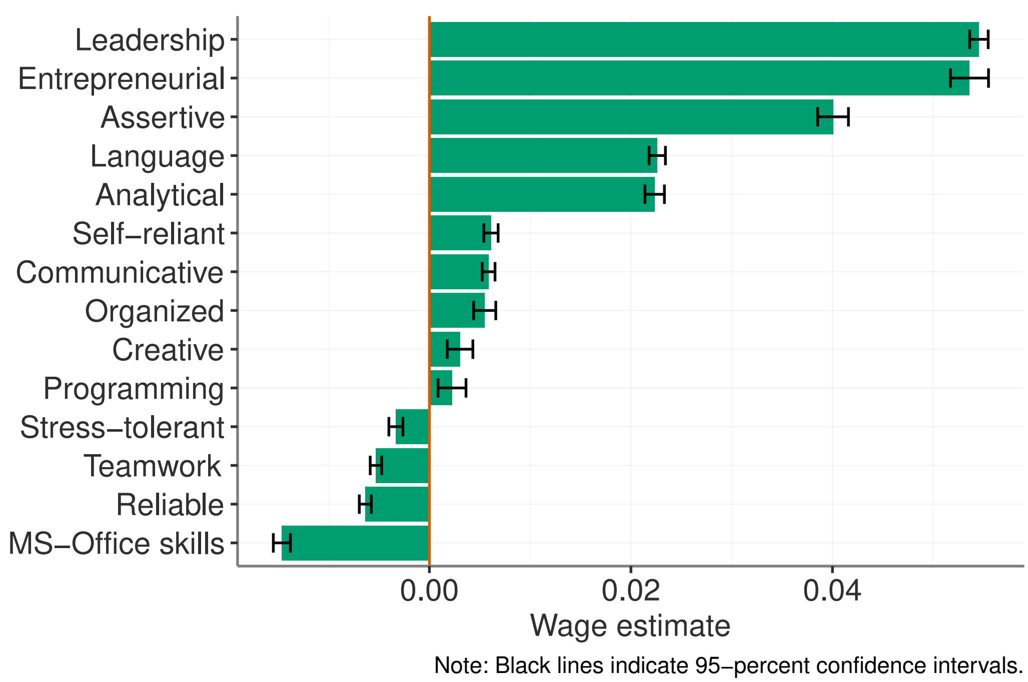


Figure 4: Posted-wage effect by skill type



4.3 Starting wages

While there exists a robust association between skills and posted wages, these differences do not need to translate into actual wage differences of the same magnitude for hired workers. Posted wages are only lower bounds for realized wage payments, which also depend on worker characteristics such as work experience, age and qualification. Because of these hire-specific differences, the wage postings may, in fact, be a more precise measure of the employer's willingness to pay for a worker with the outlined skill profile. Yet, many employers could be reluctant to commit to higher wages in the job ad and rather report the minimum wage of the collective bargaining agreement although they eventually pay higher wages to hired workers. In this case, posted wages do not reveal the skill valuation of employers and the average skill effect will be attenuated. Moreover, high wage postings might be used a strategic tool in the search process to increase the number of applications. If labor market tightness is correlated with the skill content of jobs, strategic wage posting behavior can distort the estimated skill returns.

Linking vacancy posts to social security records, I can examine whether skill effects on realized wages differ from those on posted wages. Table 5 shows skill associations with log posted wages and log starting wages in the sample of matched full-time hires, where starting wages are defined as average monthly earnings in the first year. All estimates, again scaled by factor 100, are obtained from regressions with the full set of controls, which includes required work experience and education as well as district, firm and occupation fixed effects. For comparison, the first column reports effects on log posted wages estimated for the full sample. As shown in the previous section, vacancies of matched hires are characterized by lower skill content. Comparing estimates in column 1 and 2 shows that also the skill associations are weaker in this subsample. The coefficient on the number of skills is about half the size compared to estimates for the full sample. Similarly, I find smaller differences in posted wages for most of the skill groups.

The last column of Table 5 provides estimates for skill associations with log starting wages. Although being estimated with larger standard errors, most coefficients are similar to those obtained for posted wages. One additional skill requirement is associated with 0.5 percent higher wages. Again, managerial skills show the strongest wage effect, followed by analytical skills and other hard skills. While I do not find evidence for an impact of communication skills on posted wages in the sample of full-time hires, the effect on starting wages is positive and statistically significant.

To understand how these estimates are affected by the inclusion of fixed effects, I provide results for various specifications in Appendix Table A.4. The observed changes closely mimic those discussed in the previous subsection. The skill estimate in the base specification is, to a large extent, explained by correlated occupation fixed effects, while differences caused by firm fixed effects are smaller.

Overall, the estimation results show that differences in wage postings explained by the skill content of vacancies translate into actual wage differences of hires. Although wages mentioned in job ads often only constitute a lower bound, the corresponding skill associations serve as a good proxy for the eventual effect on realized wages.

Table 5: Starting-wage regressions

	Full-time vacancies	**Matched hires**	
	log(posted wage)	log(posted wage)	log(starting wage)
# skills	0.702 (0.012)	0.414 (0.035)	0.533 (0.079)
Analytical skills	2.156 (0.054)	1.355 (0.228)	1.606 (0.509)
Communication skills	0.804 (0.040)	0.139 (0.128)	0.621 (0.286)
Managerial skills	6.665 (0.053)	4.443 (0.186)	3.738 (0.416)
Other hard skills	1.106 (0.043)	1.456 (0.146)	0.826 (0.326)
Other soft skills	-0.368 (0.032)	-0.237 (0.081)	0.171 (0.181)

NOTE: The estimation sample is restricted to full-time vacancies. N = 1,114,201. (Matched hires sample: N = 136,444). All estimates are scaled by 100. Standard errors are reported in parantheses.

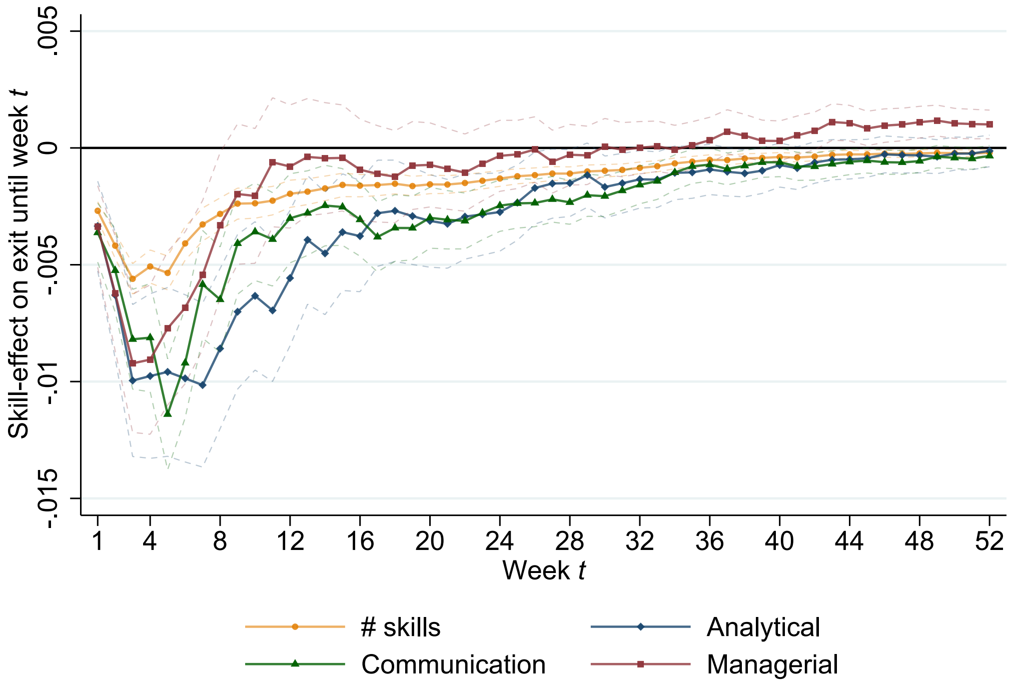
4.4 Vacancy duration

Conditional on offered wages, the skill content of jobs might also affect the time that employers need to fill the vacancies. Whether the number or type of skill requirements prolongs or shortens vacancy filling depends on the supply of workers in different skill groups relative to the respective demand. If, for instance, workers with a large number of skills are relatively scarce, it might take longer to find a suitable match. In a standard search and matching model, the probability of filling a vacancy is given by $\frac{m(U,V)}{V}$, where $m(U, V)$ denotes the matching function for a given number of unemployed job seekers U and vacancies V. It is plausible that the filling rate also depends on the skill content of jobs. First, the matching technology captured by $m(U, V)$ can differ by skill level. Recruiters likely need more time to screen higher skilled applicants, which delays a successful match. Second, skill requirements might deter low-skilled workers from applying to high-skilled jobs but not vice versa. Albrecht and Vroman (2002) and Dolado et al. (2009) propose search and matching models with heterogenous workers and assume that high-skilled workers also search for jobs with low skill requirements. By construction, the number of potential matches is then higher for vacancies with a low skill content. For simplicity, assume that there are only two skill groups, l (low) and h (high). Labor market tightness, defined by the ratio of vacancies and job seekers ($\theta = V/U$), is larger for high-skilled jobs unless there exist many more vacancies for low-skilled workers compared to the number of available job seekers in both groups ($\frac{V_h}{V_l} \leq \frac{U_h}{U_l+U_h}$). As a consequence, the arrival rate is lower for jobs with high skill requirements and it will take longer to fill these vacancies.

To analyze differences by skill content, I regress indicators for having exited until week t after vacancy entry on the different skill measures. Again, I use the full set of controls to remove correlated differences caused by observable job characteristics. Figure 5 plots the corresponding skill effects on the cumulative exit probabilities up to one year after vacancy entry. As shown in the previous section, almost all vacancies have been removed within this time span.Consistent with the theoretical prediction, I find that vacancies with higher skill demand remain longer on the job board. One additional skill requirement reduces the likelihood of having left in the first four weeks by about 0.5 percentage points. This corresponds to a 1-2 percent decrease relative to the share of vacancies without any skill requirements that have been removed during this period. As the share of still available vacancies substantially shrinks in later months, differences by skills also decrease to zero and fade to be significant. When I examine the demand for analytical, communication and managerial skills separately, estimated exit rates are about 1 percentage point lower in all three groups after the first month. In the subsequent weeks, jobs that require managerial skills tend to get filled at a faster rate.

About 16 percent of vacancies in the estimation sample were not filled. It is unclear why these postings were removed without a hire. One reason might be that firms retract vacancies for economic reasons. It is also possible that employers are unable to find suitable candidates and give up searching. Yet, these exits do not affect the observed relation between vacancy duration and skill requirements. When I remove unfilled vacancies from the sample, estimated skill effects remain very similar.

Figure 5: Vacancy-exit regressions



Note: The dotted lines show 95%-confidence intervals.

5 Discussion

5.1 Interpretation of findings

The positive effect of skill requirements on both wages and vacancy duration is consistent with previous evidence by Mueller et al. (2020). Using the same vacancy database for an earlier period, the study estimates a positive raw elasticity between starting wages and filling duration of vacancies. When they decompose wages into worker and firm fixed effects, they find that the positive elasticity is, to a large extent, driven by the worker component of wages. In part, this association can be attributed to differences in skill demand. Higher skilled workers are more productive, which should yield higher wages. As a consequence, the variation in worker fixed effects partly reflects skill differences between workers. If higher skilled workers are also relatively more scarce, firms require more time to fill vacancies with many skill requirements. Thus, the positive correlation between filling duration and starting wages can, at least in part, be explained by the underlying differences in skill content of vacancies.

In such a framework, vacancy duration and wages may also depend on each other. If firms anticipate that vacancies for the high skilled are more difficult to fill, they can post higher wages to speed up the search for suitable candidates. As a result, part of the positive relation between skills and wages might be due to the fact that vacancy filling rates differ by the skill content of jobs. To examine this hypothesis, I again regress vacancy exit indicators on skill measures and additionally control for posted wages. Table A.5 in the appendix reports regression estimates for selected weeks. The coefficients on posted wages are negative in all weeks, which shows that vacancies with higher wage offers need somewhat longer to get filled. Moreover, the skill coefficients are similar to estimates from the corresponding regressions that exclude posted wages as control. Assuming that the included covariates can sufficiently control for all relevant differences between vacancies, these results do not support the hypothesis that wage postings are used as a tool to reduce vacancy duration.

Compared to the findings of Deming and Kahn (2018), who analyze the effect of skill requirements on wages using US job ads, my wage estimates are overall smaller. This might be explained by differences in the measure of pay. While they use average wages by region and occupation as outcome, I focus on posted wages and starting wages. Average wages tend to be higher than starting wages because pay often increases with tenure. If these pay raises are steeper for jobs with high skill requirements, the skill effect will also be larger for average wages than for starting wages.

Differences in the estimation strategy can explain lower effects, too. Using vacancy-level variation in wages allows to account for firm and region fixed effects, which may be correlated with skill requirements. Estimates in Table 4 show indeed that most coefficients decrease when I control for differences between firms.

Finally, it is also possible that institutional differences between the United States and Austria can explain different skill-wage associations. The Austrian labor market is more homogenous both in terms of workforce characteristics and pay. First, wages in Austria tend to be less dispersed than in the United States, which suggests that skill returns are lower, too. Second, it is possible that the skill profile of Austrian workers is less heterogeneous. One reason could be differences in education. While

US institutions of higher education can differ substantially in the quality of education, differences among universities and colleges in Austria are much less pronounced. The uniform apprenticeship system further contributes to more homogeneous skill profiles. This makes it less important to filter applicants by skill requirements in job postings. If firms in Austria are less likely to describe the required skills, wage-skill associations will be lower.

The strong interaction effects between analytical and communications skills, which are shown in Table A.3, correspond to findings from previous studies. As pointed out by Weinberger (2014), skill-biased technical change in the labor market induces a rising demand for workers with both cognitive and non-cognitive skills. This notion is also in line with the finding that entrepreneurial and leadership skills have the largest wage effects. These skills require cognitive and non-cognitive abilities, and are often mentioned jointly with other hard and soft skills, as shown in the descriptive section.

5.2 Measurement error

Since text pattern matching is used to infer the skill content of job postings, the obtained skill measures may suffer from some degree of measurement error. More specifically, it is possible that the keywords fail to identify skills (*under-detection*) or wrongly attribute skills (*over-detection*) in some cases. Some employers might paraphrase required skills in the job description instead of naming them directly. Typing errors or the use of infrequent terms can be other sources of mismeasurement. Conversely, the classifying procedure might also mistake unrelated terms for skills. One example are keywords that describe the workplace rather than the applicant. Although both errors are rather unlikely, it is informative to analyze whether minor inaccuracies can lead to significant changes.

To quantify the impact of over- and under-detection of skill requirements, I assume in the following that the classifying error, similar to a classical measurement error, is not correlated with the error term u_{ij} in the wage regressions. In other words, posted wages conditional on all observables should not differ by the degree of measurement error in skills. Under this assumption, it is possible to back out actual posted-wage effects for given rates of under- and over-detection. Let indicator variables $\tilde{S}_i$ and S_i denote the observed and the actual occurrence of a specific skill in vacancy i. Over- and under-detection rates, $p_o = P(S_i = 0|\tilde{S}_i = 1)$ and $p_u = P(S_i = 1|\tilde{S}_i = 0)$, are defined as the probabilities that I attribute the skill to job ads which do not contain it, and vice versa. The true skill effect on outcome y_i is given by

$$\beta = \underbrace{E(y_i|S_i = 1)}_{\mu_1} - \underbrace{E(y_i|S_i = 0)}_{\mu_0}$$

Under over- and under-detection of skills, I instead observe

$$\begin{aligned} b &= E(y_i|\tilde{S}_i = 1) - E(y_i|\tilde{S}_i = 0) \\ &= (1 - p_o)\mu_1 + p_o\mu_0 - [(1 - p_u)\mu_0 + p_u\mu_1] \\ &= (1 - p_o - p_u)\beta \end{aligned}$$

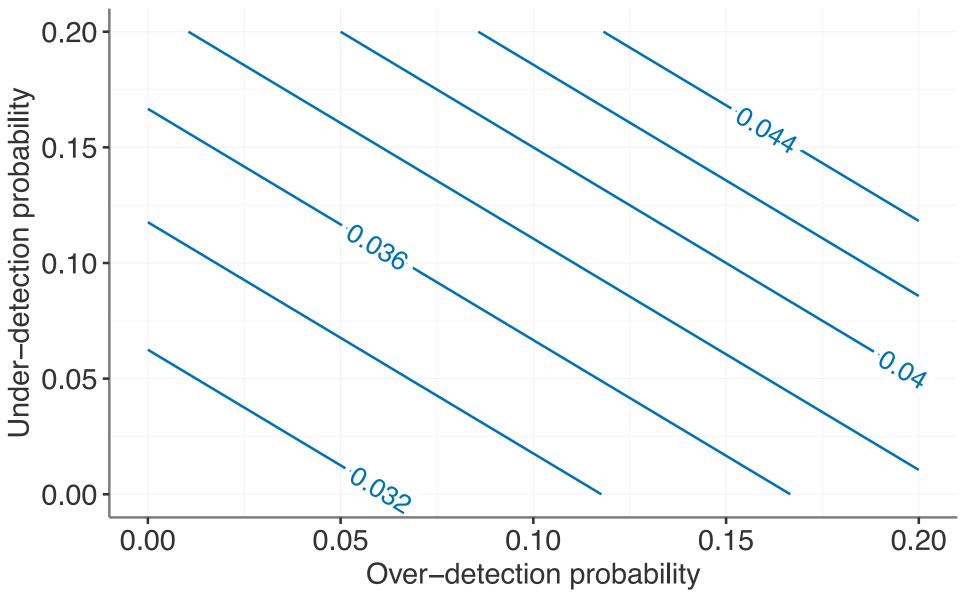
Most likely, p_o and p_u are lower than 0.5, since this value would correspond to random assignment of $\tilde{S}_i$.[14] As a result, mismeasurement of skills leads to a downward bias of the true impact towards zero. The relation between true and estimated effect sizes is illustrated in Figure 6. For an estimated impact of 0.03, it depicts the combinations of p_o and p_u that are associated with different levels of actual skill returns. The contour plot shows that even under substantial over- and under-detection rates of around 20 percent, the underlying actual impact would not be much larger than the estimated effect.

5.3 Alternative job board

Vacancies posted on the AMS job board might not be representative for labor demand in the entire labor market. As discussed in Section 3, the public employment service only covers about 50-60 percent of all vacancies, and there might be selection with respect to education, profession and other unobservables. Next to the AMS, several other providers operate job posting websites in Austria. To test the robustness of my estimates, I redo the analysis of skill requirements and wage effects using vacancy postings from the job board of a large commercial competitor. Whereas around 80,000 entries are available on the AMS job board at a time, this provider only lists about 20,000 ads. Information on wage postings can be extracted from the ad texts but there exist no data on vacancy duration or on the workers who filled the vacancies. Furthermore, the classification of job ads on this website is much less detailed. Vacancies are sorted into 20 occupation groups, and there is no general classification of required

[14] For p_o and p_u larger than 0.5, assignment of skills would be reversed, leading to effect-size measures between 0 and $-\beta$.

Figure 6: Actual effect sizes under measurement error ($b = 0.03$)



education. This makes it more difficult to take out confounding effects due to differences in occupation and education requirements. Despite these limitations, the data allow to examine whether skill shares and wage estimates of comparable specifications are similar to those found in the main analysis.

All available job posts were extracted from the website every 2-4 weeks between June and October 2018. The measurement of skills follows again the procedure outlined in Section 3.2. Restricting the sample to observations with non-missing information on skills, location and wage posting, the final sample consists of 41,374 job ads. Because job posts are not classified by education, I infer from the ad text whether any higher education is required. Measured skill shares and other descriptive statistics are provided in Appendix Table A.6. Compared to the AMS job board, I observe clear differences in most characteristics. Job ads on the website of the commercial competitor are, on average, longer, offer higher wages and are much more often located in the six urban districts. Also, the measured skill requirements are substantially higher. This is consistent with the notion that private employment websites tend to overrepresent job posts for professionals (see, for instance, Deming and Kahn, 2018). In fact, the estimated skill shares are comparable in size to those of ads on the AMS job board which are targeted at high-educated workers. The comparison of vacancy characteristics between the two samples suggests that both sources complement each other. Whereas the commercial website clearly lacks the majority of job posts for low-skilled workers, the public employment service lists fewer job postings for high-skilled workers.

Table A.7 in the appendix reports results of the wage regressions. The specifications closely mimic those presented in the previous section. Yet, due to the more general classification of vacancies, the included controls for occupation and education are less detailed. Estimated effects for both the number of skills and skill types are mostly in line with the main results presented in Table 4. One additional skill leads to about 1 percent higher wages, which is robust to the inclusion of occupation, firm and district fixed effects. For the separate skill groups, I find again initially large point estimates that tend to decrease in richer specifications. Managerial skills are associated with the highest wage gains, followed by analytical skills. In this sample, the coefficient on other soft skills remains even in the last specification significantly negative. Overall, the estimates are somewhat larger than in the main analysis. This is consistent with the finding that effect sizes are less pronounced in specifications with many covariates. If a more detailed classification of education and occupation was available for vacancies posted on the commercial job board, regression estimates might even be more closely aligned between the two samples. These results show that the estimated effects are robust to the use of a different job board as data source. Although the commercial website covers very different vacancies in regard most observable characteristics, estimated wage associations remain similar.

6 Conclusion

Given the vast amount of vacancy data on the Internet, many economists have started to exploit its potential and provide new evidence on a variety of research questions. This paper argues that such vacancy data, complemented with administrative records on work spells, contain unique information for the analysis of skill demand on the labor market. The results show that employers frequently refer to a number of soft and hard skills in job descriptions. Controlling for a large set of job characteristics including firm, occupation, required education and work experience, I estimate that posted wages steadily increase in the number of skill requirements. While managerial and analytical skills show relatively high returns, most soft skills have small wage effects. Linking the vacancy posts to administrative earnings data, I observe similar differences in starting wages of workers who were hired for the jobs. Consistent with predictions of a standard search and matching model with downward mobility of higher skilled workers, employers also need longer to fill vacancies with more skill requirements. Robustness tests show that measurement error is unlikely to explain these findings. Even under considerable misclassification of skills, actual effect sizes would not be very different from obtained estimates.

A shortcoming of this analysis is that observed skill requirements can only serve as a rough proxy for a job's actual skill content. Because employers need to depict the job profile in just a few sentences, the ads cannot comprise the same level of detail as surveys or occupational dictionaries. For the same reason, it is also more difficult to describe the relative importance of mentioned skills. Despite these limitations, the linked vacancy data offers several important features. First, the sample covers a large share of the labor market, which renders it feasible to obtain precise estimates even for small effects. Second, the detailed classification of vacancies allows to account for many confounding factors that are often not observed in other datasets on skills. Third, linking vacancies to employment records makes it also possible to examine how labor market outcomes of workers differ by skill requirements. Exploiting these advantages, the analysis can complement previous evidence on skill differentials obtained from other sources.

References

Abowd, J. M., Kramarz, F., and Margolis, D. N. (1999). High wage workers and high wage firms. *Econometrica*, 67(2):251–333.

Albrecht, J. and Vroman, S. (2002). A matching model with endogenous skill requirements. *International Economic Review*, 43(1):283–305.

Atalay, E., Phongthiengtham, P., Sotelo, S., and Tannenbaum, D. (2020). The evolution of work in the United States. *American Economic Journal: Applied Economics*, 12(2):1–34.

Autor, D. H. and Handel, M. J. (2013). Putting tasks to the test: Human capital, job tasks, and wages. *Journal of Labor Economics*, 31(S1):S59–S96.

Autor, D. H., Levy, F., and Murnane, R. J. (2003). The skill content of recent technological change: An empirical exploration. *Quarterly Journal of Economics*, 118(4):1279–1333.

Cahuc, P., Postel-Vinay, F., and Robin, J.-M. (2006). Wage bargaining with on-the-job search: Theory and evidence. *Econometrica*, 74(2):323–364.

Card, D., Heining, J., and Kline, P. (2013). Workplace heterogeneity and the rise of West German wage inequality. *Quarterly Journal of Economics*, 128(3):967–1015.

Cheron, A. and Decreuse, B. (2016). Matching with phantoms. *Review of Economic Studies*, 84(3):1041–1070.

Deming, D. and Kahn, L. B. (2018). Skill requirements across firms and labor markets: Evidence from job postings for professionals. *Journal of Labor Economics*, 36(S1):S337–S369.

Deming, D. J. and Noray, K. (2020). Earnings dynamics, changing job skills, and STEM careers. *Quarterly Journal of Economics*, 135(4):1965–2005.

Dolado, J. J., Jansen, M., and Jimeno, J. F. (2009). On-the-job search in a matching model with heterogeneous jobs and workers. *Economic Journal*, 119(534):200–228.

Hanushek, E. A., Schwerdt, G., Wiederhold, S., and Woessmann, L. (2015). Returns to skills around the world: Evidence from PIAAC. *European Economic Review*, 73:103–130.

Heckman, J. J., Stixrud, J., and Urzua, S. (2006). The effects of cognitive and noncognitive abilities on labor market outcomes and social behavior. *Journal of Labor Economics*, 24(3):411–482.

Kuhn, P. and Shen, K. (2012). Gender discrimination in job ads: Evidence from China. *Quarterly Journal of Economics*, 128(1):287–336.

Lalive, R., Landais, C., and Zweimüller, J. (2015). Market externalities of large unemployment insurance extension programs. *American Economic Review*, 105(12):3564–96.

Lazear, E. P. (2004). Balanced skills and entrepreneurship. *American Economic Review*, 94(2):208–211.

Leoni, T. and Pollan, W. (2011). Lohnentwicklung und Lohnunterschiede in der Industrie seit 2000. *WIFO Monatsberichte (Oktober)*.

Lindqvist, E. and Vestman, R. (2011). The labor market returns to cognitive and noncognitive ability: Evidence from the Swedish enlistment. *American Economic Journal: Applied Economics*, 3(1):101–28.

Marinescu, I. (2017). The general equilibrium impacts of unemployment insurance: Evidence from a large online job board. *Journal of Public Economics*, 150:14–29.

Modestino, A. S., Shoag, D., and Ballance, J. (2020). Upskilling: Do employers demand greater skill when workers are plentiful? *Review of Economics and Statistics*, 102(4):793–805.

Moretti, E. (2004). Human capital externalities in cities. In *Handbook of Regional and Urban Economics*, volume 4, pages 2243–2291. Elsevier.

Mueller, A. I., Osterwalder, D., Zweimüller, J., and Kettemann, A. (2020). Vacancy durations and entry wages: Evidence from linked vacancy-employer-employee data. Technical report, National Bureau of Economic Research.

OECD (2012). Labour losing to capital: What explains the declining labour share? Technical report, OECD Employment Outlook 2012.

Weinberger, C. J. (2014). The increasing complementarity between cognitive and social skills. *Review of Economics and Statistics*, 96(4):849–861.

Appendix

Figure A.1: Number of skills and vacancy exit

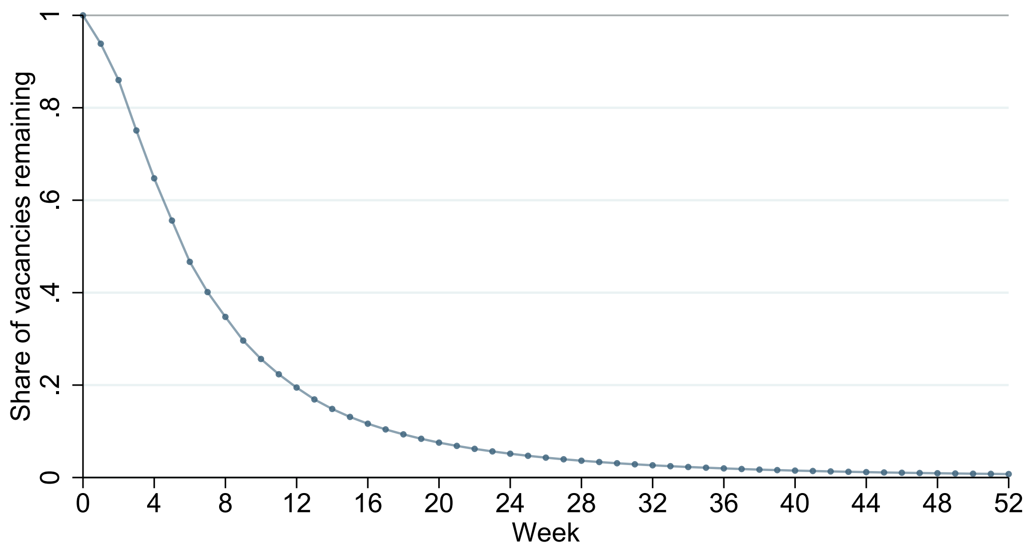


Figure A.2: Average skill content by district

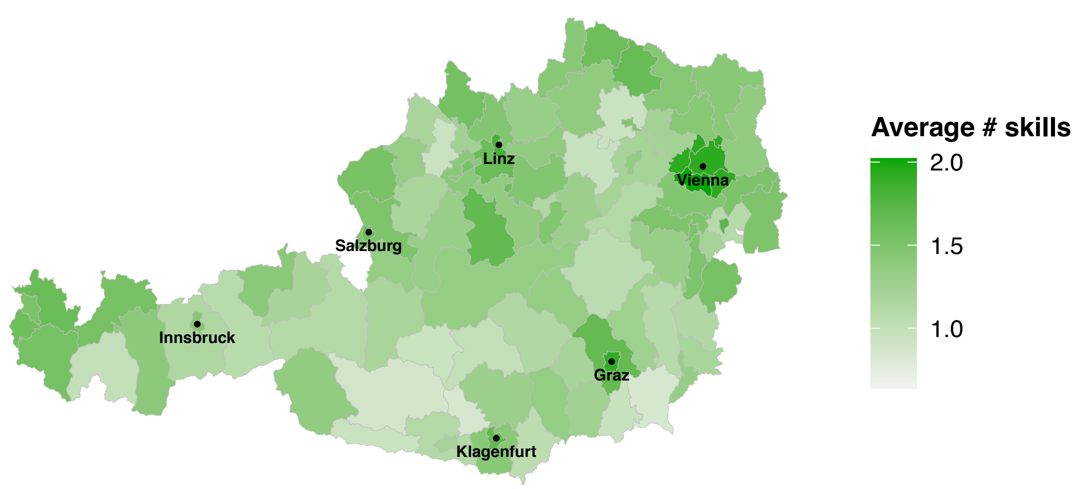


Table A.1: Skill correlation matrix

	Ana.	Comm.	Entr.	Lead.	Progr.	MS-Off.	Lang.	Team.	Org.	Self-rel.	Asser.	Creat.	Str.-tol.
Comm.	**0.18**												
Entr.	**0.08**	**0.08**											
Lead.	**0.09**	**0.12**	**0.14**										
Progr.	**0.20**	**0.06**	**-0.01**	**-0.01**									
MS-Off.	**0.15**	**0.19**	**0.06**	**0.10**	-0.00								
Lang.	**0.27**	**0.24**	**0.06**	**0.10**	**0.16**	**0.27**							
Team.	**0.10**	**0.15**	**0.03**	**0.07**	**0.06**	**0.11**	**0.10**						
Org.	**0.07**	**0.15**	**0.08**	**0.15**	**-0.01**	**0.17**	**0.12**	**0.07**					
Self-rel.	**0.13**	**0.16**	**0.07**	**0.10**	**0.07**	**0.15**	**0.13**	**0.14**	**0.11**				
Asser.	**0.14**	**0.12**	**0.08**	**0.13**	0.00	**0.12**	**0.12**	**0.06**	**0.11**	**0.07**			
Creat.	**0.04**	**0.05**	**0.01**	**0.03**	**0.04**	**0.01**	**0.06**	**0.07**	**0.06**	**0.07**	**0.02**		
Str.-tol.	**0.01**	**0.09**	**0.01**	**0.06**	**-0.03**	**0.06**	**0.03**	**0.17**	**0.08**	**0.06**	**0.06**	**0.02**	
Rel.	**-0.05**	**-0.04**	**-0.02**	**-0.05**	**-0.04**	**-0.02**	**-0.08**	**0.06**	**-0.02**	**-0.03**	**-0.03**	**-0.04**	**0.04**

NOTE: N=1,569,760. **Bold** coefficients indicate significance at the 1%-level.

Table A.2: Comparison between full sample and matched hires

	All vacancies	Matched hires
Posted monthly wage	2147.50	1909.09
	(649.79)	(386.58)
Education:		
- Compulsory schooling	0.27	0.45
	(0.44)	(0.50)
- Vocational training	0.54	0.49
	(0.50)	(0.50)
- Higher voc.-techn. schools/gymnasium	0.13	0.05
	(0.33)	(0.23)
- (Applied) university	0.06	0.01
	(0.24)	(0.10)
Skills:		
# skills	1.64	1.18
	(1.62)	(1.30)
Analytical skills	0.08	0.03
	(0.28)	(0.16)
Communication skills	0.20	0.12
	(0.40)	(0.32)
Managerial skills	0.10	0.05
	(0.30)	(0.21)
Other hard skills	0.25	0.12
	(0.43)	(0.32)
Other soft skills	0.59	0.56
	(0.49)	(0.50)
N	1,114,201	136,444

NOTE: The table reports means with standard deviations in parentheses. The estimation sample is restricted to full-time vacancies.

Table A.3: Posted-wage regressions - Complementarities

	(1)	(2)	(3)	(4)	(5)
Analytical skills	17.670	7.540	3.236	2.158	1.825
	(0.100)	(0.074)	(0.073)	(0.063)	(0.062)
Communication skills	1.959	1.152	0.859	0.605	0.500
	(0.049)	(0.042)	(0.035)	(0.035)	(0.035)
Analyt. $\times$ comm. skills	3.686	1.068	2.864	1.498	1.299
	(0.145)	(0.105)	(0.101)	(0.086)	(0.085)
Firm FE		✓		✓	✓
Occupation FE			✓	✓	✓
Education FE					✓

NOTE: N=1,569,760. All estimates are scaled by 100. Standard errors are reported in parantheses. All regressions control for entry month, district, experience and extent of work. See Table 2 for skill group classification.

Table A.4: Starting-wage regressions - Other specifications

	(1)	(2)	(3)	(4)	(5)
# skills	1.825	1.583	0.640	0.572	0.533
	(0.060)	(0.078)	(0.056)	(0.079)	(0.079)
Analytical skills	15.159	8.116	2.613	1.792	1.606
	(0.465)	(0.505)	(0.415)	(0.509)	(0.509)
Communication skills	-2.340	1.459	0.458	0.669	0.621
	(0.244)	(0.293)	(0.211)	(0.286)	(0.286)
Managerial skills	7.257	10.879	3.514	3.871	3.738
	(0.360)	(0.406)	(0.328)	(0.417)	(0.416)
Other hard skills	5.699	3.669	2.325	1.003	0.826
	(0.246)	(0.296)	(0.252)	(0.326)	(0.326)
Other soft skills	0.839	-0.458	0.287	0.192	0.171
	(0.155)	(0.191)	(0.130)	(0.182)	(0.181)
Firm FE		✓		✓	✓
Occupation FE			✓	✓	✓
Education FE					✓

Note: $N = 136{,}444$. The estimation sample is restricted to full-time vacancies. All estimates are scaled by 100. Standard errors are reported in parantheses.

Table A.5: Skills, posted wages and vacancy exit

	Week 4		Week 8		Week 12		Week 26	
# skills	-0.507	-0.498	-0.282	-0.273	-0.196	-0.189	-0.116	-0.115
	(0.036)	(0.036)	(0.035)	(0.035)	(0.030)	(0.030)	(0.016)	(0.016)
log(posted wage)		-1.408		-1.434		-1.186		-0.259
		(0.304)		(0.296)		(0.250)		(0.133)
Analytical skills	-0.845	-0.812	-0.794	-0.760	-0.522	-0.492	-0.151	-0.144
	(0.180)	(0.180)	(0.175)	(0.175)	(0.148)	(0.148)	(0.079)	(0.079)
Communication skills	-0.665	-0.656	-0.582	-0.572	-0.254	-0.246	-0.218	-0.216
	(0.119)	(0.119)	(0.116)	(0.116)	(0.098)	(0.098)	(0.052)	(0.052)
Managerial skills	-0.806	-0.729	-0.269	-0.188	-0.042	0.028	0.016	0.033
	(0.163)	(0.164)	(0.159)	(0.160)	(0.135)	(0.135)	(0.072)	(0.072)
Other hard skills	-0.317	-0.302	0.106	0.122	0.190	0.204	0.134	0.137
	(0.137)	(0.137)	(0.133)	(0.133)	(0.113)	(0.113)	(0.060)	(0.060)
Other soft skills	-0.997	-1.001	-0.515	-0.518	-0.513	-0.516	-0.259	-0.260
	(0.097)	(0.097)	(0.095)	(0.095)	(0.080)	(0.080)	(0.043)	(0.043)
log(posted wage)		-1.376		-1.440		-1.242		-0.304
		(0.306)		(0.297)		(0.252)		(0.134)
Mean w/o skills:	0.377		0.664		0.815		0.961	

NOTE: N = 1,569,760. All estimates are scaled by 100. Standard errors are reported in parantheses. The outcome variable indicates vacancy exit until week t. Estimates are obtained from regressions that include the full set of covariates.

Table A.6: Job ad characteristics (alternative job board)

	Mean	Std. Dev.	Min	Max
Monthly salary	2701.85	866.08	500	10000
# words	266.57	95.55	32	1101
Urban area	0.63	0.48	0	1
University required	0.24	0.43	0	1
For job beginners	0.04	0.19	0	1
# days online	5.26	3.80	0	15
# skills	3.29	1.75	0	12

Skill	Share	Skill	Share
Communicative	0.48	Leadership	0.18
Language	0.48	Stress-tolerant	0.15
Teamwork	0.40	Programming	0.14
Self-reliant	0.34	Organized	0.10
Analytical	0.32	Creative	0.09
MS-Office skills	0.28	Assertive	0.07
Reliable	0.20	Entrepreneurial	0.05

NOTE: N=41,374. A vacancy is classified as *urban* if the job is located in a district of the six largest Austrian cities (Vienna, Graz, Linz, Salzburg, Innsbruck and Klagenfurt).

Table A.7: Posted-wage regressions (alternative job board)

	(1)	(2)	(3)	(4)	(5)
# skills	1.246	1.344	1.323	1.418	1.388
	(0.080)	(0.076)	(0.076)	(0.074)	(0.074)
Analytical skills	8.937	5.568	5.863	4.463	4.418
	(0.297)	(0.287)	(0.254)	(0.248)	(0.247)
Communication skills	1.333	1.977	1.495	1.568	1.585
	(0.273)	(0.261)	(0.240)	(0.233)	(0.232)
Managerial skills	12.168	12.130	12.821	11.733	11.811
	(0.325)	(0.322)	(0.294)	(0.295)	(0.294)
Other hard skills	5.421	4.771	1.379	2.142	1.956
	(0.289)	(0.281)	(0.269)	(0.264)	(0.264)
Other soft skills	-6.614	-4.643	-2.798	-1.859	-1.848
	(0.308)	(0.291)	(0.274)	(0.264)	(0.263)
Occupation group FE		✓		✓	✓
Firm FE			✓	✓	✓
District FE					✓

NOTE: N=41,374. All estimates are scaled by 100. Standard errors are reported in parantheses. All regressions control for the number of days that an ad is online and indicators for university education and whether an ad is specifically for job beginners. See Table 2 for skill group classification.