Open access • Journal Article • DOI:10.1257/AER.104.3.1014

Do Employers Use Unemployment as a Sorting Criterion When Hiring? Evidence from a Field Experiment — Source link

Stefan Eriksson, Dan-Olof Rooth

Published on: 01 Mar 2014 - The American Economic Review (American Economic Association)

Topics: Unemployment

Online Appendix

Do Employers Use Unemployment as a Sorting Criterion When Hiring? Evidence from a Field Experiment

Stefan Eriksson and Dan-Olof Rooth

This appendix provides some additional material. Appendix A contains a description of the occupations in the experiment and their shares of total employment. Appendix B contains an analysis of duration dependence by occupation using Swedish administrative data. Appendix C uses the same data to analyze how past spells of unemployment affect the probability of finding a job. Appendix D describes the administrative data in more detail. Appendix E contains the analysis when occupations are excluded. Appendix F contains some additional descriptive statistics.

Appendix A: The occupations in the experiment and their shares of total employment

In this section, we present information about the occupational shares of total employment in Sweden and the US for the twelve occupations included in the experiment. The Swedish shares are based on own calculations from the total Swedish population in employment[1] in 2005 (LISA database, Statistics Sweden). We calculate the shares both for the age category used in the experiment (23-32 years old) [2], and for all prime-age workers (20-50 years old). These shares are then compared to the US occupational shares for the same age categories and occupations, taken from the 5 percent extraction of the US Census (IPUMS; cf. Ruggles *et al.*, 2010). The results are presented in Tables A1 and A2, while Tables A3 and A4 give a detailed description of which occupations are being used and how the coding is done.

Overall, the workers employed in the occupations included in the experiment cover around one third of all employed workers. The high skill occupations cover a somewhat lower share, 30 percent (8.9/29.7) and the medium/low skill occupations a somewhat higher share, 36 percent (25.4/70.3).[3] Further, six of the occupations are among the top 10 most common occupations in Sweden in this age group.[4] In addition, the share of total employment by occupation is very similar to the corresponding shares for the US, except for retail sales persons and cashiers. The reason for this divergence is that, unlike in the US, this category in Sweden includes jobs where a person sells a firm's product without necessarily being employed by the firm; i.e. sells at a commission.

We also present the shares of all vacancies reported to the Swedish Public Employment Service in 2007. In this case, the occupations in the experiment cover around 39 percent (9.2/23.6) of all high skill vacancies and 35 percent (26.8/76.4) of all medium/low skill vacancies. The occupational mix of the vacancies is rather similar to the occupational mix of employed workers. The only exception is the two sales categories, where again it is difficult to separate sellers who are employed from sellers operating on commission.

[1] Defined as workers having an occupational code in the data, which is the case for 88 percent of the population.

[2] We use 23-32 years old workers since 23 is the youngest age where an applicant in the experiment can search for both high and medium/low skill jobs and 32 is the highest age of the applicants in the experiment.

[3] The division into high (codes 1-3) and medium/low (codes 4-9) skill occupations are somewhat arbitrary around the threshold categories 3 and 4 in the Swedish classification. Some of the occupations that are classified as category 3 could be viewed as high skill, as accountants, while others are more medium skill, such as purchasing agents. In Table 1, we define *Other high skill occupations* as high skill if they belong to category 1-3.

[4] Missing occupations from the top 10 list are nursing assistants (1st place), engineers and technicians (4th place) and various types of office personnel (warehouse assistants in 6th place and a misc category in 9th place).

Table A1. Shares of total employment/unemployment by occupation in Sweden and the US. 23-32 year olds. Percent.

Occupational categories	Share in Sweden in 2005		Share in US total employment in 2000	Share of Swedish vacancies in 2007	Occupational rank in Sweden	Occupational rank in the US
	In total employment[b)]	In unemp-loyment				
High skill occupations						
Computer occupations	2.3	1.1	2.0	2.2	7	46[a)]
Accountants and auditors	1.2	0.8	1.0	1.0	26	15
Registered nurses	1.7	0.6	0.8	2.9	22[a)]	23
Middle school teachers	2.7	2.5	1.5	1.7	5[a)]	2
Secondary school teachers	1.0	1.0	0.3	1.4	29	86
All other high skill occupations	20.8	13.1	n.a.[c)]	14.4		
Medium/low skill occupations						
Sales representatives and buying and purchasing agents	3.9	2.2	1.2	11.3	3	36[a)]
Retail sales persons and cashiers	9.0	9.4	2.9	3.5	2	4[a)]
Installation, maintenance and repair occupations	2.2	1.7	1.6	1.7	24[a)]	27[a)]
Construction laborers and carpenters	2.3	3.6	1.8	1.5	8	20[a)]
Bus, truck and taxi drivers	2.1	2.0	1.9	4.0	12	6[a)]
Janitors and cleaners	1.6	2.9	0.8	1.5	18	24
Food serving and waitress	4.3	6.5	1.6	3.3	9[a)]	11[a)]
All other low/medium skill occupations	44.9	52.6	n.a.[c)]	49.6		
Total share	100	100	-	100		

Notes: The Swedish occupational shares in total employment/unemployment are based on own calculations using (i) the population 23-32 years old employed in 2005 (LISA database, Statistics Sweden) and (ii) the population 23-32 years old starting an unemployment spell in 2005. The US occupational shares of total employment (defined as those with an occupational code) are calculated using the 5 percent extraction of the US Census (using the weights found at www.ipums.org) for the same age group, while the occupational shares for vacancies are calculated using all vacancies lasting more than ten days reported to the Swedish Public Employment Service in 2007. The occupational categories are taken from the Swedish occupational register, which includes 115 different occupational groups according to SSYK (Standard for Swedish Occupational Classification), a three-digit occupational classification code similar to the international classification (ISCO). For the US occupational categories, we have used those (sub-) categories that corresponds the closest to the Swedish SSYK definitions and are found at www.ipums.org. The occupational rank for Sweden is based on the ranking among the 115 occupational categories in SSYK for total employment (first column). The occupational rank for the US is based on the ranking among the 619 occupational categories in IPUMS for total employment (third column). Since we did not merge single categories into the broader groups in Column 3 some rankings are not correct. For instance, computer occupations make up IPUM categories 100-111 (see Table A3), but the ranking of 46 is based on the highest ranking for a single category within that group.

a) These occupational categories are made up of several separate occupations and the ranking is for the one with the largest share in total employment.

b) Employed is defined as having information about the occupational code, which is the case for about 88 percent of the total population in this age category.

c) The US occupational coding does not correspond to a distinct classification into high/medium/low skill occupations as does the Swedish coding and, therefore, these shares are not possible to calculate.

Table A2. Shares of total employment/unemployment by occupation in Sweden and the US. 20-50 year olds. Percent.

Occupational categories	Share in Sweden in 2005		Share in US total employment 2000 (IPUMS)	Share in US total employment 2010 (OES)
	Total employment[b)]	Unemployment		
High skill occupations				
Computer occupations	2.4	1.2	1.8	2.6
Accountants and auditors	1.5	1.0	0.9	0.9
Registered nurses	2.3	0.6	1.1	2.1
Middle school teachers	2.4	2.6	1.5	0.6
Secondary school teachers	1.2	1.1	0.3	1.0
All other high skill occupations	30.4	14.0	n.a.[c)]	n.a.[c)]
Medium/low skill occupations				
Sales representatives and buying and purchasing agents	4.6	2.5	1.2	1.7
Retail sales persons and cashiers	6.2	8.4	2.8	5.9
Installation, maintenance and repair occupations	2.3	1.8	1.7	3.9
Construction laborers and carpenters	2.3	4.0	1.8	1.1
Bus, truck and taxi drivers	2.3	2.4	2.3	2.8
Janitors and cleaners	1.5	2.9	1.0	2.3
Food serving and waitress	3.2	6.0	1.4	6.8
All other low/medium skill occupations	37.4	51.5	n.a.[c)]	n.a.[c)]
Total share	100	100		

Notes: See the notes to Table A1.

Table A3. Descriptions of US-IPUMS and Swedish occupational categorizations

Occupational categories	Description of occupations using the occupational scheme in IPUMS	US occupational code (IPUMS)	Swedish occupational code (SSYK)
High skill occupations:			
Computer occupations	Selected categories under the broad category “Computer and mathematical occupations”.	100-111	213
Accountants and auditors	Own category under “Financial Specialists”.	80	343
Registered nurses	Own category under “Healthcare Practitioners and Technical Occupations”.	313	223, 323
Middle school teachers	Own main category under “Education, Training, and Library Occupations”, but also includes elementary school teachers.	231	233, 234
Secondary school teachers	Own main category under “Education, Training, and Library Occupations”**.**	232	232
Medium/low skill occupations:			
Sales representatives and buying and purchasing agents	Here we have extracted subgroups in two broad categories. The first is “Sales occupations” and we use “Sales representatives” from categories 484-485, while the second is “Business Operations Specialists” and we use categories 51-53 capturing purchasing agents.	484-485 51-53	341
Retail sales persons and cashiers	We merge two separate categories under “Sales occupations”: “Retail salespersons” and “Cashiers”.	476, 472	522
Installation, maintenance and repair occupations	The broad category is “Installation, maintenance and repair workers” and we include only occupations related to maintenance and repair of automobiles, buses and trucks.	715-726	723, 724
Construction laborers and carpenters	The broad category is “Construction trades” and we take out categories capturing construction laborers and carpenters.	623-626	712
Bus, truck and taxi drivers	Three different categories of drivers; Bus, taxi and truck drivers, under “Transportation and Material Moving Occupations”	912-914	832
Janitors and cleaners	Own category under “Transportation and Material Moving Occupations”.	422	912
Food serving and waitress	The broad category is “Food preparation and serving occupations” and we take out four categories capturing bartenders, waitresses, and food serving workers.	404-411	512, 913

Table A4. Descriptions of US-OES and Swedish occupational categorizations

Occupational categories	US OES category	Swedish occupational code (SSYK)
High skill occupations:		
Computer occupations	The broad category is "Computer and mathematical occupations" and we withdraw mathematical occupations and arrive at 2.6.	213
Accountants and auditors	The broad category is "Business and financial operations occupations". We use the subcategory "Accountants and auditors".	343
Registered nurses	Own main category.	223, 323
Middle school teachers	Own main category.	233, 234
Secondary school teachers	Own main category.	232
Medium/low skill occupations:		
Sales representatives and buying and purchasing agents	Here we have extracted subgroups in two broad categories. The first is "Sales and related occupations" and we use "Sales representatives" (1.4%), while the second is "Business and financial operations occupations" and we use "Buyers and purchasing agents" (0.3%).	341
Retail sales persons and cashiers	We merge two separate main categories: "Retail sales persons" and "Cashiers".	522
Installation, maintenance and repair occupations	The broad category is "Installation maintenance and repair occupations" and we include only occupations related to machine operators.	723, 724
Construction laborers and carpenters	The broad category is "Construction occupations" and we take out "Construction laborers and carpenters".	712
Bus, truck and taxi drivers	The broad category is "Transportation and material moving occupations" and we take out "Bus, truck and taxi drivers".	832
Janitors and cleaners	Includes maids and housekeeping cleaners, which are not part of the Swedish category.	912
Food serving and waitress	The broad category is "Food preparation and serving related occupations" and we withdraw "Cooks" and "Dish washers".	512, 913

Appendix B: Duration dependence by occupation

In this section, we first present Kaplan-Meier survival functions for the transition from unemployment to work for each of the occupations included in the experiment. Then we present a more formal analysis of duration dependence using the piecewise constant exponential model. We use administrative data from the Swedish Public Employment Service's Event Database (Händel) that contains detailed information on unemployment status and duration at the individual level.[5] By linking this data with data from administrative records maintained by Statistics Sweden, we obtain information about demographics and occupations for the same individuals.

Data[6]

Our sample is drawn from the inflow to the unemployment register between January 1 and December 31, 2005. We follow these individuals until they escape unemployment or, at the most, until August 22, 2007. To make this unemployment sample comparable to the demographic groups in the experiment, we only include those born in Sweden[7] and who were 23-32 years old in 2005. This sampling procedure results in a total of 193,622 unemployment spells divided between 150,921 individuals.[8] 92,200, or 48 percent, of these spells ended with the worker finding a job.

To get information about what type of job the unemployed worker is searching for, we use the occupational registers at Statistics Sweden for the years 2001, 2003, and 2005. The Swedish occupational register includes 115 occupational groups based on the Standard for Swedish Occupational Classification, a three-digit occupational classification code similar to the international classification ISCO. We use 2005 as the base year and then add information on occupation from 2003 and 2001, respectively, when missing. In this way, we add information on occupation for about 90 percent of the unemployment spells.[9] Table B1 shows descriptive statistics for unemployed workers searching for jobs in the occupations included in the experiment. These numbers indicate that the occupational coding has worked since

[5] According to Carling *et al.* (2001), around 90 percent of those who are unemployed according the labour force surveys also register at the Employment Service.

[6] For a detailed description of the construction of the duration data see online Appendix D.

[7] Note that all ethnic minority applicants in the experiment are born in Sweden.

[8] 76 percent of these individuals had only one spell, while 19 percent had two spells. Hence, only five percent had more than two unemployment spells.

[9] 83 percent of the unemployment spells have an occupational classification in the occupational register for 2005.

those defined as searching for high skill jobs have around two more years of schooling than those searching for jobs in median/low skill jobs.

Table B1. Descriptive statistics. Unemployed workers searching for jobs in 2005. 23-32 years old.

Occupational categories	Male Share	Age in 2005	Years of schooling in 2003	Has found a job	Number of spells
High skill occupations:					
Computer occupations	0.82	28.0	13.7	0.55	1,931
Accountants and auditors	0.28	27.9	13.4	0.56	1,445
Registered nurses	0.11	27.3	13.7	0.76	990
Middle school teachers	0.31	27.8	14.0	0.62	4,400
Secondary school teachers	0.46	28.0	13.8	0.66	1,722
Other high skill occupations	0.46	27.8	13.4	0.60	22,782
Medium/low skill occupations:					
Sales representatives and buying and purchasing agents	0.50	27.7	12.7	0.56	3,742
Retail sales persons and cashiers	0.36	26.4	11.8	0.46	16,379
Installation, maintenance and repair occupations	0.91	26.8	11.6	0.50	2,966
Construction laborers and carpenters	0.98	27.1	11.3	0.65	6,202
Bus, truck and taxi drivers	0.90	27.1	11.4	0.55	3,478
Janitors and cleaners	0.28	26.4	11.2	0.39	5,084
Food serving and waitress	0.38	26.4	11.5	0.46	11,317
Other medium/low skill occupations	0.51	26.7	11.7	0.48	91,431
Cases with no SSYK	0.60	26.1	11.1	0.19	19,753

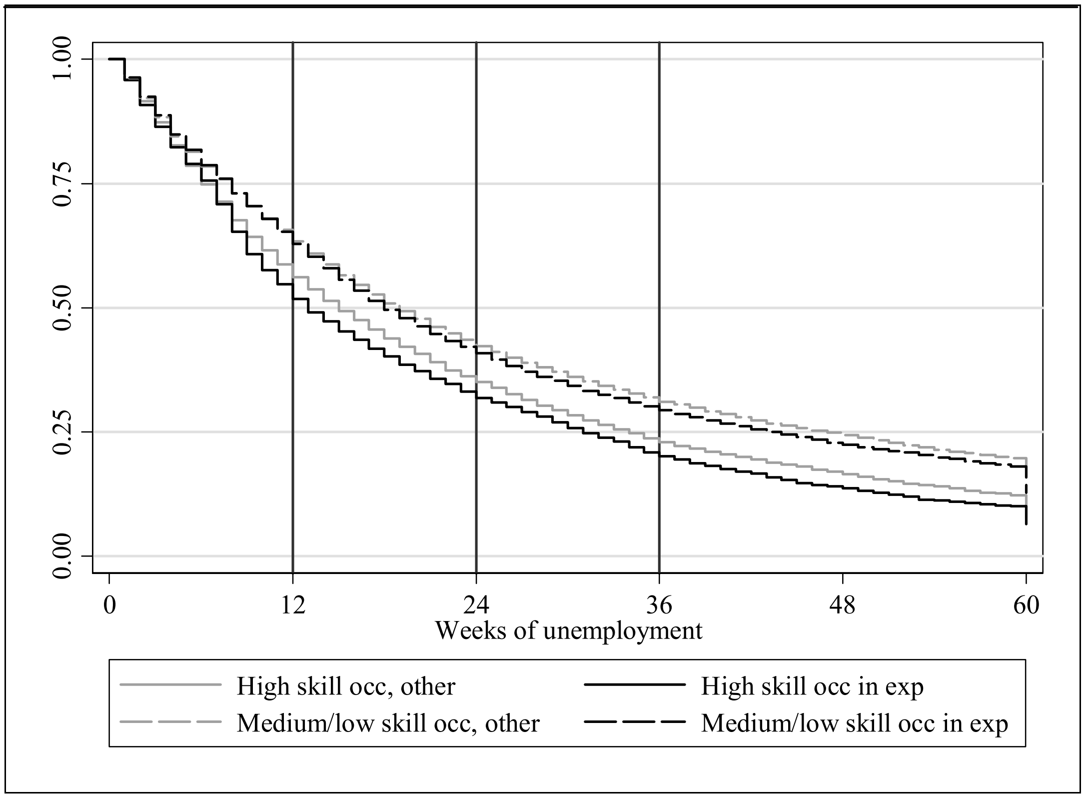
For each spell, we have also calculated the total time spent as unemployed and the number of unemployment spells since January 1, 2001. This information is used to estimate hazard rates in online Appendix C.

Kaplan-Meier survival estimates by occupation

In this subsection, we present Kaplan-Meier survival estimates of the exit rate from unemployment to work for high and medium/low skill occupations included and not included in the experiment as well as for each of the occupations in the experiment separately. This analysis achieves two objectives. First, it serves as a motivation for our choice of spell lengths in the experiment. Second, it shows that the occupations we bundle together as high and medium/low skill occupations in the experiment are very similar in terms of the survival estimates.

We start by presenting Kaplan-Meier survival estimates for high skill and medium/low skill occupations included and not included in the experiment (Figure B1). These functions have a very similar shape, with the outflow rate from unemployment being somewhat faster for high skill occupations, but the differences are rather small. After nine months around 70 percent has left unemployment for work, with nine months being indicated by the rightmost vertical line.

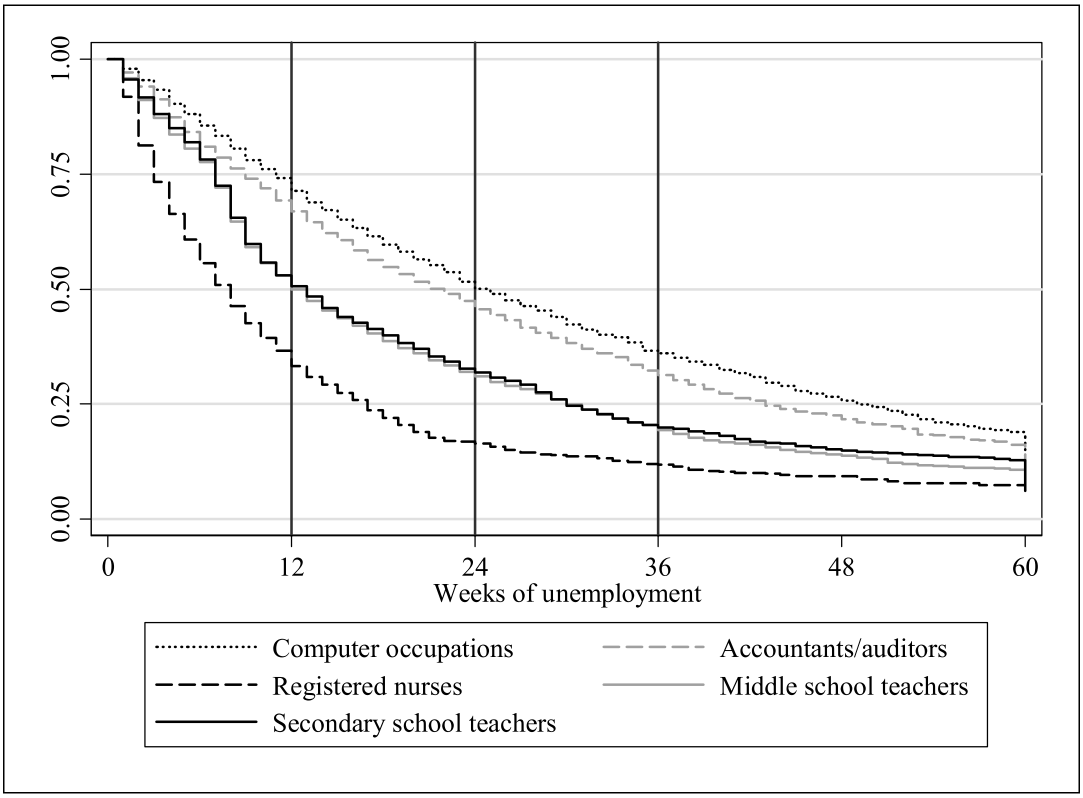
Figure B1. Kaplan-Meier survival estimates for the transition from unemployment to work by occupation. 23-32 year olds. Weeks unemployed.



Note: The vertical lines represent 3, 6, and 9 months of unemployment.

These aggregated categories could hide differences across more detailed occupational groupings. We therefore present Kaplan-Meier survival estimates for each occupation included in the experiment, and do this separately for high and medium/low skill occupations (Figures B2a and B2b). For high skill occupations, the fastest outflow rate from unemployment is found for registered nurses, followed by middle and secondary school teachers. After nine months, more than 80 percent in these occupations have found a job. The outflow rate is slower for computer occupations and accountants/auditors, but still, after nine months more than 65 percent have found a job.

Figure B2. Kaplan-Meier survival estimates for the transition from unemployment to work for the high skill occupations in the experiment. 23-32 year olds. Weeks unemployed.

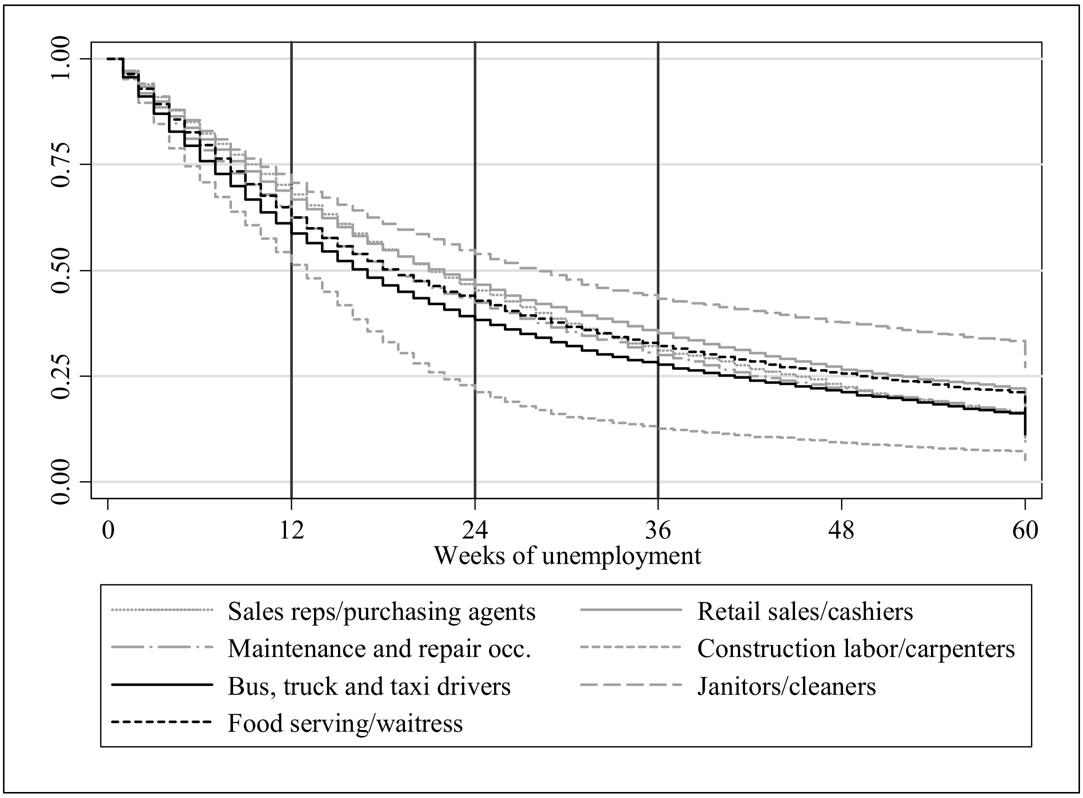


Note: The vertical lines represent 3, 6, and 9 months of unemployment.

For medium/low skill occupations, we find that most of the occupations; sales representatives/purchasing agents, retail sales/cashiers, maintenance/repair occupations, bus/truck/taxi drivers, food serving/waitress, all have similar outflow rates from unemployment to work, and after nine months approximately 60 percent has found a job. Two occupations stand out, but in different directions. Construction laborers/carpenters have a faster outflow rate compared to the other occupations and after nine months almost 90 percent has left unemployment for work. In contrast, janitors/cleaners have a slower outflow rate from unemployment.

Overall, although there are some differences across occupations, the outflow rate patterns are rather similar across the occupations, which is supportive of our strategy of bundling occupations into high skill and medium/low skill occupations in the empirical analysis.

Figure B3. Kaplan-Meier survival estimates for the transition from unemployment to work for medium/low skill occupations in the experiment. 23-32 year olds. Weeks unemployed.



Note: The vertical lines represent 3, 6, and 9 months of unemployment.

An estimate of the baseline hazard rate using the piecewise constant exponential model

It is not possible to verify whether the unemployment spells exhibit duration dependence by just viewing the Kaplan-Meier survival functions. Therefore, we estimate the baseline hazard using the piecewise constant exponential hazard function for each of the occupational categories in Figure B1. We use this particular model since we want to have a flexible form for the baseline hazard. The piecewise constant exponential model is non-parametric in the sense that it does not assume a particular parametric form for the hazard over all durations, while it is parametric in the sense that it assumes that the hazard is constant (exponential) over sub-periods. We define the time intervals for which the hazard function is constant so that they correspond to the experimental margins of 3, 6 and 9 months of unemployment. For the high skill occupations in the experiment, the "risk" that an unemployed worker will find a job is the highest in the first three months and then declines for every three-month sub-period, see Column 1 in Table B2. The "risk" of finding a job is more than 50 percent higher in the first three months compared to after nine months. A similar pattern is found for the medium/low skill occupations in the experiment (Column 3), as well as for the occupations not included in the experiment (Columns 2 and 4). Hence, this non-experimental data on unemployment durations exhibit patterns consistent with duration dependence.

Table B2. Hazard rates for different unemployment durations by occupational categories. Unemployed workers searching for jobs in 2005. 23-32 years old. Piecewise constant exponential model.

	High skill occupations		Medium/low skill occupations	
	In experiment	Other	In experiment	Other
Time unemployed (months)				
1. < 3	0.052	0.047	0.038	0.038
	(0.001)	(0.001)	(0.000)	(0.000)
2. ≥ 3 but < 6	0.042	0.040	0.037	0.034
	(0.001)	(0.001)	(0.001)	(0.000)
3. ≥ 6 but < 9	0.037	0.035	0.028	0.026
	(0.002)	(0.001)	(0.001)	(0.000)
4. ≥ 9 but < 12	0.033	0.027	0.023	0.021
	(0.002)	(0.001)	(0.001)	(0.001)
5. ≥ 12	0.026	0.024	0.017	0.016
	(0.002)	(0.001)	(0.001)	(0.000)
Relative hazard rate (2/4)	1.27	1.48	1.61	1.62
Number of observations	10,488	22,782	49,168	91,431

Note: All estimates are statistically significant at the one percent level. Standard errors in parentheses. No other controls are included. These estimates are calculated using the stpiece module in Stata12.

We can also calculate the baseline hazard rate by occupation, see Table B3. If we compare the relative hazard rate for 3-6 months to the hazard rate for 9-12 months, it is larger for medium/low skill occupations than high skill occupations. In fact, the hazard rate is more than 50 percent higher for four out of seven medium/low skill occupations, while that is the case for only two out five high skill occupations.

Table B3. Hazard rates for different unemployment durations by occupation. Unemployed workers searching for jobs in 2005. 23-32 years old. Piecewise constant exponential model.

Time Unemployed (months)	Computer occ.	Accountants and auditors	Registered nurses	Middle school teachers	Secondary school teachers	Sales reps. and buying agents	Retail sales and cashiers	Installation and repair occ.	Constr. labor and carpenters	Bus, truck and taxi drivers	Janitors and cleaners	Food serving and waitress
1. < 3	0.029	0.038	0.101	0.057	0.057	0.036	0.035	0.038	0.053	0.046	0.029	0.039
	(0.001)	(0.002)	(0.004)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
2. ≥ 3 but < 6	0.035	0.038	0.080	0.045	0.044	0.040	0.032	0.034	0.066	0.040	0.025	0.034
	(0.002)	(0.003)	(0.008)	(0.002)	(0.003)	(0.002)	(0.001)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)
3. ≥ 6 but < 9	0.032	0.033	0.038	0.038	0.047	0.033	0.025	0.031	0.048	0.033	0.020	0.026
	(0.003)	(0.004)	(0.009)	(0.003)	(0.005)	(0.002)	(0.001)	(0.003)	(0.003)	(0.003)	(0.002)	(0.001)
4. ≥ 9 but < 12	0.029	0.037	0.039	0.036	0.029	0.032	0.023	0.024	0.028	0.021	0.015	0.022
	(0.004)	(0.005)	(0.017)	(0.004)	(0.006)	(0.003)	(0.001)	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)
5. ≥ 12	0.030	0.026	0.007	0.026	0.017	0.030	0.016	0.021	0.016	0.023	0.011	0.015
	(0.004)	(0.005)	(0.007)	(0.004)	(0.005)	(0.003)	(0.001)	(0.003)	(0.002)	(0.003)	(0.002)	(0.002)
Relative hazard rate (2/4)	1,21	1,03	2,05	1,25	1,52	1,25	1,39	1,42	2,36	1,90	1,67	1,55
Number of observations	1,931	1,445	990	4,400	1,722	3,742	16,379	2,966	6,202	3,478	5,084	11,317

Note: All estimates are statistically significant at the one percent level. Standard errors in parentheses. No other controls are included. These estimates are calculated using the stpiece module in Stata12.

Appendix C: Past spells of unemployment and the probability of finding a job

In this section, we present estimates of the association between the incidence and duration of past unemployment spells and the probability of finding a job using the piecewise constant exponential hazard rate model.[10] The estimation uses the same dataset as the analysis in online Appendix B, but also includes information about past unemployment spells from January 1, 2001 and onwards. Table C1 shows the estimates as hazard ratio coefficients, and we focus on the estimates for the unemployment variables. The estimates for the variable *Months unemployed in the past* are remarkably similar across estimation samples: The estimate of 0.96 implies that having been unemployed one additional month in the past is associated with a four percent lower exit rate from unemployment to work.[11] Another stable result is found for the number of unemployment spells in the past: The estimate of 1.04 implies a four percent higher exit rate from unemployment to work per spell of unemployment in the past. The positive association between this variable and the transition rate from unemployment to work probably captures that, conditional on months unemployed in the past, it is better to have several short-term spells than fewer long-term spells, again indicating duration dependence in observational data.

Table C1. Hazard rates for unemployment to work transitions by occupational categories. 23-32 year olds. Piecewise constant exponential model.

	High skill occupations		Medium/low skill occupations	
	In experiment	Other	In experiment	Other
Male	0.758	0.775	1.209	1.042
	(0.020)	(0.013)	(0.016)	(0.010)
Age	0.963	0.966	0.971	0.969
	(0.005)	(0.003)	(0.002)	(0.002)
Months of past unemployment	0.960	0.963	0.968	0.961
	(0.004)	(0.002)	(0.002)	(0.001)
Number of past unemployment spells	1.041	1.077	1.064	1.067
	(0.012)	(0.008)	(0.005)	(0.004)
Number of observations	10,488	22,782	49,168	91,431

Note: All estimates are statistically significant at the one percent level. Standard errors in parentheses. No other controls are included. These estimates are calculated using the stpiece module in Stata12.

[10] These estimates are practically identical if we use the Cox model instead. Also, the pattern of a declining hazard rate with time unemployed in Table B2 is the same with and without these covariates being included. These results are available on request.

[11] For the full data, the first column in Table C1, the mean number of months unemployed in the past is 27 with a standard deviation of 27, while the mean number of unemployment spells in the past is 2.6 with a standard deviation of 2.3.

Appendix D: Detailed description of the construction of the unemployment spells

The data is taken from the Public Employment Service's Event Database (Händel). This data contains information on all unemployed individuals registered at the Employment Service. For each unemployed individual, it gives the duration of the unemployment spell, the reason for ending the spell, and placements in labor market programs. The sample we use consists of all individuals who flowed into unemployment between January 1 and December 31, 2005. The spells are followed until August 22, 2007 (if they did not end earlier) when the time window was closed. The Händel data consists of two registers containing what is called *Register periods* and *Search category periods*. *Register periods* contains the date for registering at the Employment Service and the date for which the individual leaves the register. Each individual can be registered several times. During each period as registered, the individual can have several different statuses. For example, the individual can be unemployed for some time, and then participate in labor market training programs or have subsidized work. Each start and end date of these *states* are registered in *Search category periods*. Each individual's *Register periods* and *Search category periods* are in chronological order in the data. The construction of the data implies that *Register periods* cannot be used directly to construct spells of unemployment. The reason is that, as mentioned, within each period an individual can have different statuses and transitions from unemployment, not only to work but also to states which counts as out-of-the-labor-force. From an out-of-labor-force state, the individual can then have a transition back to a status that counts as unemployed (which is counted as a new spell in the register). Therefore the spells of unemployment are instead calculated from *Search category periods*, and *Register periods* serves only as a time frame for the spells. There were some inconsistencies in the data that had to be corrected before constructing spells of unemployment. In some cases, the deregistration date was before the registration date and there was also occurrences of overlapping periods for the same individual. The following corrections were made: All *Search category periods* which were not within the time frame defined by *Register periods* were deleted. In cases of overlapping *Search category periods*, we followed the strategy that later entries (in chronological order) contain more accurate information than previous entries. For example, if a previous *Search category period* has an end date after a more recent spell's start date, the end date of the previous was set to the start date of the more recent. Negative *Search category periods* were deleted. After having corrected the dates, the different states in *Search category periods* were classified as employed, unemployed, or out-of-the-labor force, and spells of unemployment were constructed.[12] Spells ending with the status out of the labor force and spells not ending before the time window was closed (August 22, 2007) were treated as right censored. Since the sample is a flow sample, left censoring is not an issue.

[12] We define unemployed as being in the search categories; SOKKAT={11, 12, 13 and 14}, while for finding a job we use the deregistration categories; AVORS={1, 2, 3 and 30}. A more detailed description of how the data was constructed is available from the authors on request.

Appendix E: Excluding occupations

Table E1. The effects of the workers' attributes on the callback rate (marginal effects), excluding occupations. Medium/low skill jobs.

	Exclude Sales representatives	Exclude Retail sales and cashiers	Exclude Installation, maintenance and repairs	Exclude Construction laborers and carpenters	Exclude Bus, truck, and taxi drivers	Exclude Janitors and cleaners	Exclude Food serving and waitress
Contemporary unemployment 3 months	0.012	0.008	0.012	0.004	0.001	0.011	0.002
	(0.017)	(0.017)	(0.015)	(0.015)	(0.015)	(0.016)	(0.015)
Contemporary unemployment 6 months	0.005	0.006	0.009	0.004	0.003	0.007	0.013
	(0.018)	(0.019)	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)
Contemporary unemployment 9 months	-0.037**	-0.034*	-0.035**	-0.043***	-0.034**	-0.043**	-0.044**
	(0.018)	(0.019)	(0.016)	(0.016)	(0.016)	(0.017)	(0.016)
Past unemployment after graduation	0.010	-0.002	-0.002	-0.010	-0.005	-0.005	-0.011
	(0.016)	(0.017)	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)
Past unemployment between jobs	0.038*	-0.000	0.013	0.012	0.015	0.007	-0.003
	(0.020)	(0.020)	(0.017)	(0.017)	(0.017)	(0.018)	(0.017)
Average callback rate	0.20	0.24	0.21	0.21	0.19	0.23	0.21
Number of observations	3,797	4,178	4,940	4,837	4,607	4,755	4,734

Notes: The table reports marginal effects for the probability of being invited to a job interview based on Probit regressions estimated with the dprobit command in Stata12. All regressions also include control variables for work experience, number of employers, gender, ethnicity, personality traits, leisure activities, visiting US high school, work experience during the summer breaks, having more education than required, and fixed effects for each of the occupations and regions. The reference category is a worker with no contemporary unemployment and no history of past unemployment. The standard errors (in brackets) are clustered at the job advertisement level. ***, ** and * denote statistical significance at the 1, 5 and 10 percent levels, respectively.

Table E2. The effects of the workers' attributes on the callback rate (marginal effects), excluding occupations. High skill jobs.

	Exclude Computer occupations	Exclude Registered nurses	Exclude Middle school teachers	Exclude Secondary school teachers	Exclude Accountants and auditors
Contemporary unemployment 3 months	0.001	-0.004	-0.007	0.006	-0.000
	(0.026)	(0.022)	(0.025)	(0.024)	(0.024)
Contemporary unemployment 6 months	-0.008	-0.011	-0.024	-0.000	-0.032
	(0.030)	(0.025)	(0.028)	(0.027)	(0.028)
Contemporary unemployment 9 months	0.025	-0.000	-0.017	0.018	0.019
	(0.028)	(0.025)	(0.026)	(0.026)	(0.027)
Past unemployment after graduation	-0.015	-0.024	-0.015	-0.001	-0.032
	(0.024)	(0.021)	(0.023)	(0.022)	(0.023)
Past unemployment between jobs	0.031	-0.013	0.017	-0.008	0.007
	(0.031)	(0.025)	(0.029)	(0.027)	(0.028)
Average callback rate	0.29	0.27	0.31	0.30	0.32
Number of observations	2,170	2,715	2,502	2,711	2,534

Notes: The table reports marginal effects for the probability of being invited to a job interview based on Probit regressions estimated with the dprobit command in Stata12. All regressions also include control variables for work experience, number of employers, gender, ethnicity, personality traits, leisure activities, visiting US high school, work experience during the summer breaks, having more education than required, and fixed effects for each of the occupations and regions. The reference category is a worker with no contemporary unemployment and no history of past unemployment. The standard errors (in brackets) are clustered at the job advertisement level. ***, ** and * denote statistical significance at the 1, 5 and 10 percent levels, respectively.

Appendix F: Additional descriptive statistics

Table F1. The means of other characteristics by unemployment categories.

Variables	All	Contemporary unemployment				Past unemployment	
		0 months	3 months	6 months	9 months	No	Yes
Work experience	3.02 (1.27)	3.02 (1.27)	3.02 (1.25)	3.07 (1.29)	3.00 (1.27)	2.82 (1.30)	3.34 (1.14)
Native Swedish male	0.33 (0.47)	0.34 (0.47)	0.35 (0.48)	0.33 (0.47)	0.32 (0.47)	0.34 (0.47)	0.32 (0.47)
Native Swedish female	0.33 (0.47)	0.33 (0.47)	0.33 (0.47)	0.32 (0.47)	0.36 (0.48)	0.33 (0.47)	0.35 (0.48)
Ethnic minority male	0.33 (0.47)	0.33 (0.47)	0.32 (0.47)	0.35 (0.48)	0.32 (0.47)	0.33 (0.47)	0.33 (0.47)
High skill job	0.37 (0.48)	0.36 (0.48)	0.39 (0.49)	0.35 (0.48)	0.40 (0.49)	0.36 (0.48)	0.39 (0.49)
Low/medium skill job	0.63 (0.48)	0.64 (0.48)	0.61 (0.49)	0.65 (0.48)	0.60 (0.49)	0.64 (0.48)	0.61 (0.49)
Stockholm	0.59 (0.49)	0.58 (0.49)	0.59 (0.49)	0.62 (0.49)	0.61 (0.49)	0.59 (0.49)	0.60 (0.49)
Gothenburg	0.23 (0.42)	0.24 (0.43)	0.23 (0.42)	0.22 (0.42)	0.23 (0.42)	0.24 (0.43)	0.23 (0.42)
Rest of the country	0.17 (0.38)	0.18 (0.38)	0.17 (0.38)	0.16 (0.37)	0.16 (0.37)	0.17 (0.37)	0.18 (0.38)
Number of observations	8,466	4,207	1,737	1,245	1,277	5,249	3,217

Notes: Past unemployment includes unemployment immediately after graduation or between jobs. Standard deviations within parentheses.

References

Carling, Kenneth, Bertil Holmlund, and Altin Vejsiu. 2001. "Do Benefit Cuts Boost Job Finding? Swedish Evidence from the 1990s." *Economic Journal* 111 (474): 766-790.

Ruggles, Steven J., Trent Alexander, Katie Genadek, Ronald Goeken, Matthew B. Schroeder, and Matthew Sobek. 2010. Integrated Public Use Microdata Series Version 5.0 [Machine-readable database]. Minneapolis: University of Minnesota. http://www.ipums.org (accessed January 18, 2013).