

# How wage announcements affect job search behaviour - a field experimental investigation

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## Abstract

In this study we introduce a small number of “artificial” vacancies with randomised wages in an otherwise standard job search platform. We study how job seekers respond to wage announcements, and test the main implications of directed search: high wages should attract more applicants, but some applicants apply only to low wages even if higher wage offers are present. Both parts of the theory find support among the randomised job offers, suggesting an allocative role for wage competition in search markets. We calibrate a directed search model with multiple applications and on-the-job search and find that it can reproduce our findings quantitatively.

**Keywords:** Online job search, directed search, wage competition, field experiments.

**JEL-codes:** J31, J63, J64, C93

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# 1 Introduction

Directed search models (Jovanovic, 1979) have become popular in describing the search and matching process in the labor market. The model, in which workers can only apply to a subset of all vacancies they observe (because of time or other constraints), predicts that the likelihood of being hired will be taken into consideration when selecting the vacancy or vacancies to which one applies. *One important prediction of these models is that it is possible that some workers refrain from applying to suitable high wage vacancies because they expect the competition for these jobs to be high. This prediction is in contrast with standard random search models where workers would apply to any vacancy as soon as the wage is above their reservation wage (PHILIPP)*

However, empirically investigating the search and matching process, and in particular this implication of directed search, is complicated due to limited availability of data. It is common to observe outcomes (hiring), but much less common to observe detailed search behavior by workers (or even unsuccessful applications) or unsuccessful hiring attempts by firms. This complicates investigation of how workers respond to different attributes of vacancies. A number of recent studies have been based on detailed information on vacancies and job applications, which we discuss in the next Section. However, most are based on observational data, which have the drawback that the posted wage likely correlates with other characteristics of the vacancy. While some can be controlled for (occupation, required experience, etc.), this is impossible for other information such as the flow text description of the position. It is therefore very difficult to ensure that the estimated effects of the wage on the behaviour of job seekers is not contaminated by the effects of other characteristics of the vacancy.

In this paper, we propose an experimental approach and exogenously manipulate the wages attached to vacancies. This approach follows the traditional approach of audit studies, which now have a long tradition in sociology and economics. Most labour market audit studies in economics have so far focused on the demand side and have provided important insights in how employers react to applicant characteristics such as skills, age, gender, unemployment duration, and ethnicity. The power of these studies comes from their clean identification: applicants or applications are randomised, so any differences can be attributed to the employer. This paper advocates a similar approach to study the reaction of job seekers to differences in the vacancies that are posted.

We are focusing here on how wage offers affect search behaviour. By randomising the wage offer, one can study how wage competition works, and test different theories of the labor market. In particular, we aim to provide clean evidence on two assumptions that set models of direct wage competition (competitive or directed search) apart from models where workers encounter wages more randomly (random search): (1) more workers apply to jobs with higher wages, but (2) job seekers do not have the time to apply to all job offers and sometimes apply to low wages even if high wage offers are present. The first point implies that wages have a competitive character in attracting workers, which generates positive welfare theorems akin to classical general equilibrium theory in competitive search models.<sup>1</sup> This has been the main reason why these theories have attracted larger interest as an alternative to random search. The second point is also crucial for the theory: if workers send applications to all jobs that surpass their reservation

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<sup>1</sup>Related literature.

wage the main selectivity argument underlying these theories is lost (see next Section for a more detailed discussion).

A limited number of research vacancies would allow to shed light on this additional source of minority wage differentials if these could reach a sufficiently large and diverse set of job seekers. Unfortunately current ethical approval practices did not allow this approach to proceed without prior informed consent, even after laying out procedures that substantially curb the downsides.

Consent of all market participants is unfeasible, as is the case with standard audit studies of employers. We overcame this hurdle by conducting a smaller scale field experiment. We created our own job matching platform at the experimental laboratory in Edinburgh. We recruited 300 job seekers to participate in our study once a week for a duration of 12 weeks. Per session they spent at least half an hour searching for jobs that they can save to apply later, and they can spend up to two hours to actually apply or they can do the actual applications from home. Conducting the study in our lab allows us to ask participants explicitly for consent, to verify their identities, to distribute compensation, and to provide support in case of platform problems. For the other side of the market we provided access to some 600.000 up-to-date vacancies from the database of Universal Jobmatch, the UK government’s job search site which is the most comprehensive in the UK market. We informed participants that a small fraction (less than 2% of vacancies) would be posted for research purposes to understand which vacancies should be attracted to the region.<sup>2</sup> Job seekers were informed about the source of our regular vacancies. We did not specify the exact nature of our research vacancies.

In praxis, these were expired vacancies from half a year prior to our study that did not allow direct name identification and for which we artificially multiplied the original wage by some random factor. Since the multiplicative factor is assigned independent of the description of the vacancy, we can answer the first question by regressing the amount of interest on the wage factor. We created pairs of vacancies that are nearly identical except for minor changes in wording and are posted at roughly the same time but with different wages. This allows us to answer the second research question whether there exist people who apply only to the low wage even if higher wage jobs, located in the same geographical area, are present (even though the higher wage should on average attract more/better applicants). The random assignment of wages is crucial to our identification strategy, as wages are usually correlated with other indicators of hierarchy or status that are conveyed in the flow text and that are difficult to control for.

Thus, we apply the audit methodology to the demand side of the labour market and post pairs of vacancies that differ only in the announced wage. We combine this with a setting in which job seekers use our job search interface during a three month period. This combination has several advantages. First, posting vacancies with randomized wages breaks the correlation with other vacancy characteristics. Second, in our experimental setting we observe the complete search behavior of the applicants in the study through detailed data generated from our online search platform (including for example the set of vacancies that each job seeker sees). Combined with posting pairs of vacancies, this allows us to assess individual job search strategies such as preferring a low wage vacancy when a similar vacancy with higher wage exists. Third, this setup enables passing ethical consent, which is challenging when a study concerns posting artificial vacancies. Fourth,

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<sup>2</sup>We chose this formulation based on the interest of policy makers in understanding how important more attractive vacancies are for job seekers relative to providing more jobs at all even at lower wages.

the fact that we consider artificial vacancies, implies that we can post vacancies in a wide range of different occupations and skill levels, rather than focusing on one narrowly defined job type (which is for example the case in ?, ? and ?). As a result we extend external validity.

We do not expect or have evidence that the presence of some non-real vacancies alters the job search of our participants substantially. Even in the absence of our postings, online datasets are not pristine collections of open vacancies. Newspaper reports and investigations into fake job advertisements about websites like Monster.com, Careerbuilder.com and Universal Jobmatch, and a large number of online advice websites inform job seekers of this general problem. For our particular vacancy source from Universal Jobmatch, investigative broadsheet journalism in the UK places the lower bound of non-real vacancies at 2%, while the tabloid press warns of much higher numbers.<sup>3</sup> Nevertheless, the database is regarded as reliable by the UK government, who considers making search on this platform mandatory for Job Seekers Allowance recipients in the future. We take from this that a low number of non-real vacancies are standard in current online job search. We also survey our participants at the end of the study, and the vast majority specified that the presence of research vacancies was immaterial for how they search for jobs, nor do they deem it possible to distinguish our vacancies from real ones.

As measure of interest we record both whether individuals view the details of a particular vacancy and whether they save it. After saving a vacancy they can apply for it once they leave the search phase after a minimum of half an hour. For ethical reasons we informed participants right after the initial search phase, and therefore prior to actual applications, in case they saved any vacancies that we had posted for research purposes. This avoids unnecessary work and anxiety of applying to jobs that are not real. It also ensures that they never see any research vacancy twice, as we delete it from their search set thereafter. It implies that we do not observe actual applications, however viewing or saving a vacancy is a strong indicator of interest in the vacancy and likelihood of applying.<sup>4</sup> In this respect our study is similar to audit studies for resumes, where the outcome is the callback rate rather than actual job offers.

Our main results are in line with the two main predictions of directed search models. First, we find that higher wages result in significantly more interest in the vacancy. A 1 % increase in the wage results in 0.7-0.9 % more saves. Second, we find that 42 % of those that save the low wage vacancy within a vacancy-pair do not also save the high wage vacancy. This percentage remains almost constant when conditioning on individuals that have seen both vacancies listed on their screen (39 %). It becomes somewhat smaller when also conditioning on pairs in which the high wage vacancy appeared higher in the list (because it was posted at a more recent date), though even in this scenario 16 % does not save the high wage vacancy. When using viewing of the vacancy (rather than saving) as the outcome the results are very similar. In a robustness analysis we exclude that this finding is due to (1) study participants identifying the research vacancies, (2) differences in location between the vacancies in a pair or (3) learning over time.

Our randomized experimental setup ensures that pairs of high and low wage vacancies are *objectively* nearly identical in terms of all other aspects of the job. But of course and directly in line with the directed search theories we are interested in, it is plausible that participants *perceive* these vacancies differently, that is, that they use the wage as a signal

<sup>3</sup>See for example ? and ?.

<sup>4</sup>In our study, almost one-third of all saved (real) vacancies is eventually applied to.

of other relevant characteristics of the vacancy. Directed search theories suggest that high wage vacancies should attract more interest (and from better workers), and therefore high wage vacancies could be perceived as such. There could however be other signals attached to high wage vacancies, such as worse working conditions, in line with a compensating differentials hypothesis.

To understand better how vacancies are perceived, we designed and conducted a complementary survey (with different participants). We find that the high wage vacancy within a pair is, on average, perceived to (1) attract more competition, (2) require an applicant to be of higher quality to be considered and (3) have better non-monetary working conditions. Findings (1) and (2) support a directed search interpretation of our empirical results, while finding (3) rules out a compensating differential hypothesis (in which workers do not apply to high wage jobs because they expect non-monetary conditions to be worse).

To provide a benchmark for the magnitude of our estimates, we build a directed search model with multiple applications and on-the-job search. We calibrate the model using UK data and compute the variables of interest: the queue length elasticity of a vacancy with respect to its posted wage and the worker’s probability of applying to low-wage job but not to a high wage job when both are observed. We show that the model is able to reproduce values reasonably close to our empirical findings.

Note that because of sample size, we evaluate average effects, since the restrictions limit our power to answer the more detailed questions relating to heterogeneous job search behaviour along different dimensions. We hope this will become feasible in future studies.

The general methodology we propose here could also be used to study wider questions, such as whether minorities react differently to higher wages or employer ethnicity or gender.

The rest of the paper is organized as follows. Section 2 provides an overview of related literature. In Section 3 we describe the set up of the experiment and present some descriptive statistics on the participating job seekers. The details on how the artificial vacancies were created and posted are explained in section 4. Section 5 presents the empirical analysis and results. In Section 6 a simple directed search model is described and its predictions are compared to our empirical findings. Section 7 concludes.

## 2 Related literature

There are few existing studies on the relationship between wage offers and job search behaviour. Exceptions are ? who exploit a rich survey performed in 1980-82 to assess the relationship between the starting wage of a vacancy and the number of applicants and interviews. They find that the wage is negatively related to the number of applicants. ? analyze applications data and find that firms that are restricted to pay a minimum wage receive more applicants than firms that pay either slightly less or slightly more than the minimum wage.

The recent rise in popularity of online job search platforms has improved data availability and has helped getting insights into job search behaviour, and in particular into how applications relate to wage offers. For example, ? use data from Careerbuilder.com and show that higher wages are associated with fewer applicants, even when controlling

for occupation and industry. Only when conditioning on the exact job title, the association reverses and higher wages attract more applicants. In addition, the quality of the applicants (education and experience) increases with the posted wage. ? use data from an online labor market in Chile and find that higher wages attract significantly more applicants, even after controlling for a detailed set of job characteristics that includes job title category dummies.

Despite the great level of details of the data, it is impossible to ensure that one has controlled for everything that could be relevant to the job search behaviour. Even in the analysis of ? that includes job title fixed effects, two lines of flow text remain which cannot be controlled for.

To overcome this problem, some studies have performed experiments in which offered wages are randomized. ? randomize the wage offers in job openings for civil servants in Mexico. They find that higher wages lead to significantly more applicants, while higher wages also increase the quality of the applicants as measured by IQ level. With a different focus, ? post job ads to investigate gender differences in response to whether salaries are negotiable. They find that while women are generally less likely to negotiate the wage, the difference disappears when the ad explicitly mentions that the wage is negotiable. ? also post vacancies with randomized salaries, but focus on estimating willingness to pay for flexible working arrangements. Furthermore, some studies estimate the labour supply wage elasticity by randomly varying the offered wage (e.g. ? who exogenously vary the wage in the day labor market in rural Malawi and ? who exogenously vary the wage of bicycle messenger service workers in Zurich).

We propose and implement a methodology that is parallel to audit studies in which the success of pairs of applicants is compared, when they differ in only one particular characteristic. This approach followed from studies in which applicant pairs are matched to be as closely comparable as possible when applying for a job opening (see for example ?, who consider gender discrimination and ? who apply the same approach to a car sales setting). These studies were criticized for a number of reasons, leading to a new approach in which pairs of fictional resumes were sent out. The study by ? considers ethnic discrimination in the hiring process, by varying the names of the applicants between 'African-American'- and 'White-American'-sounding. This approach has become popular and has been applied to identify discrimination based on different grounds such as age (?), gender (?) and physical appearance (?), and also to assess the impact of unemployment duration on the hiring probability (?).

## 3 Experimental Design<sup>5</sup>

### 3.1 Recruitment Procedure and Experimental Sample

The participants in the study were job seekers recruited in the area of Edinburgh. The eligibility criteria were: being unemployed, searching for a job for less than 12 weeks (a criterion that we did not enforce), and being above 18 years old. We imposed no further restrictions in terms of nationality, gender, age or ethnicity. Most participants were re-

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<sup>5</sup>This section contains a concise description of the recruitment process, institutional setting and experimental setup. We copied and pasted parts of the description presented in ?. Further details on all of these aspects can be found in this companion paper.

Table 1: Characteristics of study participants

|                                | Study participants |      |     |      | Population <sup>a</sup> |
|--------------------------------|--------------------|------|-----|------|-------------------------|
|                                | mean               | sd   | min | max  |                         |
| Demographics:                  |                    |      |     |      |                         |
| gender (%)                     | 43                 | 50   | 0   | 1    | 33                      |
| age                            | 36                 | 12   | 18  | 64   | 35                      |
| high educated <sup>b</sup> (%) | 43                 | 50   | 0   | 1    |                         |
| white (%)                      | 80                 | 40   | 0   | 1    | 89                      |
| number of children             | .53                | 1    | 0   | 5    |                         |
| couple (%)                     | 23                 | 42   | 0   | 1    |                         |
| any children (%)               | 27                 | 45   | 0   | 1    |                         |
| Job search history:            |                    |      |     |      |                         |
| vacancies applied for          | 64                 | 140  | 0   | 1000 |                         |
| interviews attended            | .48                | 0.84 | 0   | 6    |                         |
| jobs offered                   | .42                | 1.1  | 0   | 8    |                         |
| at least one offer (%)         | 20                 | 40   | 0   | 1    |                         |
| days unempl. (mean)            | 260                | 620  | 1   | 5141 | 111                     |
| days unempl. (median)          | 80                 |      |     |      | 81                      |
| less than 183 days (%)         | 76                 | 43   | 0   | 1    |                         |
| less than 366 days (%)         | 85                 | 35   | 0   | 1    |                         |
| job seekers allowance (£)      | 52                 | 75   | 0   | 1005 |                         |
| housing benefits (£)           | 64                 | 129  | 0   | 660  |                         |
| other benefits (£)             | 14                 | 65   | 0   | 700  |                         |
| Observations                   | 295                |      |     |      |                         |

<sup>a</sup> Average characteristics of the population of job seeker allowance claimants in Edinburgh over the 6 months of the study. The numbers are based on NOMIS statistics, conditional on unemployment duration up to one year. <sup>b</sup> High educated is defined as a university degree.

cruited at local public unemployment agencies (Job Centres) and received unemployment benefits (Job Seekers Allowance).

We reproduce here one of the Tables from ?, which presents basic background characteristics of our participants (collected at baseline in the first week of the study) and compares them to average characteristics of the population of job seekers in Edinburgh. Both are presented in Table ?? . Only a limited number of characteristics is available for the population of job seekers in Edinburgh, which are based on the NOMIS dataset on Job Seeker Allowance (JSA) Claimants. We find that we slightly oversample females and non-whites, while the average age is very close to the population average. The population statistics are based on JSA claimants with unemployment duration up to 6 months, because for these the median duration is almost equal to the median duration of the participants (80 days). For the participants we further observe that they have, on average, sent out 64 applications and attended 0.48 job interviews.

## 3.2 Experimental Procedure

Job seekers were invited to search for jobs once a week for a period of 12 weeks (or until they found a job) in the computer facilities of the School of Economics at the University of Edinburgh. The study consisted of two waves: wave 1 started in September 2013 and wave 2 started in January 2014. We conducted sessions at six different time slots, on Mondays or Tuesdays at 10 am, 1 pm or 3:30 pm. Participants chose a slot at the time of recruitment and were asked to keep the same time slot for the twelve consecutive weeks.

Participants were asked to search for jobs using our job search engine (described later in this section) for a minimum of 30 minutes.<sup>6</sup> After this period they could continue to search or use the computers for other purposes such as writing emails, updating their CV, or applying for jobs. They could stay in our facility for up to two hours. All participants received a compensation of £11 per session attended (corresponding to the government authorized compensation for meal and travel expenses) and we provided an additional £50 clothing voucher for job market attire for participating in 4 sessions in a row.<sup>7</sup>

Participants were asked to register in a dedicated office at the beginning of each session. At the first session, they received a unique username and password and were told to sit at one of the computer desks in the computer laboratory. The computer laboratory was the experimental laboratory located at the School of Economics at the University of Edinburgh with panels separating desks to minimize interactions between job seekers. They received a document describing the study as well as a consent form that we collected before the start of the initial session (the form can be found in the Online Appendix ??). We handed out instructions on how to use the interface, which we also read aloud (the instructions can be found in the Online Appendix ??). We had assistance in the laboratory to answer questions. We clarified that we were unable to provide any specific help for their job search, and explicitly asked them to search as they normally would.

Once they logged in, they were automatically directed to our own job search platform<sup>8</sup> They were first asked to fill in an initial survey. From week 2 onwards, they only had to complete a short weekly survey asking about job search activities and outcomes. For vacancies saved in their search in our facility, we asked about the status (applied, interviewed, job offered). We asked similar questions about their search through other channels than our study.

After completing the survey, the participants were re-directed towards our search engine and could start searching. A timer located on top of the screen indicated how much time they had been searching. Once the 30 minutes were over, they could end the session and obtain a list of all the vacancies they had saved.<sup>9</sup> They could then leave the facilities and receive their weekly compensation.<sup>10</sup> Once participants left the facility, they

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<sup>6</sup>Given that participants spent around 12 hours a week on job search, requiring a minimum of 30 minutes of job search in the lab is unlikely to affect job search behavior.

<sup>7</sup>All forms of compensation effectively consisted of subsidies, i.e. they had no effect on the allowances the job seekers were entitled to. The nature and level of the compensation were discussed with the local job centres to be in accordance with the UK regulations of job seeker allowances.

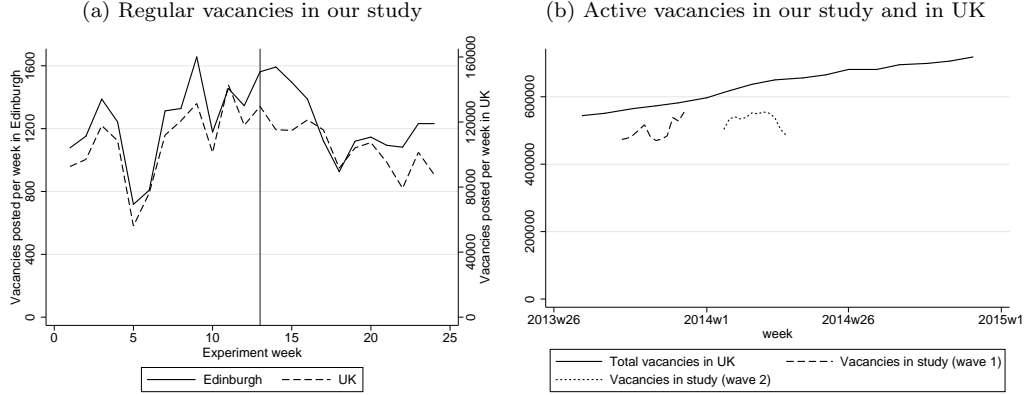
<sup>8</sup>[www.jobsearchstudy.ed.ac.uk](http://www.jobsearchstudy.ed.ac.uk)

<sup>9</sup>We received no additional information about the search activities or search outcomes from the Job-centres. We only received information from the job seekers themselves. This absence of linkage was important to ensure that job seekers did not feel that their search activity in our laboratory was monitored by the employment agency.

<sup>10</sup>Participants were of course allowed to leave at any point in time but they were only eligible to receive



Figure 1: Number of vacancies



could still access our website from home, for example in order to apply for the jobs they had found.

### 3.3 The search interface

We designed a job search engine in collaboration with the computer applications team at the University of Edinburgh. It was designed to replicate the search options available at the most popular search engines in the UK (such as monster.com and Universal Jobmatch), but allowing us to record precise information about how people search for jobs (what criteria they use, how many searches they perform, what vacancies they click on and what vacancies they save), as well as collecting weekly information (via the weekly survey) about outcomes of applications and search activities outside the laboratory.

In order to provide a realistic job search environment, the search engine accesses a local copy of the database of real job vacancies of the government website Universal Jobmatch. This is the largest job search website in the UK in terms of the number of vacancies. This is a crucial aspect in the setup of the study, because results can only be trusted to resemble natural job search if participants use the lab sessions for their actual job search. The large set of available vacancies combined with our carefully designed job search engine assures that the setting was as realistic as possible. Panel (a) of Figure ?? shows the number of vacancies available through our search engine in Edinburgh and in the UK for each week of the study (the vertical line indicates the start of wave 2). Each week there are between 800 and 1600 new vacancies posted in Edinburgh. Furthermore, there is strong correlation between vacancy posting in Edinburgh and the UK. In panel (b) the total number of active vacancies in the UK is shown over the second half of 2013 and 2014.<sup>11</sup> As a comparison the total number of active vacancies in the database used in the study in both waves is shown. It suggests that the database contains over 80% of all

the weekly compensation if they had spent 30 minutes searching for jobs using our search engine.

<sup>11</sup>Panel (b) is based on data from our study and data from the Vacancy Survey of the Office of National Statistics (ONS), dataset ‘‘Claimant Count and Vacancies - Vacancies’’, url: [www.ons.gov.uk/ons/rel/lms/labour-market-statistics/march-2015/table-vacs01.xls](http://www.ons.gov.uk/ons/rel/lms/labour-market-statistics/march-2015/table-vacs01.xls)

Figure 2: Standard search interface

UK vacancies, which is a very extensive coverage compared to other online platforms.<sup>12</sup> It is well-known that not all vacancies on online job search platforms are genuine, so the actual number might be somewhat lower.<sup>13</sup>

Figure ?? shows a screenshot of the main page of the search interface. Participants can search using various criteria (keywords, occupations, location, salary, preferred hours), but do not have to specify all of these. Once they have defined their search criteria, they can press the search button at the bottom of the screen and a list of vacancies fitting their criteria will appear. The information appearing on the listing is the posting date, the title of the job, the company name, the salary (if specified) and the location. They can then click on each individual vacancy to reveal more information. Next, they can either choose to “save the job” (if interested in applying) or “do not save the job” (if not interested). If they choose not to save the job, they are asked to indicate why they are not interested in the job from a list of suggested answers.

As in most job search engines, they can modify their search criteria at any point and launch a new search. Participants had access to their profile and saved vacancies at any point in time outside the laboratory, using their login details.

From week 4 onward, half of the participants were offered to use an “alternative” interface which was designed to investigate how occupational breadth of job search affects job prospects. Since it is not directly related to the research question addressed in this paper, we only briefly describe the “alternative” interface here. An extensive descrip-

<sup>12</sup>For comparison, the largest US jobsearch platform has 35% of the official vacancies; see ?, ? and ?. The size difference might be due to the fact that the UK platform is run by the UK government.

<sup>13</sup> For Universal Jobmatch evidence has been reported on fake vacancies covering 2% of the stock posted by a single account (?) and speculations of higher total numbers of fake jobs circulate (?). Fishing for CV’s and potential scams are common on many sites, including Careerbuilder.com (?) and Craigslist, whose chief executive, Jim Buckmaster, is reported to say that “it is virtually impossible to keep every scam from traversing an Internet site that 50 million people are using each month” (?).

tion as well as an empirical analysis of the impact of the interface can be found in ?. The key goal of the alternative interface was to offer suggestions to job seekers about occupations that might be of interest to them. This was achieved by creating a list of potentially interesting occupations, based on the preferred occupation of the participant. Two methodologies were applied to create this list. First, labor market surveys were used to identify the most common transitions between occupations. Second, occupations that require the same set of skills as the preferred occupation (based on the US based website O\*Net) were suggested. Participants selected which suggestions they found interesting after which a search was performed over all selected occupations. Even though the alternative interface affects individual job search behavior, it is orthogonal to the randomized set up of the artificial vacancies. Therefore it does not affect the empirical analysis.

### 3.4 Artificial vacancies

A small number of artificial vacancies was introduced during the study. Participants were fully informed about this. They were told that “we introduced a number of vacancies (about 2% of the database) for research purposes to learn whether they would find these vacancies attractive and would consider applying to them if they were available”. Participants were asked for consent to this small percentage of research vacancies at the start of the study.<sup>14</sup>

Research vacancies were to be posted only in occupations with many job seekers and many applicants so that rejections to any particular vacancy are the norm rather than a source of major frustration. Survey evidence indicates that most individuals only search a few minutes per day, and by focusing on occupations where this is in the lower end avoids high costs of wasted effort. Many online platforms feature a non-trivial fraction of fictitious jobs, which websites for job search advice openly discuss. Relative to these our intervention would have been small in scale. We elaborate on these considerations in the conclusions.

The artificial vacancies were created and posted on a weekly basis, where the number was determined such that the overall share of artificial vacancies in the stock of vacancy in the Edinburgh area never exceeded 2%. We also checked whether the share of artificial vacancies within all vacancies saved by participants did not exceed 2%, and adjusted the number in subsequent weeks in case it did. The vacancies were added to the database of real vacancies during the days on which lab sessions for participants took place, however in case participants searched from home they could not encounter them. Each artificial vacancy was only active during one particular week, such that participants would never observe them in multiple sessions. In this section we describe the procedure used to create the artificial vacancies and present some statistics on comparability to the set of real vacancies.

#### 3.4.1 Selection procedure and representativeness

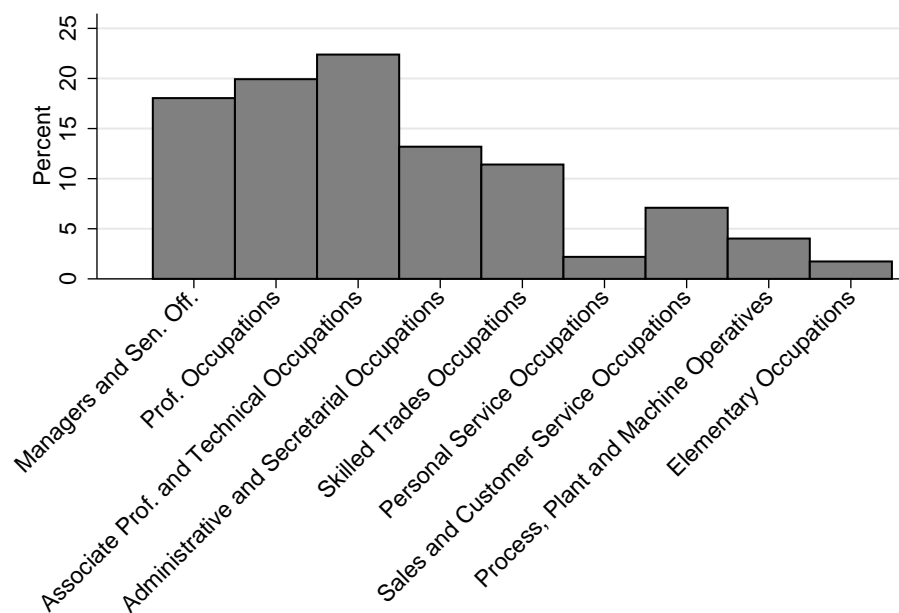
The artificial vacancies were produced in the following manner. We selected an old set of real vacancies that were posted in the UK on Universal Jobmatch during the summer

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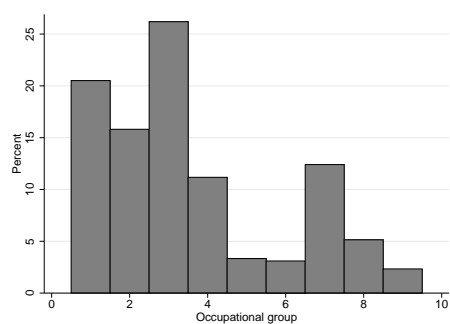
<sup>14</sup>In an exit survey the vast majority of participants (86%) said that this did not affect their search behavior. This is likely due to the very low numbers of artificial vacancies and to the fact that fake advertisements are common in any case to online job search sites (see footnote ??) and that this is mentioned to job seekers in many search guidelines (see e.g. ?).

Figure 3: Occupational distribution of vacancies

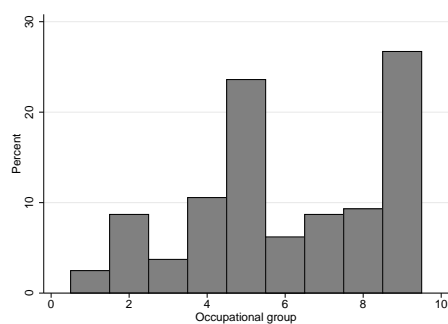
(a) Real vacancies



(b) Real vacancies with posted salary



(c) Artificial vacancies



of 2013, which is several months before our study started. From these we selected all vacancies with a wage indication (either a minimum or a maximum wage or both). No restriction was made on whether these were hourly, weekly, monthly or annual salary indications. From this set of vacancies we selected vacancies to use as templates for the artificial vacancies. One key restriction in this process was that the vacancy would have to be sufficiently compact and general in order to be easily manipulated and remain unidentifiable. This restriction is likely to lead to a selective bias towards lower-skilled vacancies (with less extensive vacancy text etc.). From each selected vacancy we removed all identifying information (company name, contact person, telephone number, website, etc.).<sup>15</sup> Subsequently we randomly changed the location and the salary of the vacancy, the details of this step are described in the next section. First we discuss to what extent the artificial vacancies are representative of real vacancies.

Given the selection procedure for creating the artificial vacancies, these are likely to differ somewhat from the distribution of real vacancies. In order to manipulate the salary, we required the vacancy to post some salary. Approximately 58% of all vacancies on Universal Jobmatch post a salary, and vacancies that post salaries may differ from those that do not.<sup>16</sup> Panel (a) of Figure ?? shows the distribution across occupations, of vacancies that were posted on Universal Jobmatch during the study.<sup>17</sup> The vacancies are classified by the first digit of their UK SOC code. We present the same distribution for the selection of vacancies that post a salary in panel (b) of Figure ?. The distribution of vacancies with posted salaries is quite similar to the overall distribution, with only occupational groups 3 and 7 being more likely to post a salary. The second step in the selection procedure required vacancies to have a ‘simple’ description that allows easy manipulation. To select suitable vacancies, we went through a set of outdated vacancies posted on Universal Jobmatch, and checked one by one whether a vacancy was simple enough to manipulate. Clearly, the vacancies that we selected are not representative of all vacancies posted on Universal Jobmatch. We show the occupational distribution of all artificial vacancies in panel (c) of Figure ?.<sup>18</sup> We oversample vacancies from occupational group 5 (Skilled Trades Occupations) and from groups 9 (Elementary Occupations). This is not surprising as jobs in these categories typically have a shorter description, making them easier to manipulate. Still, there is considerable variation across occupations, as these two categories make up only about 50 % of all artificial vacancies and in each occupational group we have at least some artificial vacancies.

Employers can post an hourly, daily, weekly, monthly or annual wage in their vacancy. Since hourly and annual salaries are most common, we show the distribution of salaries for these two types in Figure ?. Panels (a) and (b) compare annual salaries of real vacancies and artificial vacancies (before manipulating the wage), while panels (c) and (d) do the same for hourly salaries. From both comparisons it is clear that the artificial

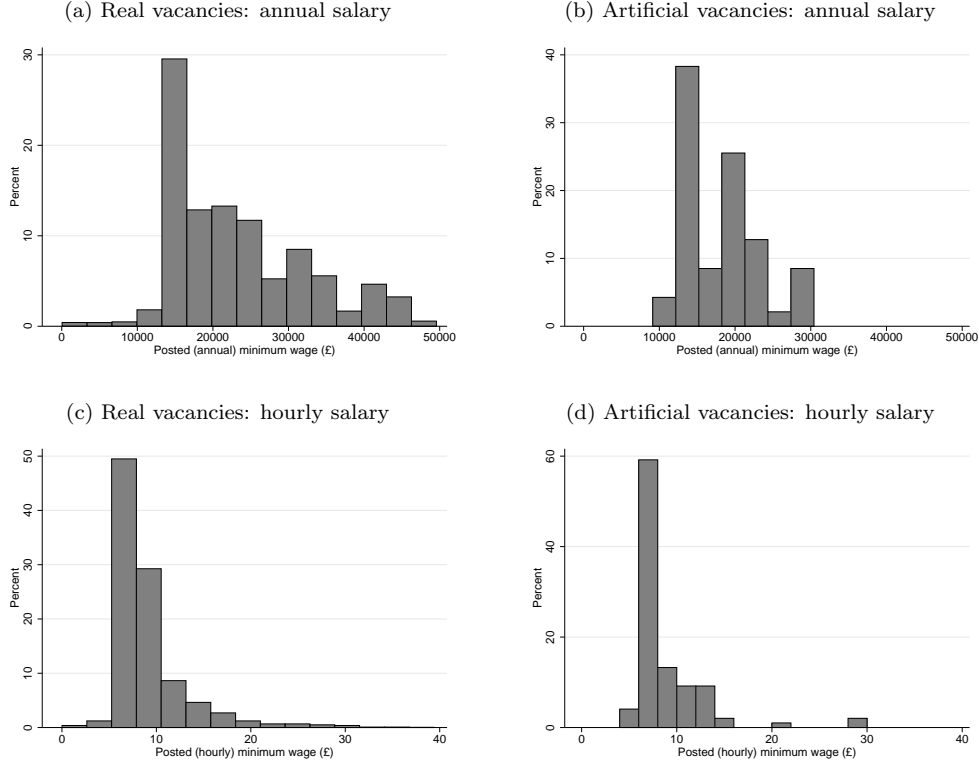
<sup>15</sup>We also made sure that applying to the vacancy would go through an integrated button saying ‘apply now’ (which is quite common on Universal Jobmatch) rather than by directly contacting the company or through a company website.

<sup>16</sup>Note that this share is considerably higher than for example documented by ?, who find that only 20% of vacancies on careerbuilder.com specify wages.

<sup>17</sup>It is based on a sample of 30,000 vacancies posted in the Edinburgh area around the start of the study.

<sup>18</sup>Note that the SOC code of the vacancy is not always ‘correctly’ specified by the employer. To keep the artificial vacancies as close as possible to the real vacancies, we did not correct the codes. The statistics that we present here are however based on corrected codes in order to provide a more precise picture of the type of vacancies that we created.

Figure 4: Distribution of posted salaries



vacancies lack some mass in the tails of the distribution, but other than that they are quite similar.<sup>19</sup>

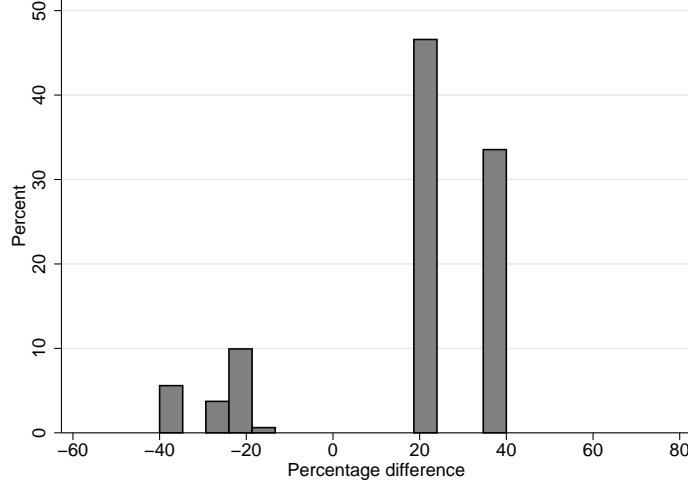
### 3.4.2 Manipulation of wages and locations

Our strategy is to create variation in the posted salary while keeping all other vacancy characteristics constant. We create pairs of vacancies. Both share all key vacancy attributes, and differ only in terms of the posted wage.

This approach is parallel to the randomized audit studies in which pairs of applicant's résumés are sent out with random variation in one particular dimension. To be able to test the implications of directed search directly, we decided to make both vacancies accessible to the same job seeker. This is in contrast to the resume audit studies, where typically employers are only sent one of the resumes from a pair. The other resume is sent to a different employer. We make both vacancies accessible here because that allows us to observe whether job seekers consider both vacancies or only one of them and in case of the latter, which one of the two (s)he chooses to leave out. The use of pairs of artificial vacancies allows to compare the number of applicants within the pair, thereby controlling

<sup>19</sup>Only vacancies with annual salaries up to £50,000 or hourly wages up to £40 are shown in the Figure. This excludes 7.7% (annual wage) and 3.4% (hourly wage) of the vacancies.

Figure 5: Salary difference within the artificial vacancy pairs



for all unobserved characteristics of the vacancy. This greatly improves precision of such an estimate. We rephrase and shuffle around the descriptive text of the vacancies in a pair to make sure it is not obvious that they are the same. See the online appendix ?? for two examples of vacancy pairs. The key point is that the information conveyed by the two vacancies is the same and the change in the posted salary is independent of other vacancy characteristics. Our setup even allows to check whether a particular job seeker sees both vacancies on his/her screen and thus made a conscious decision to save only one of the two.

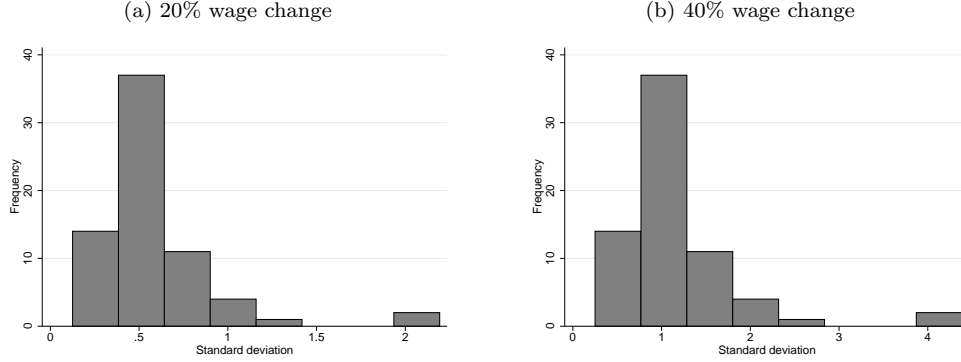
The construction of the artificial vacancy pairs was done in the following manner. We created pairs of vacancies from the same template vacancy, and for both vacancies we changed the location to the Edinburgh area (with a random postal code). One of the two would keep the original salary, the other one would have a lower or higher wage, 20% or 40%.<sup>20</sup> There were two stages of randomization here. First it was randomly decided which vacancy would have a changed salary, second it was randomly decided what the salary change would be. We made sure however, that in case of a salary reduction the new salary would not be below the minimum wage.<sup>21</sup> As a result our sample contains relatively more wage increases among low wage vacancies than among high wage vacancies, while also overall we have more wage increases than decreases. During the second wave of the study, the same set of artificial vacancies was used, however the wage was switched around within the pair. In total, we created 322 vacancies, based on 94 original vacancies.<sup>22</sup>

<sup>20</sup>Note that this is in the same order of magnitude as the wage increase implemented by ?, which is 33 %.

<sup>21</sup>In case the assigned wage decrease resulted in a wage below the minimum wage, we assigned a (random) wage increase instead. We did so to prevent the vacancy from looking suspicious, though the set of real vacancies actually contains posted wages below the minimum wage.

<sup>22</sup>In addition, we created pairs similar to the ones described, with location being the Glasgow area, which is located at about 1.5 hours of commuting time from Edinburgh. Since the willingness of our participants to apply to jobs in the Glasgow area is very small, we have few observations for these pairs

Figure 6: Salary changes in terms of standard deviations across 3-digit occupations



We show the distribution of the difference in the posted salary compared to the salary of the *original* vacancy in Figure ???. The manipulated wages are spread across increases and decreases of 20 % or 40 %, with substantially more increases than decreases.<sup>23</sup>

It is important that the artificial vacancies do not appear suspicious to potential applicants. Therefore the manipulated wages should be reasonable in the sense that they should be within the support of the distribution of wages for the particular occupation. To show that this is the case, we present a measure of wage dispersion at the 3-digit occupational code level. We compute for each 3 digit code the magnitude of a 20 or 40 % wage change in terms of the standard deviation of wages.<sup>24</sup> We find that on average a 20% wage increase or decrease corresponds to 0.44 of a standard deviation, while a 40% wage changes corresponds to 0.88 of a standard deviation. The distribution of these numbers across occupations is shown in Figure ??. For almost all occupations a 20 or 40% change in the wage is not likely to be outside the support of the wage distribution.

At the end of the study we performed a small survey to assess whether participants felt that the artificial vacancies had affected their behavior. When asked whether they were able to distinguish the artificial vacancies from real vacancies, 68% answered ‘never’ or ‘rarely’. Only 4% said they could ‘often’ distinguish them, while 26% answered ‘sometimes’. We also asked whether the existence of the artificial vacancies changed their job search behavior. 86% said that it had no effect, 11% answered to save somewhat more vacancies and 1% saved less vacancies. So overall, it did not seem to have a large effect on job search behavior. In section ??? we show that there is also no indication of any

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and we focus our analysis on the Edinburgh pairs. Furthermore, we also created some “single” vacancies located in either Edinburgh or Glasgow. These were merely created to make sure participants would not be able to “detect” artificial vacancies from the fact that there were two somewhat similar vacancies. Also for these vacancies we randomly changed the salary. Finally, we created pairs of vacancies, where one would be located in the Edinburgh area and one in the Glasgow area. For these pairs, either the salary of the vacancy in Glasgow would be increased by 20, 40 or 60%. All results in this paper are, unless mentioned otherwise, based on “Edinburgh pair” artificial vacancies only. In the appendix we show that including the Glasgow pairs does not change our results.

<sup>23</sup>Initially we only created artificial vacancies with increased wages, while later we decided to also add some decreased wage vacancies. In addition, not all wage decreases were feasible due to the minimum wage lower bound. As a result we have many more wage increases than decreases.

<sup>24</sup>These computations are based on vacancies that post a minimum annual wage above 1000£.



learning among job seekers in terms of identifying artificial vacancies.

## 4 Empirical analysis

We now turn to the empirical analysis. We will focus on our two main research questions: First, do we find evidence that higher wages increase interest in vacancies, all else equal? Second, do we find evidence for the reservation wage property, that is an inherent property of random search models but is violated in directed search models? We will then present an analysis of the complimentary survey on how the vacancies are perceived. Before doing so, we briefly describe the outcome variables we use in the analysis.

### 4.1 Outcome variables

The search process was structured as follows. After specifying search criteria the job seeker observed a list of search results (“listed vacancies”). If a particular vacancy seemed interesting, (s)he could click on the vacancy to view the detailed description of the vacancy (“viewed vacancies”). After reading the details, (s)he could save the vacancy to apply later (“saved vacancies”). In case the vacancy was not interesting (s)he could return to the search results after indicating from a list of options why the vacancy was not interesting. At the end of the session the list of saved vacancies would be shown (which could also be accessed from home by logging in to the system). In case the list contained artificial vacancies (s)he would, at this point, be informed about the nature of these vacancies.

Our main analysis focuses on the decision to save a vacancy. This is a clear signal of interest in the job and the closest proxy of applying to the job as almost one-third of all saved (real) vacancies is eventually applied to.

The distribution of the number of times an artificial vacancy was saved is shown in panel (a) of Figure ???. Of all artificial vacancies, 42% is never saved (134 vacancies), 38% is saved between 1 and 3 times (123 vacancies), and 20% is saved more than 3 times (65 vacancies). The mean number of saves is 1.9. As a robustness check we also present all analysis using the decision to view a vacancy as the outcome. The distribution of the number of times an artificial vacancy was viewed is shown in panel (b) of Figure ???. Of all artificial vacancies, 22% is never viewed (73 vacancies), 50% is viewed between 1 and 5 times (163 vacancies), and 28% is viewed more than 5 times (90 vacancies). The mean number of views is 3.6.<sup>25</sup>

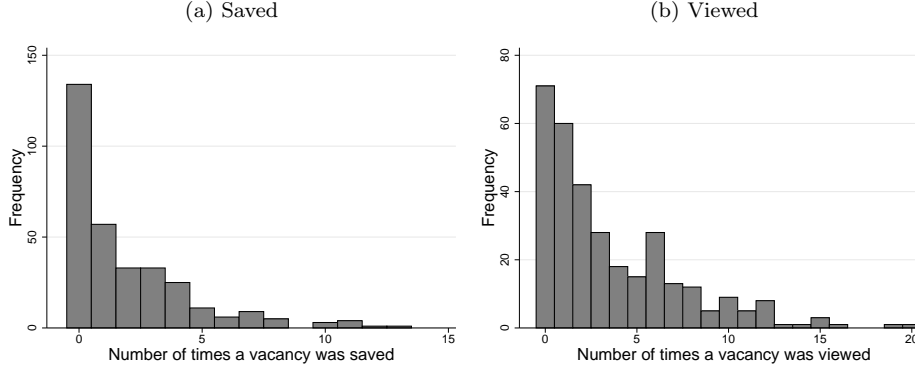
### 4.2 Do higher wages generate more interest in vacancies?

#### *DISCUSSION OF PREDICTIONS; PHILIPP? [MORE ON DIRECTED SEARCH]*

An example where higher wages attract more applicants but search is undirected is the following slight variation on undirected on-the-job search models: Assume that workers encounter wage offers by firms randomly as in ?, but workers only bother to send a formal application if the wage is above their reservation wage. All outcomes are identical to those in ?, but higher wage firms attract more applicants if applicants differ in their utility of leisure.

<sup>25</sup>In the appendix we present statistics for Glasgow vacancies (Figure ??).

Figure 7: Number of times a vacancy was viewed and saved



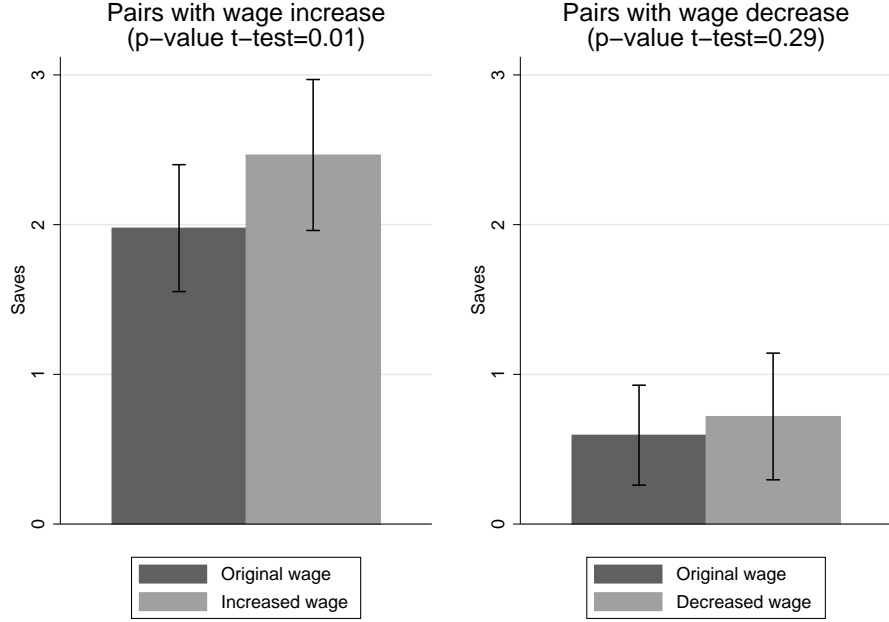
Before turning to our experimental analysis, we shortly report results from a simple analysis of real vacancies that were posted during our study. We observe how often each of these vacancies was saved by participants in the study. Since the number of saves is a count variable, we perform a Poisson regression on the logarithm of the offered wage. We include a subset of all vacancies that fulfills the following requirements: (1) the vacancy is posted in the Edinburgh area, (2) it has a wage announcement (3) the wage is annual.<sup>26</sup> Results are presented in the appendix in Table ?? . We find that a higher wage is associated with significantly less saves (column (1)). The association remains (though with slightly smaller magnitude) when controlling for occupation fixed effects (column (2)). Additional controls for a temporary contract, for part time jobs, for not listing a company name and for the posting month are all highly significant, but hardly change the negative wage coefficient (columns (3)-(6)). When analysing jobs that post an hourly wage, we find a similar negative wage coefficient that is slightly smaller in magnitude (column (6)). Finally, also a simple log-log regression leads to very similar results (column (7)).<sup>27</sup> The significantly negative relation between the wage and the number of interested job seekers is in line with the findings of ? who analyse jobs from Careerbuilder.com (when not controlling for job titles) as well as the results of ?.

Clearly, the posted wage of real vacancies is highly correlated with other characteristics. Therefore, we consider our experimental vacancies, in which we randomly assigned the wage. In Figure ?? we show the mean number of times that the artificial vacancies were saved. In the left panel we include vacancy pairs where the wage was increased for one of two (129 pairs). We compare the mean number of saves for the vacancy with the original wage (left bar) with the mean number of saves for the vacancy with increased wage (right bar) and include a 95 % confidence interval. We find that vacancies with an increased wage attract more saves. A two-sided paired t-test rejects that the means are

<sup>26</sup>The first restriction is to make the analysis comparable to our experimental results. The second restriction removes 54 % of the vacancies as they report no salary. The third restriction is used to prevent a problematic comparison of hourly, daily, weekly, monthly and annual wage announcements. Of all vacancies that report a salary, 54 % reports an annual wage and thus we focus on this category.

<sup>27</sup>When using viewing a vacancy as the outcome (instead of saving a vacancy) we find very similar results, see Table ?? in the appendix.

Figure 8: Mean number of saves (with 95% confidence interval)



Note that the confidence intervals should not be used to visually estimate statistical significance of the estimates, as they do not take the paired structure of the data into account.

equal with a p-value of 0.01. In the right panel we show the same statistics for pairs in which the wage was reduced for one of the two (32 pairs). The mean number of saves is very similar for vacancies with a decreased wage and we cannot reject that the means are equal (p-value=0.29). In Figure ?? in the appendix we show that the results are very similar when using the number of views rather than saves (significant increase for wage increases, no significant difference for wage decreases). It is important to note that the artificial vacancies with wage decreases differ from those with wage increases, because wage decreases were only possible for vacancies with sufficiently high wage. This requirement was absent for wage increases. This difference also explains the different base levels of interest between the left and right panel in Figure ??.<sup>28</sup>

To exploit the variation in the magnitude of the wage changes we perform a regression analysis, in which the number of saves ( $S$ ) is regressed on the percentage change in the wage ( $\Delta w$ ). To exploit the pair structure of the data, we include pair fixed effects ( $\gamma_p$ ):

$$V_{ip} = \alpha + \gamma_p + \beta \Delta w_{ip} + \epsilon_{ip} \quad (1)$$

Vacancies are indexed by subscript  $i$  and vacancy pairs by subscript  $p$ . Since our outcome variable is a count variable, we estimate the model using Poisson regression. As a result the parameter of interest,  $\beta$ , can easily be transformed to measure the percentage effect

<sup>28</sup>In the appendix we show the cumulative distribution of within pair differences in Figure ??.

Table 2: Effect of wage change on number of saves

|                          | Poisson regression |                 |                   |                   |                   | Log-linear regression |                    |
|--------------------------|--------------------|-----------------|-------------------|-------------------|-------------------|-----------------------|--------------------|
|                          | (1)                | (2)             | (3)               | (4)               | (5)               | (6)                   | (7)                |
| Salary difference (in %) | 0.70**<br>(0.44)   | 0.69*<br>(0.45) | 0.92***<br>(0.43) |                   |                   | 0.54**<br>(0.25)      |                    |
| Salary dif.*increases    |                    |                 |                   | 0.96***<br>(0.45) |                   |                       | 0.68**<br>(0.30)   |
| Salary dif.*decreases    |                    |                 |                   | 0.24<br>(0.74)    |                   |                       | -0.12<br>(0.46)    |
| Sal. dif.*low*increases  |                    |                 |                   |                   | 1.21***<br>(0.61) |                       |                    |
| Sal. dif.*high*increases |                    |                 |                   |                   | 0.31<br>(0.46)    |                       |                    |
| Sal. dif.*high*decreases |                    |                 |                   |                   | 0.23<br>(0.74)    |                       |                    |
| Appearing first          |                    |                 | 0.58***<br>(0.13) | 0.57***<br>(0.13) | 0.56***<br>(0.13) | 0.48***<br>(0.085)    | 0.48***<br>(0.084) |
| Pair fixed effects       | yes                | yes             | yes               | yes               | yes               | yes                   | yes                |
| Postal code f.e.         | no                 | yes             | yes               | yes               | yes               | yes                   | yes                |
| N                        | 240                | 240             | 240               | 240               | 240               | 322                   | 322                |

\*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ . Clustered standard errors (by pair) in parentheses. Columns (1)-(5) are Poisson model where  $\exp(\beta) - 1$  is reported (which is the percentage effect). Columns (6)-(7) are log-linear models where the independent variable is  $\log(\text{views}+0.1)$

of a one percent increase in salary on the number of saves, which is the wage elasticity. Note that most of the artificial vacancies were used twice: in the first and in the second wave. This implies that each pair typically has four artificial vacancies, where two have the original salary and the other two have the same altered wage.<sup>29</sup> To correct for the correlation between these four vacancies, we cluster standard errors at the pair level.<sup>30</sup> As an extension to this simple specification we also add additional controls for the geographical location of the job and for the posting order.

Estimation results are presented in Table ???. We report  $\exp(\beta) - 1$ , which is the percentage change in saves due to a 1-percent increase in the wage (the elasticity). In

<sup>29</sup>Due to the restriction on the number of artificial vacancies, we posted somewhat less vacancies during the second wave. As a result not all artificial vacancies were used twice.

<sup>30</sup>The fact that each job seeker in the study might save vacancies from different pairs can create correlation between the pairs. There is no straightforward way to correct for this, but one approach is to group vacancies that are 'similar' and thus are likely to be of interest to the same job seekers and cluster standard errors at this group level. We use the two-digit occupational code (SOC) of the vacancies to do so. However, standard errors clustered at this level are actually smaller, and thus we prefer to be conservative and do not report these results.

Table 3: Effect of wage change on number of views

|                          | Poisson regression |                  |                    |                    | Log-linear regression |                    |                    |
|--------------------------|--------------------|------------------|--------------------|--------------------|-----------------------|--------------------|--------------------|
|                          | (1)                | (2)              | (3)                | (4)                | (5)                   | (6)                | (7)                |
| Salary difference (in %) | 0.70**<br>(0.35)   | 0.71**<br>(0.36) | 0.86***<br>(0.29)  |                    |                       | 0.62**<br>(0.26)   |                    |
| Salary dif.*increases    |                    |                  |                    | 0.82***<br>(0.29)  |                       |                    | 0.48*<br>(0.27)    |
| Salary dif.*decreases    |                    |                  |                    | 1.84*<br>(1.62)    |                       |                    | 1.27*<br>(0.67)    |
| Sal. dif.*low*increases  |                    |                  |                    |                    | 0.88***<br>(0.35)     |                    |                    |
| Sal. dif.*high*increases |                    |                  |                    |                    | 0.63*<br>(0.47)       |                    |                    |
| Sal. dif.*high*decreases |                    |                  |                    |                    | 1.84*<br>(1.62)       |                    |                    |
| Appearing first          |                    |                  | 0.50***<br>(0.075) | 0.50***<br>(0.076) | 0.50***<br>(0.075)    | 0.49***<br>(0.088) | 0.49***<br>(0.088) |
| Pair fixed effects       | yes                | yes              | yes                | yes                | yes                   | yes                | yes                |
| Postal code f.e.         | no                 | yes              | yes                | yes                | yes                   | yes                | yes                |
| N                        | 304                | 304              | 304                | 304                | 304                   | 322                | 322                |

\*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ . Clustered standard errors (by pair) in parentheses. Columns (1)-(5) are Poisson model where  $\exp(\beta) - 1$  is reported (which is the percentage effect). Columns (6)-(7) are log-linear models where the independent variable is  $\log(\text{views}+0.1)$

column (1) we find a highly significant positive elasticity of 0.70. Postal codes were varied within pairs of vacancies to make sure the pair was not identifiable. The postal codes were assigned independently of the wage variation. In column (2) we add fixed effects for the outward code (the first three or four digits of the postal code). There are 14 of such areas in our dataset for which we have sufficient observations to include a fixed effect. As expected, we find that including these fixed effects does not influence the estimate for the salary difference coefficient. In column (3) we additionally include a dummy equal to one for vacancies that appeared first in the search results due to having the later posting date within the pair. The difference in posting date was never more than a few days, but we find that it has a significant impact on the number of views. The posting dates were assigned independent of the wage, and as expected we find that the wage coefficient only changes slightly. In column (4) we interact the salary difference with a dummy for the pair having a wage increase or a decrease. Thus, we estimate different elasticities based on the sample of increases and the sample of decreases. We find that significant wage effect appears only among the vacancy-pairs with a wage increase, while the estimate is small and insignificant for wage decreases. This is likely to be due to a selective sample

of vacancies for which the wage could be reduced. To investigate the difference further, we interact the salary difference with three groups in column (5). First, the pairs of vacancies for which the original wage was low, such that a wage decrease would move it below the minimum wage. For this group all wage changes are increases. Second, the pairs of vacancies for which the wage was increased, but the original wage was high enough such that a wage reduction would have been possible. Third, the pairs of vacancies for which the wage was decreased, and thus also these vacancies have a high original wage. The results show that we only find a significant wage effect among the pairs with a low original wage. Thus, the fact that we find little effect among wage decreases seems to be caused by the fact that these are all high-wage vacancies, and the wage effect is less pronounced (or even absent) among high wage vacancies.

As an alternative to the Poisson model, we can estimate a log-linear model where the dependent variable is the logarithm of the number of saves. While we prefer the Poisson specification, we present results from this approach in columns (6) and (7), for the sake of comparison. To handle vacancies that were never saved we use  $\log(\text{saves}+0.1)$ .<sup>31</sup> The results are very similar. We find a significantly positive wage effect that is slightly smaller in magnitude compared to the Poisson model.

Rather than using saving a vacancy as the outcome variable, we can also consider viewing a vacancy (which is clicking on the vacancy appearing in the listing to view detailed information). The results are presented in Table ?? and are very similar. The estimated wage elasticity is statistically significant and around 0.7 - 0.9 depending on the exact specification. A slight difference is that when considering the wage-decrease pairs we do find a wage effect on the number of views.<sup>32</sup>

Our findings for the elasticity are very similar to the results of ?, who report that a 33 % increase in wages offered by local governments in Mexico led to a 26 % increase in applications (which implies an elasticity of 0.79). They are also close to the findings of ?, who report that (when controlling for job titles) a 10 % increase in wage is associated with a 7.4 % increase in applications.

### 4.3 Is the reservation wage property satisfied?

The second part of the empirical analysis will focus on whether the reservation wage property, *which is that if a job seeker sees both vacancies and shows interest in the low wage vacancy, he should also be interested in the high wage vacancy*. This is an inherent feature of random search models but is violated in directed search models, holds in this context. To do this, we focus on individuals' decisions regarding vacancies from the same pair. Again, we proxy applications by looking at saves and views.

We first document a number of statistics relating to the relationship between saving one or both of the vacancies in a pair. First, we will show the probability of not saving

<sup>31</sup>We prefer the Poisson model, as it has been argued to have several advantages over log-linear regressions (e.g. ? and ?). For example, the log-linear regression requires adding a constant to the outcome to handle zeros. We add a constant equal to 0.1, but find that results are rather sensitive to the choice of this constant (see discussion in the appendix ??).

<sup>32</sup>In Tables ?? and ?? in the appendix we show that the results are almost identical when also Glasgow pairs are included in the analysis.

the high-wage vacancy, conditional on saving the low wage vacancy and vice versa:

$$P(S_h = 0 | S_l = 1) \quad (2)$$

$$P(S_l = 0 | S_h = 1) \quad (3)$$

Where  $S_l = 1$  if the low wage vacancy in a pair was saved, and similar for  $S_h$ . These probabilities are shown in column (1) of Table ??, in the first and second row. The number of observations are given in brackets. We find that out of all individuals that save the low wage vacancy in a pair, 42% does not save the high wage vacancy. The reverse probability, not saving the low wage vacancy when the high wage vacancy is saved, is 49%. If the reservation wage property holds, one would expect none of the individuals that save the low-wage vacancy to not also save the high wage vacancy.

One may worry that these probabilities do not fully represent conscious decisions of job seekers. For example, due to a large number of search results one of the vacancies in the pair may not appear on the first screen of results. If the job seeker does not continue browsing to the next page (s)he may simply not observe the second vacancy.<sup>33</sup> The advantage of our experimental setup is that we can observe which vacancies a job seeker has 'listed' on their screen. So we can compute the above probabilities conditional on listing both vacancies:

$$P(S_h = 0 | S_l = 1, L_l = 1, L_h = 1) \quad (4)$$

$$P(S_l = 0 | S_h = 1, L_l = 1, L_h = 1) \quad (5)$$

These probabilities are listed in the column (2) of Table ?. We find that the conditional probabilities of not saving one of the two are only slightly lower for individuals that have listed both. Still in 39% of the cases that an individual saves the low wage vacancy, (s)he does not save the high wage vacancy. Note however from the almost identical number of observations, that almost all participants that save one of the two vacancies have listed both vacancies.

#### 4.3.1 Alternative explanations

We would like to exclude as much as possible that the decision to only save one of the two vacancies is caused by other factors than the wage itself. We propose here a number of tests to exclude possible alternative explanations. First, we control for the timing of posting of the vacancy. Second, we exclude individuals that save an artificial vacancy, then view the second vacancy in the pair and do not save it indicating "it is posted twice/already viewed" as the reason for not saving. Third, we exclude individuals that responded in an exit survey that they sometimes, often or always could identify artificial vacancies. Fourth, we exclude vacancy pairs for which the geographical distance within the pair was more than 1 kilometer. Finally, we discuss possible learning effects among participants.

**Timing of the vacancy** A first factor that could explain why job seekers do not save both vacancies is the timing at which the vacancies were posted. In order to make the

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<sup>33</sup>If, on the other hand, it occurs because one of the two vacancies does not fulfill the search criteria imposed by the job seeker, it is less of worry. In that case the choice as to save one of the two can be regarded as simply revealing preferences.

Table 4: Saving and viewing probabilities

|  |            | conditional on listing both |                              |                             |
|--|------------|-----------------------------|------------------------------|-----------------------------|
|  |            |                             | high wage<br>appearing first | low wage<br>appearing first |
|  | (1)        | (2)                         | (3)                          | (4)                         |
| Saving   |            |                             |                              |                             |
| $P(S_h = 0 S_l = 1)$                               | 0.42 (278) | 0.39 (267)                  | 0.16 (97)                    | 0.54 (170)                  |
| $P(S_l = 0 S_h = 1)$                               | 0.49 (337) | 0.48 (318)                  | 0.61 (185)                   | 0.36 (133)                  |
| P-value test for<br>equal proportions <sup>a</sup> | 0.08       | 0.03                        | 0.00 <sup>b</sup>            | 0.18 <sup>b</sup>           |
| Viewing  |            |                             |                              |                             |
| $P(V_h = 0 V_l = 1)$                               | 0.38 (520) | 0.36 (500)                  | 0.21 (200)                   | 0.50 (300)                  |
| $P(V_l = 0 V_h = 1)$                               | 0.47 (623) | 0.45 (590)                  | 0.55 (344)                   | 0.34 (246)                  |
| P-value test for<br>equal proportions <sup>a</sup> | 0.00       | 0.00                        | 0.00 <sup>b</sup>            | 0.20 <sup>b</sup>           |

Number of observations in brackets. All of the reported fractions in this table are significantly different from zero with  $p\text{-value} < 0.001$ . <sup>a</sup> P-values from testing  $P(S_h = 0|S_l = 1) = P(S_l = 0|S_h = 1)$  and similar for viewing (both are two-sided tests). <sup>b</sup> Note that these are tests for cross probabilities (for column (3)  $H_0: 0.16=0.36$  and for column (4)  $H_0: 0.54=0.61$ ) and similar for viewing (for column (3)  $H_0: 0.21=0.34$  and for column (4)  $H_0: 0.50=0.55$ )

artificial vacancies less suspicious, the posting dates within the pair were varied slightly. The difference was never more than 2 days. Since by default search results were ordered by posting date, this prevented the two vacancies from appearing directly below each other. One may worry that job seekers start at the top of the list when scanning vacancies, and therefore the ones that appear lower on the list are not saved simply because the individual does not reach that part of the list. This reasoning is supported by the robust finding in section ?? that the latest posted vacancy in the pair receives more attention.

To address this concern, we compute probabilities similar to (??) and (??), but condition on which vacancy was posted first. Remember that posting dates were assigned at random, and are therefore independent of the wage. The results are presented in columns (3) and (4) of Table ??. We find that, as expected, the likelihood of saving increases when the vacancy appears first (due to being posted more recently). For those that save the low wage vacancy while the high wage one appears first, 16 % does not save the high one. This percentage is considerably lower than the 39 % in column (2), however it is still a non-trivial share. The reverse probability (not saving the low one when one saves the high one and the low one appear first) is 36 % (column (4)).

We perform two tests to assess the statistical significance of these probabilities. First, we test whether these probabilities of not saving are significantly different from zero. A one-sample proportion test for each of the saving probabilities shows that each of these is highly significantly different from zero ( $p\text{-value}$  always smaller than 0.001). Second, we test for differences between saving the high and low wage vacancies. In particular,



we test whether  $P(S_h = 0|S_l = 1) = P(S_l = 0|S_h = 1)$ . Using a two-sample proportion test we find that the unconditional probabilities (column (1)) are significantly different (p-value=0.08). Also the probabilities conditional on listing both (column (2)) are significantly different (p-value<0.03). When conditioning on the posting order, we find that the probability of not saving the high one when the low one appears first (0.54) is not significantly different from the reverse probability (0.61) (p-value=0.18). However, the probability of not saving the high one when the high one appears first (0.16) is significantly different from the reverse probability (0.36) (p-value<0.01). Overall, these findings are in line with the results in subsection ???: a higher wage significantly increases the interest expressed by job seekers.

We can compute similar probabilities for viewing vacancies. These probabilities are reported on the third and fourth row of Table ??. The probability of not viewing a high wage vacancy when one has viewed the low wage vacancy is 0.38. If, in addition, the high wage vacancy appears first on the list, this probability becomes 0.21. All of these are quite close to the corresponding saving probabilities, and lead to the same conclusion: higher wages attract more interest, but a non-trivial share of job seekers is only interested in the low-wage vacancy.

**Posted twice/already viewed** One may worry about individuals that save an artificial vacancy, then view the second vacancy in the pair and do not save it indicating “it is posted twice/already viewed” as the reason for not saving. These individuals may have either identified the artificial pair or simply believe they already saw the second vacancy since it closely resembles the first one. We have some evidence that this is the case from the responses after not saving a viewed vacancy. A significantly larger share indicates “Already viewed/job listed twice” as a reason to not save a vacancy, when they have already viewed the other artificial vacancy in the pair.

In either case it provides an explanation for not saving the second one, which has nothing to do with the wage and is therefore different from the hypothesis we are testing. Note however that this can affect the saving decision, but not the viewing decision. To investigate whether these events drive our results, we remove all the viewings and savings of this type from our data. This implies removing 37 pair-viewings, or 74 vacancy-viewings (out of a total of 1145 vacancy-viewings). The new probabilities are presented in Table ??, which has the same structure as Table ??. We find that removing the 74 observations has very little effect on the probabilities: the non-saving probabilities decrease slightly (row 1), while the non-viewing probabilities increase slightly (row 3).<sup>34</sup> We conclude that the small number of cases in which participants suspect the pair to be the same vacancy does not drive the result that a non-trivial share of job seekers is interested in the low wage vacancy but not in the high wage vacancy.

**Identifying artificial vacancies** At the end of the study we performed a short exit survey, asking participants whether they felt they could identify the artificial vacancies. The responses were: ‘Never’ (48%), ‘Rarely’ (20%) ‘Sometimes’ (28%) ‘Often’ (6%) ‘Always’ (1%). Participants that (believe they) can identify the artificial vacancies might

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<sup>34</sup>This is as expected: we removed observations in which both vacancies were viewed, such that the probability of only viewing one of the two must increase. On the other hand, in the removed observations only one of the two vacancies was saved, such that the probabilities of saving only one of the two must decrease.

Table 5: Saving and viewing probabilities excluding participants that indicate “it is posted twice/already viewed” after having saved the first vacancy

|                      | conditional on listing both |            |                              |                             |
|----------------------|-----------------------------|------------|------------------------------|-----------------------------|
|                      |                             |            | high wage<br>appearing first | low wage<br>appearing first |
|                      | (1)                         | (2)        | (3)                          | (4)                         |
| $P(S_h = 0 S_l = 1)$ | 0.38 (263)                  | 0.35 (252) | 0.15 (96)                    | 0.49 (156)                  |
| $P(S_l = 0 S_h = 1)$ | 0.46 (315)                  | 0.45 (296) | 0.56 (169)                   | 0.34 (127)                  |
| $P(V_h = 0 V_l = 1)$ | 0.40 (483)                  | 0.38 (463) | 0.22 (183)                   | 0.53 (280)                  |
| $P(V_l = 0 V_h = 1)$ | 0.50 (586)                  | 0.48 (553) | 0.58 (327)                   | 0.37 (226)                  |

Number of observations in brackets

Table 6: Saving and viewing probabilities including only participants that respond in exit survey that they could never or rarely identify artificial vacancies

|                      | conditional on listing both |            |                              |                             |
|----------------------|-----------------------------|------------|------------------------------|-----------------------------|
|                      |                             |            | high wage<br>appearing first | low wage<br>appearing first |
|                      | (1)                         | (2)        | (3)                          | (4)                         |
| $P(S_h = 0 S_l = 1)$ | 0.36 (120)                  | 0.34 (116) | 0.06 (34)                    | 0.52 (82)                   |
| $P(S_l = 0 S_h = 1)$ | 0.51 (148)                  | 0.48 (139) | 0.57 (76)                    | 0.37 (63)                   |
| $P(V_h = 0 V_l = 1)$ | 0.38 (226)                  | 0.36 (218) | 0.16 (73)                    | 0.52 (145)                  |
| $P(V_l = 0 V_h = 1)$ | 0.49 (263)                  | 0.45 (246) | 0.53 (129)                   | 0.36 (117)                  |

Number of observations in brackets

change their behavior accordingly. To assess whether this is the case we redo our analysis including only those that responded ‘Never’ or ‘Rarely’.<sup>35</sup> This implies dropping 654 vacancies viewings, or 57% of the observations. The resulting viewing and saving probabilities are presented in Table ?? . The probabilities of not saving or viewing the high wage one (rows 1 and 3) are slightly lower. Only the probability of not saving the high one when it appeared higher is reduced quite a bit, to 0.06 (but this figure is based on a very small sample).

**Geographical distance within a pair** We attribute differences in interest for the vacancies within a pair to the wage differences. However, within a pair, the location was varied slightly in order to make sure the two vacancies would not appear to be the same. In some cases this implied only a small difference in geographical location, however in other cases the difference can be larger. Both are however always posted in Edinburgh. Based on the ‘outward code’ (the first three or four digits of the post code), we compute

<sup>35</sup>Note that since the exit survey was performed after the last session, we only have responses for those who participated in the final session (about 50%). Therefore we also drop all participants that did not complete the final survey.

Table 7: Saving and viewing probabilities including only pairs with a geographical distance below 1 kilometer

|                      |            | conditional on listing both |                 |                 |
|----------------------|------------|-----------------------------|-----------------|-----------------|
|                      |            |                             | high wage       | low wage        |
|                      |            |                             | appearing first | appearing first |
|                      | (1)        | (2)                         | (3)             | (4)             |
| $P(S_h = 0 S_l = 1)$ | 0.46 (139) | 0.43 (135)                  | 0.14 (41)       | 0.61 (94)       |
| $P(S_l = 0 S_h = 1)$ | 0.52 (171) | 0.51 (158)                  | 0.65 (90)       | 0.35 (68)       |
| $P(V_h = 0 V_l = 1)$ | 0.35 (264) | 0.33 (256)                  | 0.23 (96)       | 0.43 (160)      |
| $P(V_l = 0 V_h = 1)$ | 0.46 (327) | 0.44 (306)                  | 0.55 (176)      | 0.32 (130)      |

Number of observations in brackets

the geographical distance between the two vacancies in the pair. In case this distance is small, it is unlikely to cause a difference in job seekers' interest. We find that for 50% of the Edinburgh pairs the distance between the two vacancies is at most 1 kilometer, while for the other 50% the distance varies from 2 to 12 kilometers.<sup>36</sup> As a robustness check we perform the empirical analysis including only the 50% vacancy pairs for which the distance is less than 1 kilometer. Results are presented in Table ???. Again we find that our main results persist among pairs with little geographical distance. The probabilities are almost identical to those using the entire sample of vacancies.

**Learning** A potential concern in our experimental design is learning among participants. Perhaps participants become more aware of artificial vacancies over the 12 weeks, or they become better at identifying the artificial vacancies. Such a learning process could be especially strong among those that encounter (several) artificial vacancies in the first weeks. To investigate whether learning occurs, we split the observations into three 4-week periods and check whether our empirical results differ between these periods. Both the number of participants and the number of fake vacancies decreased slightly over the 12 weeks, such that absolute numbers are uninformative. Alternatively we compute the ratio of savings per viewing. The mean of this ratio is 0.49 in period 1 (weeks 1-4), 0.41 in period 2 (weeks 5-8) and 0.59 in period 3 (weeks 9-12). Two-sided t-tests for equality show that the difference between the first and second period is not significant (p-value 0.12), while the difference between period 2 and 3 is significant (p-value<0.01). The difference between period 1 and 3 is borderline significant (p-value 0.09). Even though these results suggest differences between the periods, there is no monotone trend and the saving rate is actually highest in the last period. Such a pattern is difficult to reconcile with any plausible learning story. Rather we attribute it to differences in the pool of artificial vacancies and differences in the pool of participants (due to attrition). Furthermore, we have shown in subsection ??? that only including individuals that indicated they were unable to identify artificial vacancies makes little difference for the results.

<sup>36</sup>Note that these are straight-line differences and the corresponding travel distances will be somewhat larger.

Table 8: Wilcoxon paired signed-rank test comparing

|                         | High wage<br>response<br>higher | Low wage<br>response<br>higher | Equal<br>response | p-value | Obs. |
|-------------------------|---------------------------------|--------------------------------|-------------------|---------|------|
| Q1 (Required quality)   | 379                             | 211                            | 620               | <0.001  | 1210 |
| Q2 (Competition)        | 479                             | 230                            | 501               | <0.001  | 1210 |
| Q3 (Working conditions) | 374                             | 221                            | 615               | <0.001  | 1210 |

#### 4.3.2 Perceptions about competition and working conditions

Our results suggest that some job seekers show more interest in a low-wage job than in a high-wage job, when all other characteristics are equal. This result can be due to higher expected competition for the job at the high wage vacancy, as directed search models predict. However, the higher wage might also be interpreted as a signal of worse working conditions. If job seekers assume that higher wages are only offered to compensate for differences in working conditions, it is rational (for some) to prefer the low wage job.

To investigate whether this is the case, we designed and conducted an online survey. Participants were recruited through the behavioural lab of the University of Edinburgh, using the non-student pool. They received a £20 internet voucher in return for completing the survey. To incentivize truthful answers as well as sufficient effort, we offered an additional £20 voucher to the participant in each vacancy set whose answers were closest to the average response. The resulting sample of participants has an average age of 31 (with a range from 19 to 62), 74% is employed (parttime or fulltime), 14% is unemployed and looking for work and 6% is self employed. Of all participants, 56% indicates to be currently looking for work (even if employed). The participants included more women (68%) than men (32%). Ideally one would have collected such data on a similar sample as the one used in the field experiment and among job seekers in particular. Since recruiting job seekers is in itself an ambitious and difficult enterprise, we opted for the more convenient non-student subject pool of the laboratory of the University of Edinburgh. *We do however have a significant share of unemployed in the sample and find that their average ratings correlate well with those of other participants — PAUL: Can we say something about that (Cronbach’s alpha etc.).* **There are only 17 unemployed in the sample, thus often 1 observation per vacancy, sometimes even 0.. Thus this is difficult. I checked and the statistics from Table 8 are similar when only including unemployed respondents, but they are not statistically significant then. I am not sure if mentioning this makes our case stronger.**

Each survey participant is presented with a random set of 20 of our artificial vacancies, with 3 questions about each vacancy. The questions are as follows:

1. Given the skill and experience requirements described in the job announcement (if any), how good would you expect an applicant needs to be in order to be considered for this job?
2. For someone with the skill and experience requirements described in the job announcement (if any), how much competition would you expect for this job relative to other jobs in the same profession and area?

3. For someone with the skill and experience requirements described in the job announcement (if any), how would you expect the overall (non-monetary) working conditions of this job to be? Examples of non-monetary working conditions are working hours, career prospects, demands associated with the job, health and safety, etc.

Questions (1) and (2) directly relate to directed search models, which predict that higher wage vacancies should attract more interest and from better workers. Question (3) relates to the theory of compensating differentials.

Each question was multiple choice with five options: (1) Very much above average; (2) Above average; (3) Average; (4) Below average; (5) Very much below average. For the complete survey questions see the online appendix ???. Each artificial vacancy was presented to at least 5 participants. The 20 vacancies that each participant was presented with, always consisted of 10 pairs of vacancies, such that we can observe within-individual variation in the answers about the two vacancies that only differ in salary. The different sets of 20 vacancies were fixed, but the order in which the vacancies were shown within a set was randomized for each participant. A total of 121 participants took part in the survey, and we have between 5 and 9 responses for each vacancy.

Since the responses are ordinal, and each participant assessed both vacancies in a pair, we test for differences between high and low wage vacancies using the Wilcoxon signed rank test. Results are presented in Table ??. For all three questions, the responses are significantly higher for the high-wage vacancies. This implies that vacancies with a higher wage (but the same in all other respects) are perceived to (1) require applicants to be of higher quality, (2) attract more competition for the job and (3) have better non-monetary working conditions. These findings are in line with a directed search interpretation of our empirical findings: the high wage job is more attractive (both in monetary and non-monetary conditions), but is expected to attract more applicants (and require better applicants) and will thus be harder to get. These results also reject the alternative hypothesis that high wages compensate for worse working conditions (compensating differentials), which would have led to a reverse result on question 3. Thus, the survey results suggest that lack of interest in high-wage vacancies should be caused by higher expected competition for the job.<sup>37</sup>

Next, we investigate whether the differences in perceptions about vacancies influence our positive wage elasticity estimate. To do so, we compute the average responses across participants for each vacancy, using linear values ranging 1-5 for the response choices (where a higher number means a “higher” response). Before averaging across participants, we standardize each response by subtracting the participant’s mean response to the question, and dividing by the standard deviation of the participant’s responses to the question. We do so to correct for heterogeneity across survey participants. Next, we include the mean standardized responses as control variables when regressing log-saved on the salary difference (with a specification equal to that used in section ??). Our hypothesis is as follows. Higher wages are perceived to signal (1) higher required quality, (2)

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<sup>37</sup>To assess the quality of the measurements of perceptions about the vacancies, we compute Cronbach’s alpha for each set of individuals that judge the same 20 vacancies. There are 16 of such sets. The distribution of the 16 values is presented in the appendix in panel (a) of Figure ??. We find that 12 of the alpha’s are above 0.7 and 15 are above 0.6, suggesting high agreement of the different measures. Computing the alpha’s separately for the three questions (panels (b)-(d) in Figure ??), we find that agreement is particularly high for question 1 and 3, while somewhat lower for question 2.

Table 9: Effect of salary on saves, controlling for perceptions

|                                      | (1)               | (2)               | (3)               | (4)               | (5)               |
|--------------------------------------|-------------------|-------------------|-------------------|-------------------|-------------------|
| Salary difference                    | 0.92***<br>(0.43) | 0.74*<br>(0.58)   | 0.85**<br>(0.47)  | 0.99**<br>(0.65)  | 0.53<br>(0.41)    |
| Q1 (quality) standardized            |                   | -0.053<br>(0.18)  | 0.068<br>(0.20)   |                   |                   |
| Q2 (competition) standardized        |                   | -0.087<br>(0.15)  |                   | -0.021<br>(0.16)  |                   |
| Q3 (working conditions) standardized |                   | 0.35*<br>(0.22)   |                   |                   | 0.29*<br>(0.19)   |
| Appearing first                      | 0.58***<br>(0.13) | 0.59***<br>(0.13) | 0.58***<br>(0.13) | 0.58***<br>(0.13) | 0.58***<br>(0.13) |
| Pair fe                              | yes               | yes               | yes               | yes               | yes               |
| Postal code fe                       | yes               | yes               | yes               | yes               | yes               |
| N                                    | 240               | 240               | 240               | 240               | 240               |

\*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ . Clustered standard errors (by pair) in parentheses. All columns are Poisson model regressions where  $\exp(\beta) - 1$  is reported (which is the percentage effect).

Table 10: Effect of salary on views, controlling for perceptions

|                                      | (1)                | (2)                | (3)                | (4)                | (5)                |
|--------------------------------------|--------------------|--------------------|--------------------|--------------------|--------------------|
| Salary difference                    | 0.86***<br>(0.29)  | 0.74**<br>(0.37)   | 0.63**<br>(0.31)   | 1.10***<br>(0.45)  | 0.47**<br>(0.29)   |
| Q1 (quality) standardized            |                    | 0.13<br>(0.17)     | 0.22<br>(0.18)     |                    |                    |
| Q2 (competition) standardized        |                    | -0.16<br>(0.098)   |                    | -0.076<br>(0.11)   |                    |
| Q3 (working conditions) standardized |                    | 0.30**<br>(0.14)   |                    |                    | 0.28**<br>(0.13)   |
| Appearing first                      | 0.50***<br>(0.075) | 0.50***<br>(0.075) | 0.49***<br>(0.078) | 0.51***<br>(0.075) | 0.49***<br>(0.075) |
| Pair fe                              | yes                | yes                | yes                | yes                | yes                |
| Postal code fe                       | yes                | yes                | yes                | yes                | yes                |
| N                                    | 304                | 304                | 304                | 304                | 304                |

\*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ . Clustered standard errors (by pair) in parentheses. All columns are Poisson model regressions where  $\exp(\beta) - 1$  is reported (which is the percentage effect).

higher competition for the job and (3) better working conditions. The first and second make the high-wage vacancy less attractive to apply to, while the third makes the vacancy more attractive. Thus, we would expect the first two to have a negative impact on the number of saves/views *and* controlling for these should lead to a higher salary coefficient. The third perception (working conditions) should have a positive coefficient and lead to a reduced salary coefficient.

The regression results are presented in Table ?? . In column (2) we find that only the perception about working conditions is significant and positive. The quality (question 1) and competition (question 2) perceptions have, as expected, a negative coefficient, but are not statistically significant. In columns (3)-(5) we include the perceptions one by one to see how they affect the salary coefficient. In line with our hypothesis, the competition question leads to a higher salary coefficient and the working condition question leads to a smaller salary coefficient. The perception about quality does not however affect the salary coefficient in the direction as expected.

We perform the same exercise with the number of views (instead of saves) and present results in Table ?? and get very similar results. Competition has a negative coefficient and controlling for it leads to an increase in the salary coefficient, while the opposite holds for working conditions. However, perceived required quality (question 1) is again not in line with the hypothesis.

An alternative is to look at the conditional probabilities that we analyzed in section ?? . Thus, for those individuals that save the low-wage vacancy, we regress a dummy for also saving the high wage vacancy on the wage difference in the pair and add the perception survey results. This a more direct approach to testing whether perceptions play a role in the decision to save only the low-wage vacancy in a pair. Note that in this setup we have multiple observations for (some) individuals, and can include individual fixed effects. On the other hand, the outcome is saving the high-wage vacancy conditional on saving the low-wage vacancy and we can therefore not include pair fixed effects. To net out vacancy fixed effects, we include differences in wages and perceptions within the pair as regressors. The exact regression specification is:

$$\mathbf{1}_{(S_h)_{pj}} = \alpha + \beta \Delta w_p + \gamma_1 \Delta P_{1p} + \gamma_2 \Delta P_{2p} + \gamma_3 \Delta P_{3p} + \delta PO_p + \pi_j + \varepsilon_{pj} \quad (6)$$

Where subscript  $p$  denotes vacancy pairs and  $j$  denotes participants.  $\mathbf{1}_{(S_h)_{pj}} = 1$  if individual  $j$  saved the high wage vacancy from vacancy pair  $p$ . The percentage difference in wage within pair  $p$  is denoted by  $\Delta w_p$ , the perception differences (for each of the three questions) between the high and low wage vacancy in pair  $p$  are given by  $\Delta P_p$ . We also control for the posting order: a dummy for the high wage vacancy appearing first ( $PO_p$ ) and include individual fixed effects  $\pi_j$ . The model is estimated using all observations of individuals saving a low-wage vacancy from a pair.

Thus, this approach compares within individual variation across different vacancy pairs. We show the results in Table ?? . For comparison, we show results without perceptions in column (1) (no individual effects), column (2) (individual random effects) and column (3) (individual fixed effects). We find that individual fixed effects lead to a change in the salary coefficient, and thus include fixed in all of the further regressions. In column (4) we include the within pair difference in the three perceptions. While the precision of the estimates is again low (and none are statistically significant), the signs of the coefficients are in line with our hypothesis. Higher required quality and higher competition make it less likely that an individual is also interested in the high wage vacancy, while

Table 11: Individual level regression with  $P(S_h = 1|S_l = 1)$  as outcome (Saved)

|                                    | (1)                | (2)                | (3)                | (4)                | (5)                | (6)                | (7)                |
|------------------------------------|--------------------|--------------------|--------------------|--------------------|--------------------|--------------------|--------------------|
| Salary dif in the pair             | -0.41<br>(0.28)    | -0.37<br>(0.27)    | -0.018<br>(0.31)   | 0.083<br>(0.42)    | 0.0046<br>(0.33)   | 0.15<br>(0.40)     | -0.091<br>(0.35)   |
| Difference Q1 (Quality)            |                    |                    |                    | -0.040<br>(0.10)   | -0.028<br>(0.089)  |                    |                    |
| Difference Q2 (Competition)        |                    |                    |                    | -0.066<br>(0.11)   |                    | -0.059<br>(0.11)   |                    |
| Difference Q3 (Working conditions) |                    |                    |                    | 0.066<br>(0.10)    |                    |                    | 0.041<br>(0.086)   |
| High wage appears first            | 0.27***<br>(0.058) | 0.26***<br>(0.059) | 0.29***<br>(0.076) | 0.29***<br>(0.076) | 0.29***<br>(0.075) | 0.29***<br>(0.076) | 0.29***<br>(0.076) |
| Constant                           | 0.58***<br>(0.098) | 0.58***<br>(0.090) | 0.45***<br>(0.090) | 0.44***<br>(0.10)  | 0.45***<br>(0.090) | 0.43***<br>(0.10)  | 0.47***<br>(0.094) |
| P-val joint sign. Q1-Q3            |                    |                    |                    | .88                |                    |                    |                    |
| Individual re                      | no                 | yes                | no                 | no                 | no                 | no                 | no                 |
| Individual fe                      | no                 | no                 | yes                | yes                | yes                | yes                | yes                |
| N                                  | 278                | 278                | 278                | 278                | 278                | 278                | 278                |

\*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ . Standard errors (clustered by individual) in parentheses. Each observation is one individual saving one lower-wage vacancy from a pair. The outcome variable is a dummy for also saving the higher-wage vacancy from the pair. Columns (2)-(6) contain individual fixed effects. Note that only 63 individuals saved at least two low-wage vacancies.



Table 12: Individual level regression with  $P(S_h = 1|S_l = 1)$  as outcome (Viewed)

|                                    | (1)                | (2)                | (3)                | (4)                | (5)                | (6)                | (7)                |
|------------------------------------|--------------------|--------------------|--------------------|--------------------|--------------------|--------------------|--------------------|
| Salary dif in the pair             | 0.14<br>(0.20)     | 0.15<br>(0.20)     | 0.42*<br>(0.24)    | 0.49<br>(0.30)     | 0.42*<br>(0.25)    | 0.63**<br>(0.27)   | 0.28<br>(0.29)     |
| Difference Q1 (Quality)            |                    |                    |                    | -0.022<br>(0.067)  | -0.0065<br>(0.061) |                    |                    |
| Difference Q2 (Competition)        |                    |                    |                    | -0.10**<br>(0.052) |                    | -0.090*<br>(0.051) |                    |
| Difference Q3 (Working conditions) |                    |                    |                    | 0.10<br>(0.074)    |                    |                    | 0.078<br>(0.067)   |
| High wage appears first            | 0.26***<br>(0.041) | 0.26***<br>(0.042) | 0.24***<br>(0.051) | 0.25***<br>(0.051) | 0.24***<br>(0.051) | 0.24***<br>(0.052) | 0.24***<br>(0.051) |
| Constant                           | 0.45***<br>(0.066) | 0.46***<br>(0.067) | 0.38***<br>(0.072) | 0.38***<br>(0.079) | 0.38***<br>(0.072) | 0.35***<br>(0.075) | 0.40***<br>(0.077) |
| P-val joint sign. Q1-Q3            | .2                 |                    |                    |                    |                    |                    |                    |
| Individual re                      | no                 | yes                | no                 | no                 | no                 | no                 | no                 |
| Individual fe                      | no                 | no                 | yes                | yes                | yes                | yes                | yes                |
| N                                  | 528                | 528                | 528                | 528                | 528                | 528                | 528                |

\*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ . Standard errors (clustered by individual) in parentheses. Each observation is one individual viewing one lower-wage vacancy from a pair. The outcome variable is a dummy for also viewing the higher-wage vacancy from the pair. Columns (2)-(6) contain individual fixed effects. Note that only 120 individuals viewed at least two low-wage vacancies.

better working conditions make it more likely that (s)he is interested in the high wage vacancy. Also when including the perceptions one by one, we find that the coefficients for quality and competition are negative and increase the salary coefficient, while the opposite holds for the working conditions. Given the lack of power, these results do not provide conclusive evidence, but they are suggestive of the idea that perceptions about the probability of getting the job play a role in the choices regarding where to apply. Note that when using views instead of saves, we have slightly more power and find very similar results that are sometimes statistically significant (see Table ??).

## 5 Directed search model

In the empirical section we documented two facts. First, a job that offers a high wage attracts more interest than the same job with a lower wage. Second, a non-trivial fraction of applicants saves the low wage job, but not to the high-wage job even if they observe both jobs (i.e., both are listed on their screen). We discussed that these findings are qualitatively in line with predictions from directed search. It remains an open question whether the magnitudes - *specifically regarding the wage elasticity* - that we find are plausible as well. To this end, we calibrate a directed search model to UK data.

Our attempt is to use the simplest model that still allows us to meaningfully talk about both of the above facts. Despite our aim for parsimony, we need to include a minimum number of modelling elements in order to achieve this. We discuss these in turn to highlight exactly the role of each of them, and proceed to the formalities thereafter. In order to assess the second fact we need a model with multiple job applications. Otherwise it follows trivially that a worker who applies to the low wage will not apply to the high wage, since (s)he has no further application left, and it is impossible to match the fact that some workers do apply to both wages. Among the existing models with multiple job applications by ?, ?, ? and ? it turns out to be convenient to work with one that retains a single offered wage in equilibrium, as in one-application models with homogeneous agents. The reason is technical: for tractability nearly all directed search models use a continuum of vacancies that are observed by a continuum of workers. Fixing a given worker who applies to a low wage job, and fixing a high wage job, the chances that this worker applies there is zero (since any job attracts only a zero measure of workers). This is different if one assumes that workers observe only a finite number of jobs. It turns out that finite observability does not alter at all the equilibrium of a directed search model with a unique equilibrium wage (see ? for a first version of this insight). We will therefore use such a model and consider the reaction to a deviation away from the equilibrium wage, which allows us to talk about the points above. Only the model by ? - in which firms bid up the wage in case multiple of them pursue the same worker - has such a structure.

Finally, it is hopeless to address the first fact in a model that has no on-the-job search, as in its absence the starting wage determines the wage throughout the employment spell and workers react excessively to higher wage offers. This is the same reason why random search models without on-the-job search fail to match wage dispersion for comparable workers by orders of magnitude (Hornstein, Krusell and Violante, 2011), as workers again react too much to the presence of high wage jobs and would not want to accept low wage jobs. With on-the-job search the starting wage is an imperfect predictor of the wage during the employment spell, as subsequent search can improve the wage, making workers less

sensitive to the initial wage. We allow for on-the-job search, and for consistency again allow firms to bid for the workers' services in case another firm is also interested in the same work, which places the structure of ? into a directed search setting. Combining multiple simultaneous job applications with subsequent on-the-job search is new, but uses the existing elements from the literature and is necessary to assess the facts.

## 5.1 The model

We lay out a simple directed job search model with multiple-applications based on ? (AGV). On-the-job search is introduced in an easy way: firms observe whether an applicant already has a job or not, and always offer the job first to someone who is unemployed. The logic is the following: employed workers use another job offer to bid up their wage, and the firm makes zero profit from them. Such workers would constitute an "adverse selection" problem if the firm would not observe them. Since the firm observes them, they only consider such workers if they do not have any other worker with whom they could possibly make a profit. As a result, unemployed workers are not affected by the on-the-job search of other workers since they would always get the offer first.

Assume time is discrete,  $\beta$  is the discount factor and workers have  $N$  applications per time period. Let  $\lambda(w)$  be the number of applications from unemployed workers per job offering wage  $w$ . Assume that a random shock determines whether such an application is suitable or not. With probability  $1 - A$  an application is not suitable. This is immediately visible to the firm, and only the fraction  $A$  of applications is considered by firms. From the unemployed worker's perspective the probability of getting a job offer when applying to wage  $w$  is

$$m(\lambda(w)) = \frac{A(1 - e^{-A\lambda(w)})}{A\lambda(w)} \quad (7)$$

$A\lambda(w)$  is the queue of other eligible applications,  $(1 - e^{-A\lambda(w)})/A\lambda(w)$  is the chance that the worker gets the offer if the application is eligible, and the multiplication of the numerator by  $A$  takes into account that only with this probability the application is considered.

If the worker only gets this one job offer, (s)he is paid the announced wage for the duration of the match (unless the wage is too low so that the worker prefers to remain unemployed). If (s)he gets more than one offer (s)he is paid the marginal product  $y$  for the duration of the match as firms bid up the wage to attract the worker. If a worker does not get any job this period, (s)he gets unemployment benefits  $b$ . Once employed, there is a chance  $1 - \delta$  of losing the job between one period and the next. We assume that a worker who applies today only starts on the job next period (and the separation shock only starts once (s)he is actually on the job).

There is free entry: firm's pay entry cost  $c$  for posting a vacancy this period. They post a vacancy at their desired wage  $w$ . AGV show that in equilibrium there is only one wage  $w^*$ . If all other firms offer this wage, an individual firm maximizes

$$\max_{w \in [r, y]} n(\lambda(w)) [1 - m(\lambda(w^*))]^{N-1} \beta \Pi(w) - c$$

where  $\Pi(w)$  is the net present value of having the worker until he separates and  $n(\lambda(w)) =$

$(1 - e^{-A\lambda(w)})$ .<sup>38</sup> Note that production starts next period, therefore the discounting. The firm only gets value from the worker if the other  $N-1$  applications from this worker are not successful, otherwise it bids away all surplus. The firm cannot offer a wage below the reservation wage  $r$  of the worker, as otherwise the worker would not accept the wage even if this were the only offer. Let  $W$  be the value of this program. In equilibrium  $W = 0$ .

The net present value (NPV) of having a worker is:

$$\begin{aligned}\Pi(w) &= y - w + \beta\delta\Pi(w) \\ \Leftrightarrow \Pi(w) &= \frac{y - w}{1 - \beta\delta}.\end{aligned}\tag{8}$$

AGV show in a model without on-the-job search that the equilibrium offered wage  $w^*$  falls to the worker's reservation value  $r$  at which the worker is exactly indifferent between accepting the job and not accepting (they apply nevertheless because they hope to get two offers, in which case they can bid up the wage). However, with on-the-job search, this might not necessarily be the case and so we study the general case. In equilibrium the market utility of workers is determined by sending all  $N$  applications to firms offering  $w^*$ . Using  $m^* = m(\lambda(w^*))$  to denote the chance that in equilibrium an application by the worker yields a job offer, the worker's equilibrium utility is:

$$\begin{aligned}U^* &= b + Nm^*[1 - m^*]^{N-1}\beta V(w^*) \\ &\quad + [1 - m^*]^N\beta U^* \\ &\quad + [1 - Nm^*[1 - m^*]^{N-1} - (1 - m^*)^N]\beta V(y)\end{aligned}$$

It comprises in the first line the current payoff  $b$  and the NPV of working at the equilibrium wage  $w^*$  from next period onwards, which only happens if one of the  $N$  applications is successful but none of the others. The second line captures the possibility that none of the applications is successful, in which case the worker remains unemployed. In all other cases, captured by the last line, the worker gets to work at her marginal product  $y$ . This reduces to

$$\begin{aligned}U^* &= \frac{b + Nm^*[1 - m^*]^{N-1}\beta V(w^*)}{1 - [1 - m^*]^N\beta} \\ &\quad + \frac{[1 - [1 - m^*]^{N-1}[1 + (N - 1)m^*]]\beta V(y)}{1 - [1 - m^*]^N\beta}.\end{aligned}\tag{9}$$

where  $V(\cdot)$  is defined recursively as the value from having the job. If the worker works already at productivity  $y$ , her value is given as if (s)he continued always at this firm (there is no need to search further, but if (s)he does there are no further gains). The value function is given by

$$\begin{aligned}V(y) &= y + \beta\delta V(y) + \beta(1 - \delta)U^* \\ \Leftrightarrow V(y) &= \frac{y + \beta(1 - \delta)U^*}{1 - \beta\delta}.\end{aligned}\tag{10}$$

If the worker currently works at a job with wage  $w = w^*$  then (s)he continues searching. Assume an employed worker has  $\tilde{N}$  applications and a matching efficiency  $\tilde{A}$ . It is easily

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<sup>38</sup>Note that applications from employed workers do not show up here as they are only getting an offer if no eligible unemployed worker is present, but then they generate no profit as they bid up the wage.

possible that  $\tilde{N} < N$  since employed workers have less time, but that  $\tilde{A} > A$  if employment provides skills that make it easier for a worker to do other jobs.<sup>39</sup>

A worker employed at wage  $w < y$  gets the wage this period, but if (s)he does not loose the job (s)he has the chance to move to wage  $y$  next period if (s)he gets another job offer (with probability  $\tilde{m}^*$ ). If not (s)he continues earning wage  $w$ . If (s)he loses the job (s)he moves to unemployment. The value function is:

$$\begin{aligned} V(w) &= w + \beta\delta\tilde{m}^*V(y) + \beta\delta(1 - \tilde{m}^*)V(w) + \beta(1 - \delta)U^* \\ \Leftrightarrow V(w) &= \frac{w + \beta\delta\tilde{m}^*V(y) + \beta(1 - \delta)U^*}{1 - \delta\beta(1 - \tilde{m}^*)}. \end{aligned} \quad (11)$$

Jointly, equations (??), (??) and (??) can be solved to obtain an expression for the value of unemployment  $U^*$  as a function of  $w^*$ ,  $m^*$ ,  $\tilde{m}^*$  and the parameters  $\beta, \delta, y, b$ .

The equilibrium wage is set by firms to maximize profits (equation (??)). The first-order condition is

$$\begin{aligned} n'(\lambda(w^*))\lambda'(w^*)[1 - m(\lambda(w^*))]^{N-1}\beta(1 - \tilde{m}^*)\frac{y - w^*}{1 - \beta\delta} \\ - n(\lambda(w^*))\lambda'(w^*)[1 - m(\lambda(w^*))]^{N-1}\beta(1 - \tilde{m}^*)\frac{1}{1 - \beta\delta} \leq 0 \end{aligned} \quad (12)$$

The wage cannot fall below the reservation wage  $r$  (which is defined implicitly by  $V(r) = U^*$ ). Thus, the first-order condition holds with equality if  $w^* > r$ .

## 5.2 Deviations

Now we proceed to deviations, in order to derive the responsiveness of the number of applicants to the offered wage. Note that again only the behavior of unemployed workers is important. If a firm deviates by offering a wage  $w^d > w^*$ , the unemployed applicant's return, when sending one of the applications to the deviant vacancy, is:

$$\begin{aligned} U(w^d) &= b + m(\lambda(w^d))[1 - m^*]^{N-1}\beta V(w^d) \\ &\quad + (N-1)m^*[1 - m(\lambda(w^d))][1 - m^*]^{N-2}\beta V(w^*) \\ &\quad + [1 - m(\lambda(w^d))][1 - m^*]^{N-1}\beta U^* \\ &\quad + \left[ \begin{array}{c} 1 - m(\lambda(w^d))[1 - m^*]^{N-1} \\ -(N-1)m^*[1 - m(\lambda(w^d))][1 - m^*]^{N-2} \\ -[1 - m(\lambda(w^d))][1 - m^*]^{N-1} \end{array} \right] \beta V(y) \end{aligned} \quad (13)$$

The logic is identical to before, only now we have to separately account for the deviation wage and the regular equilibrium wages. Those who apply to the new wage cannot make

<sup>39</sup>For workers employed at a wage below productivity the job transition rate is given by  $\tilde{j}^* = 1 - \left(1 - e^{-A\lambda(w)}\tilde{A}\frac{1 - e^{-\tilde{A}\mu(w^*)}}{\tilde{A}\mu(w^*)}\right)^{\tilde{N}}$ . This expression accounts for the fact that an application is only successful if no unemployed worker applies (probability  $e^{-A\lambda(w)}$ ). In this case the application is successful if it is eligible (with probability  $\tilde{A}$ ) and gets an offer (with probability  $\frac{1 - e^{-\tilde{A}\mu(w^*)}}{\tilde{A}\mu(w^*)}$ ) where  $\tilde{A}\mu(w^*)$  is the queue length of eligible applications by employed job seekers to vacancies). With complementary probability an application fails, and raised to power  $\tilde{N}$  means that all of them fail. One minus this gives the probability that at least one application is successful.

more than the market utility, so we have  $U(w^d) = U^*$ . Applying the implicit function theorem implies that the derivative of  $\lambda(w)$  evaluated at  $w^*$  is

$$\lambda'(w^*) = - \frac{m^*[1 - m^*]^{N-1} \beta \frac{1}{1 - \delta \beta (1 - \tilde{m}^*)}}{\left( \begin{array}{l} m'(\lambda(w^*)) [1 - m^*]^{N-2} (1 - Nm^*) \beta V(w^*) \\ - m'(\lambda(w^*)) [1 - m^*]^{N-1} \beta U^*(w^*) \\ + m'(\lambda(w^*)) (N-1) m^* [1 - m^*]^{N-2} \beta V(y) \end{array} \right)}$$

And the elasticity of the queue length with respect to the offered wage is given by :

$$\frac{w^* \lambda'(w^*)}{\lambda(w^*)}$$

### 5.3 Calibration

We calibrate the model using statistics from Edinburgh or the UK, where possible for the 4th quarter of 2013, which is the start of our experimental study. All values are listed in Table ???. We take the length of a period to be one month, and set the number of applications  $N = 12$  based on an observed average of 3 applications per week in our study. We set the discount factor such that there is 10% discounting per year. Market tightness  $v/u$  follows from the UK Office for National Statistics (ONS), which, together with  $N$ , pins down the equilibrium queue length  $\lambda(w^*)$ .

According to NOMIS statistics, the off-flow of job seekers' allowance claimants implies a weekly job finding rate in the UK in the fourth quarter of 2013 between 5% and 6.4%. We pick an intermediate value of 5.2% per week, which is 20.7% per month. Since the job finding rate equals  $1 - (1 - m^*)^N$ , this determines the equilibrium job offer probability  $m^*$ . Given  $m^*$  and  $\lambda(w^*)$  we can back out the value of  $A$  from equation (??).

For the separation rate we use statistics on the UK labour market from ? and take the sum of the job-to-unemployment hazard and the job-to-inactivity hazard. The corresponding monthly separation rate is 0.0108, such that  $\delta = 0.9892$ . Productivity  $y$  is normalized to 1. For unemployment benefits we target a replacement rate of 60% of the average wage in the population and adjust  $b$  accordingly. The UK replacement rate is highly dependent on family and job characteristics and varies from 10% to 78% (based on OECD Tax-benefit models).

Job-to-job transitions are somewhat more complex. Only the share of the workers with wage  $w = w^*$  searches on the job, because there are no gains to moving jobs for those that already work at  $w = y$ . A worker receiving a competing job offer has his wage bid up to productivity, and for simplicity we assume that the worker moves to the new job with probability 1. The job-to-job transition rate observed in the data ( $\tilde{J}$ ) then equals  $n_w \tilde{j} / (n_w + n_y)$ , where  $n_w$  is the share of workers earning the low wage,  $n_y$  the share of workers earning the high wage and  $\tilde{j}$  is the matching rate for workers employed at wage  $w$ . The job-to-job transition rate in the UK in the fourth quarter of 2013 is 0.19% per week. Using steady state conditions for  $n_w$  and  $n_y$  we can back out the transition rate for employed workers  $\tilde{j}$ .<sup>40</sup>

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<sup>40</sup>See appendix ?? for the derivations.

Table 13: Calibration of parameters

| Parameter        | meaning   | value     | source   |
|------------------|---|-----------|--|
| Period length    |   | Month     |  |
| $N$              | Applications  | 12        | Based on own study   |
| $\beta$          | Discount factor                                       | 0.9914    | 10% discounting per year   |
| $v$              | Vacancies   | 573,000   | ONS statistics: vacancies in UK (2013, Q4)   |
| $u$              | Unemployment  | 2,348,000 | ONS statistics: unemployed in UK (2013, Q4)  |
| $j$              | Job finding rate                                      | 0.207     | NOMIS statistics on off-flow of JSA claimants (UK, 2013, Q4) imply a weekly outflow rate of between 5.0 and 6.4%. We pick 5.2% weekly, which is 20.7% monthly. |
| $\delta$         | 1-Separation rate                                     | 0.9892    | Sum of (UK, 1996-2010) job-to-unemployment hazard and job-to-inactivity hazard (which is 3.2% quarterly) (?)   |
| $y$              | Productivity  | 1         | Normalized   |
| Replacement rate | Ratio of benefits to average wage (in the population) | 0.6       | UK replacement ranges from 10% to 78% (depending on previous wage and family characteristics)  |
| $\tilde{M}$      | Job-to-job transition rate                            | 0.0082    | ONS statistics: 722,000 job-to-job transitions quarterly (UK, 2013, Q4) while employment was 30,288,000  |
| $\rho$           | Probability of switching jobs conditional on an offer | 1         | Set to 1.  |

## 5.4 Predictions

Now all elements necessary to compute  $r$ ,  $w^*$  and  $\lambda'^*$  are known. We present the calibration results in the upper panel of Table ?? . The queue length at jobs offering the equilibrium wage is 49. The equilibrium wage is 0.114 and slightly larger than the reservation wage.<sup>41</sup> Unemployment benefits  $b$  are 53 % of productivity. In the lower panel of Figure ?? we present the key predictions of the model. The elasticity of the queue length with respect to the offered wage ( $\lambda'^* \frac{w^*}{\lambda^*}$ ) is 0.71, which is reasonably close to the corresponding empirical value that we estimated in section ?? (0.92, presented in the third column of Table ??).

The second outcome of interest is the probability of not applying to the high wage vacancy conditional on applying to the low wage vacancy:  $P(A_h = 0|A_l = 1)$ . Calculating this probability requires setting an additional parameter  $X$ , equal to the number of vacancies that each job seeker observes. As discussed, it is required that each worker observes a random finite set of vacancies (rather than the continuum of vacancies), because otherwise the probability of applying to one particular vacancy would always be zero. To set the number of observed vacancies  $X$ , we use that the average number of vacancies the participants in our study saved was 10 per week. Thus we set  $X=40$ . Consider a vacancy that offers a wage above the equilibrium wage  $w^*$  (as was done in the manipulated vacancies used in the experiment). Denote the deviant wage as  $w^d$  and let  $p$  be the probability that an individual applies to this particular vacancy. The queue length at the deviant vacancy is given by  $p$  multiplied by the number of people that observe it:

$$\begin{aligned}\lambda(w^d) &= p \frac{Xu}{v} \\ p &= \frac{\lambda(w^d)v}{Xu}\end{aligned}$$

The value  $p$  should be such that workers are indifferent between applying to the deviant vacancy and equilibrium wage vacancies. Using equation ?? we compute  $\lambda(w^d)$  and are thus able to calculate  $p$ . As a result, each worker has in expectation  $N - p$  applications left for equilibrium wage vacancies, of which they observe  $X - 1$ . Thus, the probability of applying at each of those is:

$$q = \frac{N - p}{X - 1} \quad (14)$$

We are interested in the probability of applying low, but not high (for which we have an empirical estimate presented in Table ??). In this framework, conditioning on applying low means fixing one of the applications to be sent to an equilibrium wage vacancy. As a result, there are  $N - 1$  applications left and the probability of *not applying* to the deviant vacancy becomes  $p_c \equiv \Pr(A_h = 0|A_l = 1) = \frac{N(1-p)}{N-p}$ .<sup>42</sup> The reverse probability,

<sup>41</sup>This is not a general outcome of the model, see footnote ?? for a calibration where the equilibrium wage equals the reservation wage.

<sup>42</sup>The probability of not applying high conditional on applying to one particular low wage vacancy equals:

$$\Pr(A_h = 0|A_l = 1) = \frac{\Pr(A_h = 0, A_l = 1)}{\Pr(A_l = 1)} = \frac{\Pr(A_l = 1|A_h = 0) \Pr(A_h = 0)}{\Pr(A_l = 1)} \quad (15)$$

These three right-hand side terms are straightforward. We have  $\Pr(A_h = 0) = 1 - p$ , we have  $\Pr(A_l =$



Table 14: Model predictions

|                         | Model<br>parameter                       | Model<br>value | Experimental<br>estimate |
|-------------------------|--|----------------|--------------------------|
| Equilibrium outcomes:   |  |                |                          |
| Queue length            | $\lambda(w^*)$                           | 49             |                          |
| Equilibrium wage        | $w^*$                                    | 0.114          |                          |
| Reservation wage        | $r$                                      | 0.107          |                          |
| Unemployment benefits   | $b$                                      | 0.53           |                          |
| Employment at low wage  | $\eta_w$                                 | 6,142,989      |                          |
| Employment at high wage | $\eta_y$                                 | 38,818,320     |                          |
| Key predictions:        |  |                |                          |
| Wage elasticity         | $\frac{w^* \lambda'(w^*)}{\lambda(w^*)}$ | 0.71           | 0.92                     |
| $P(A_h = 0   A_l = 1)$  | $p_c$                                    | 0.68           | 0.36                     |
| $P(A_l = 0   A_h = 1)$  | $q_c$                                    | 0.72           | 0.45                     |

not applying low conditional on applying high, can be defined as following. Assume an individual sends one application to the deviant wage, then there are  $N - 1$  applications left for  $X - 1$  equilibrium wage vacancies. Thus, the probability of applying to each of these is simply  $\frac{N-1}{X-1}$ , and the probability of not applying to one of these is  $q_c = 1 - \frac{N-1}{X-1} = \frac{X-N}{X-1}$ .

Using a wage difference of 20 % for the deviant vacancy, we find that  $p_c = 0.68$  and  $q_c = 0.72$ , (see Table ??). The corresponding probabilities obtained from the experiment are 0.36 and 0.45 (using saved vacancies as a proxy for applications, see Table ??). Thus, while they are somewhat similar, the model overestimates both probabilities. Note that the predicted probabilities are highly dependent on the value of  $X$ , the number of vacancies that a job seeker observes. In order to get probabilities close to our empirical estimates, we would need to set  $X = 20$ . Even though we observe in our experiment that job seekers save around 40 vacancies per month, it is not obvious that all these are really of interest. Thus, one might takes the discrepancy between model and empirical findings as an indication that the actual number of ‘relevant’ jobs is smaller than the number of saved vacancies.

We conclude that using a reasonable calibration, the model is able to produce results that are of similar magnitude as those in our experiment.<sup>43</sup>

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1) =  $q$  and finally we have  $\Pr(A_l = 1 | A_h = 0) = \frac{N}{X-1}$ . Substituting these three into equation (??) and using equation (??) to replace  $q$  we find  $\Pr(A_h = 0 | A_l = 1) = \frac{N(1-p)}{N-p}$ .

<sup>43</sup>In this calibration, the equilibrium wage is larger than the reservation wage. This is not a result that holds in general. A slightly different calibration leads to an equilibrium wage equal to the reservation wage. Specifically, the empirical weekly job finding lies between 5% and 6.4% (NOMIS statistics) and if we pick a value of 5.5% (instead of 5.2%), we find an lower bound solution for the equilibrium wage. In that case, we find  $w^* = r = 0.102$ . The predictions are quite similar with this alternative calibration: a slightly lower wage elasticity of 0.51,  $P(A_h = 0 | A_l = 1) = 0.69$  and  $P(A_l = 0 | A_h = 1) = 0.72$ .

## 6 Conclusion

In this study we present results on how the wage announcement in vacancies affects behavior of potential applicants. By posting pairs of vacancies with randomly assigned wages we provide evidence that, holding all vacancy characteristics constant, a higher wage attracts more applicants. Furthermore, we find support for one key prediction of the directed search model: some applicants only show interest in a low wage vacancy even though a high-wage vacancy, which is otherwise identical, exists. This finding is inconsistent with a model in which workers apply to each vacancy with an offer that exceeds the reservation wage. It suggests that applications are costly, and that workers take into account that high wage vacancies receive more applicants and thus constitute a lower probability of a job offer. Calibrating a directed search model with multiple applications and on-the-job search we show that the model produces predictions that are quantitatively close to our empirical results.

The strength of our approach lies in the realistic setting on which the observations are based. The participants were unemployed job seekers performing their usual job search, while the set of vacancies contained up to 80 % of all job openings in the UK. This ensures that the behavior observed in the study is likely to be very close to real life behavior. One caveat is that our results are based on whether vacancies were viewed and saved, rather than whether actual applications were submitted. This limits effort and time spend by the participants on non-real vacancies, but it may not be a perfect predictor of actual applications. In this respect our study is similar to audit studies for resumes, where the outcome is the callback rate rather than actual job offers.

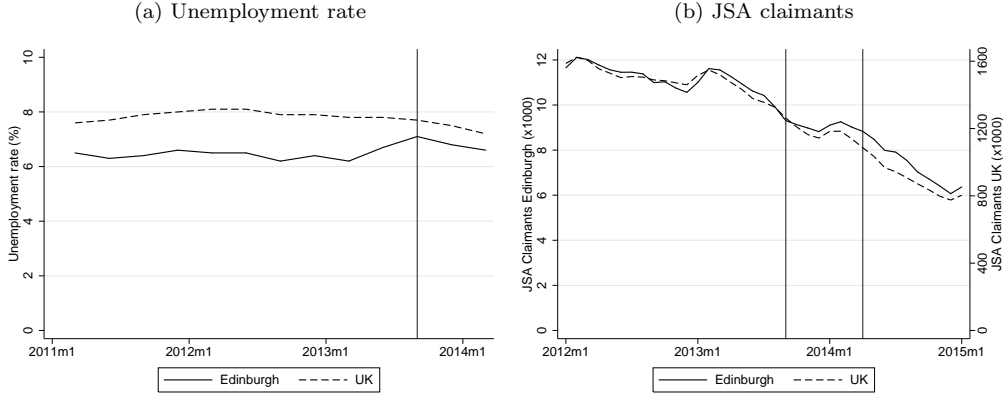
We show the potential of applying the audit study methodology to the hiring side of the labor market. Such an approach can be used to investigate important questions regarding inequality in the labor. While extensive research has been done on firm behavior when selecting applicants, little is known about whether different types of workers apply to different vacancies. Such behavior could contribute to widely observed wage differentials. Unfortunately our study lacks the sample size to provide evidence on the composition of applicants that opts for the lower-wage vacancies. We hope that by showing that our approach can be carried out with limited ethical concerns in terms of the burden on job seekers, we may contribute to further research on these topics.

## A Appendix

### A.1 Institutional Setting

In Figure ?? we present aggregate labor market statistics. Figure (a) shows the unemployment rate in the UK and Edinburgh since 2011. The vertical line indicates the start of our study. The unemployment rate in Edinburgh is slightly lower than the UK average, and is rather stable between 2011 and 2014. These statistics are based on the Labour Force Survey and not the entire population. Therefore we present the number of JSA claimants in the Edinburgh and the UK in panel (b), which is an administrative figure and should be strongly correlated with unemployment. We find that the number of JSA claimants is decreasing monotonically between 2012 and 2015, and that the Edinburgh and UK figures follow a very similar path. The number of JSA claimants in Edinburgh during our study is approximately 9,000, such that the 150 participants per wave in our study are about 2% of the stock. The monthly flow of new JSA claimants in Edinburgh during the study is around 1,800 (not shown in the graph).

Figure 9: Aggregate labor market statistics



### A.2 Model specification and robustness

In section ?? we estimate the elasticity of the number of saves or views with respect to the wage of the vacancy. The log-linear specification is given by:

$$\ln S_{ip} = \alpha + \gamma_p + \beta \Delta w_{ip} + \epsilon_{ip} \quad (16)$$

To address the problem of zeros in the outcome variable, we add a constant  $c$ . In the regression we use  $c = 0.1$  and thus we estimate:

$$\ln(S_{ip} + 0.1) = \alpha + \gamma_p + \beta \Delta w_{ip} + \epsilon_{ip} \quad (17)$$

The choice of  $c$  is arbitrary and we could have chosen a different value. It is obvious that smaller values lead to a (much) larger estimate of  $\beta$ . For example, consider a pair of

Table 15: Log-linear model with different added constants: number of saves

|  | (1)<br>+1          | (2)<br>+0.1        | (3)<br>+0.01      | (4)<br>+0.001     | (5)<br>Poisson    |
|--|--------------------|--------------------|-------------------|-------------------|-------------------|
| Salary difference                              | 0.27**<br>(0.12)   | 0.54**<br>(0.25)   | 0.81*<br>(0.44)   | 1.08*<br>(0.63)   | 0.92***<br>(0.43) |
| Appearing first                                | 0.23***<br>(0.040) | 0.48***<br>(0.085) | 0.74***<br>(0.15) | 1.00***<br>(0.21) | 0.58***<br>(0.13) |
| Elasticity evaluated<br>at mean of the outcome | 0.38               | 0.55               | 0.81              | 1.08              | 0.92              |
| Pair fixed effects                             | yes                | yes                | yes               | yes               | yes               |
| Postal code f.e.                               | yes                | yes                | yes               | yes               | yes               |
| N  | 322                | 322                | 322               | 322               | 240               |

Clustered standard errors in parentheses. \*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ . Columns (1) - (4) are log-linear models in which the outcome variable is the number of saves plus a constant. Column (5) present  $\exp(\beta) - 1$  (which is the percentage effect) from a Poisson regression.

vacancies of which one is viewed zero times and the other one time. Adding a constant of 0.001 implies that we compare 0.001 views with 1.001, resulting in a huge percentage effect. Given the range of observed values for views (0-20 with 90% of the observation below 10) and saves (0-13 with 90% of the observations below 6) this has a large impact on the estimated elasticities. In Table ?? we show the different estimates that result from using different added constants. As a comparison the last column contains the Poisson regression estimate. The estimated coefficient is always significantly positive, but varies in magnitude from 0.27 when adding a constant of 1, to 1.08 when adding a constant of 0.001.

In the log-linear model we have  $\frac{d \log V}{dx} = \beta$  which can in our setting be interpreted as the elasticity. If one adds a constant to the outcome (for example  $c = 1$ ), it is important to note that the elasticity is no longer constant across values of  $V$ . Rather, we have  $\frac{d \log V}{dx} = \beta \frac{V}{V-c}$ . If we evaluate this at the mean of  $V$  in our sample (3.55), we find an elasticity of 0.38 rather than 0.27 (see column (1) in Table ??). The difference vanishes when using smaller values for  $c$ .

### A.3 Derivation job-to-job transitions

Define the share of people employed at the low wage ( $w$ ) as  $n_w$ . Inflow  $I$  and outflow  $O$  are:

$$\begin{aligned} I_w &= uNm^*(1-m^*)^{N-1} = up_1 \\ O_w &= n_w(1-\delta+\tilde{j}\delta) \end{aligned}$$

Equating inflow and outflow gives

$$n_w = \frac{up_1}{(1-\delta+\tilde{j}\delta)} \quad (18)$$

Define the share of people employed at productivity ( $y$ ) as  $n_y$ . Inflow  $I$  and outflow  $O$  are:

$$\begin{aligned} I_y &= u(1 - Nm^*(1 - m^*)^{N-1} - (1 - m^*)^N) + n_w\delta\tilde{j} = up_2 + n_w\delta\tilde{j} \\ O_y &= n_y(1 - \delta) \end{aligned}$$

Again, equating inflow and outflow gives:

$$n_y = \frac{up_2 + n_w\delta\tilde{j}}{1 - \delta} \tag{19}$$

Finally, the aggregate job-to-job transition rate ( $\tilde{J}$ , observed in the data) is:

$$\tilde{J} = \frac{n_w\rho\delta\tilde{m}}{n_w + n_y}$$

Substituting  $n_w$  and  $n_y$  using (??) and (??) and rewriting for  $\tilde{j}$  gives the expression for the transition rate for employed workers.

## A.4 Additional descriptive statistics

Figure 10: Number of times a vacancy was saved/viewed: Glasgow pairs

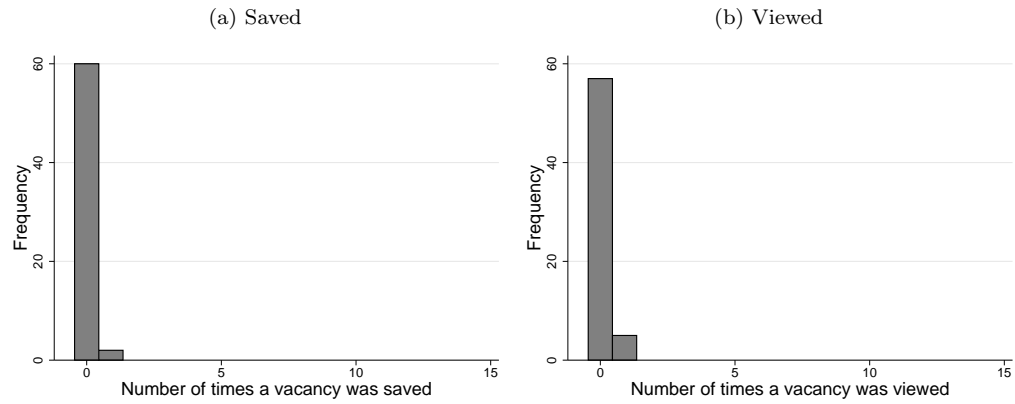


Figure 11: Salary differences of artificial vacancies

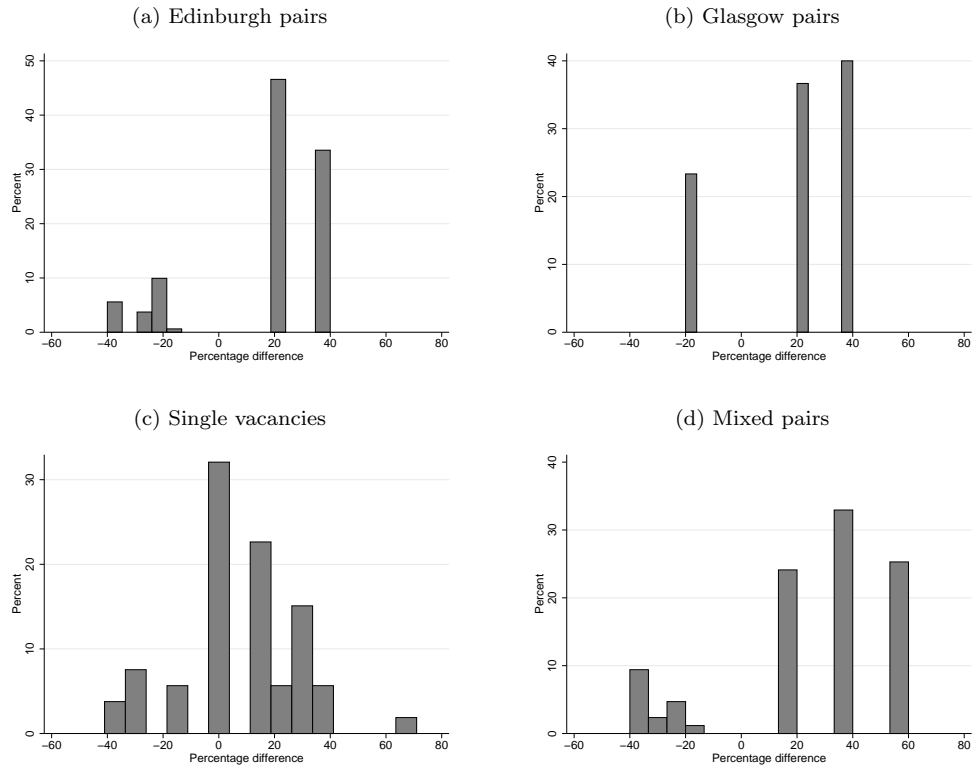
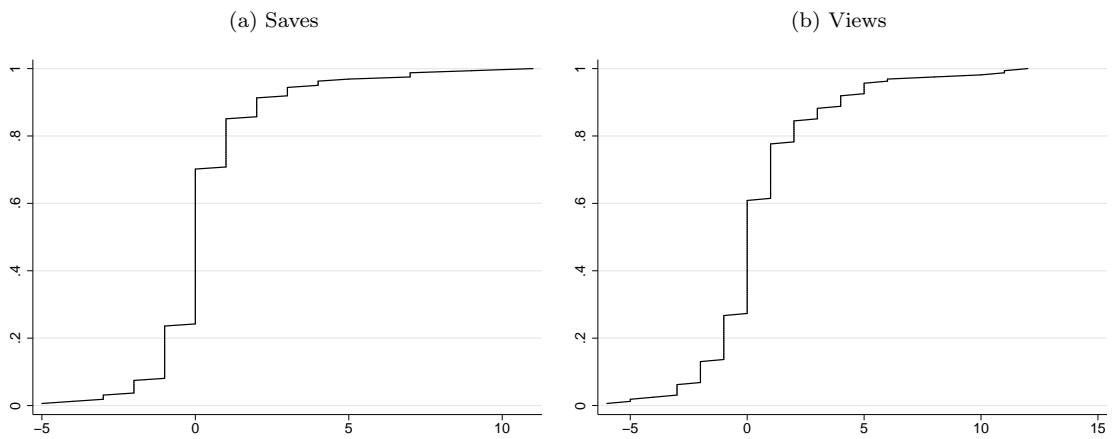


Figure 12: Cumulative distribution of the within pair difference between the higher and lower wage vacancies in the pairs



## Additional empirical results



Table 16: Effect of wage on number of saved: real vacancies

|                    | Poisson regression   |                     |                     |                     | Log-log regression  |                     |                     |
|--------------------|----------------------|---------------------|---------------------|---------------------|---------------------|---------------------|---------------------|
|                    | (1)                  | (2)                 | (3)                 | (4)                 | (5)                 | (6)                 | (7)                 |
| log(Salary)        | -0.58***<br>(0.010)  | -0.52***<br>(0.046) | -0.48***<br>(0.046) | -0.49***<br>(0.045) | -0.52***<br>(0.049) | -0.21**<br>(0.077)  | -0.38***<br>(0.060) |
| Temporary contract |                      |                     | -0.21*<br>(0.11)    | -0.20<br>(0.11)     | -0.16<br>(0.12)     | -0.32***<br>(0.073) | -0.19**<br>(0.082)  |
| Part time          |                      |                     | 0.87***<br>(0.26)   | 0.86***<br>(0.26)   | 0.81***<br>(0.25)   | 0.21*<br>(0.13)     | 0.58***<br>(0.098)  |
| No company name    |                      |                     | -0.56***<br>(0.050) | -0.61***<br>(0.044) | -0.58***<br>(0.048) | -0.17*<br>(0.090)   | -0.40***<br>(0.071) |
| No contacts in ad  |                      |                     |                     | 0.68***<br>(0.23)   | 0.73***<br>(0.24)   | 0.58***<br>(0.14)   | 0.27***<br>(0.090)  |
| Constant           | 3142.1***<br>(750.3) |                     |                     |                     |                     |                     | 1.71***<br>(0.57)   |
| Sample             | Annual wages         | Annual wages        | Annual wages        | Annual wages        | Annual wages        | Hourly wages        | Annual wages        |
| Occupation f.e.    | no                   | yes                 | yes                 | yes                 | yes                 | yes                 | yes                 |
| Month f.e.         | no                   | no                  | no                  | no                  | yes                 | yes                 | yes                 |
| N                  | 7173                 | 6812                | 6739                | 6739                | 6739                | 4336                | 7099                |

\*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ . Standard errors in parentheses. Columns (1)-(6) are Poisson model where  $exp(\beta) - 1$  is reported (which is the percentage effect). Column (7) is a log-log regression where the independent variable is  $\log(saves+0.1)$

Table 17: Effect of wage on number of viewed: real vacancies

|                    | Poisson regression   |                     |                     |                     | Log-log regression  |                     |
|--------------------|----------------------|---------------------|---------------------|---------------------|---------------------|---------------------|
|                    | (1)                  | (2)                 | (3)                 | (4)                 | (5)                 | (6)                 |
| log(Salary)        | -0.52***<br>(0.0085) | -0.47***<br>(0.012) | -0.39***<br>(0.015) | -0.40***<br>(0.015) | -0.42***<br>(0.052) | -0.18***<br>(0.020) |
| Temporary contract |                      |                     | -0.26***<br>(0.021) | -0.26***<br>(0.021) | -0.22**<br>(0.085)  | -0.21***<br>(0.022) |
| Part time          |                      |                     | 1.15***<br>(0.063)  | 1.14***<br>(0.063)  | 1.11***<br>(0.23)   | 0.42***<br>(0.036)  |
| No company name    |                      |                     | -0.48***<br>(0.016) | -0.53***<br>(0.014) | -0.48***<br>(0.045) | -0.16***<br>(0.026) |
| No contacts in ad  |                      |                     |                     | 0.55***<br>(0.050)  | 0.58***<br>(0.19)   | 0.39***<br>(0.036)  |
| Constant           | 1953.3***<br>(342.2) |                     |                     |                     |                     | 1.92***<br>(0.43)   |
| Sample             | Annual wages         | Annual wages        | Annual wages        | Annual wages        | Annual wages        | Annual wages        |
| Occupation f.e.    | no                   | yes                 | yes                 | yes                 | yes                 | yes                 |
| Month f.e.         | no                   | no                  | no                  | no                  | yes                 | yes                 |
| N                  | 7173                 | 7018                | 6944                | 6944                | 6944                | 4382                |
|                    |                      |                     |                     |                     |                     | 7099                |

\* p < 0.10, \*\* p < 0.05, \*\*\* p < 0.01. Standard errors in parentheses. Columns (1)-(6) are Poisson model where  $exp(\beta) - 1$  is reported (which is the percentage effect). Column (7) is a log-log regression where the independent variable is  $\log(\text{views}+0.1)$

Table 18: Effect of wage change on number of saved: Edinburgh and Glasgow pairs

|                          | Poisson regression |                  |                   |                   | Log-linear regression |                    |                    |
|--------------------------|--------------------|------------------|-------------------|-------------------|-----------------------|--------------------|--------------------|
|                          | (1)                | (2)              | (3)               | (4)               | (5)                   | (6)                | (7)                |
| Salary difference (in %) | 0.73**<br>(0.45)   | 0.72**<br>(0.46) | 0.96***<br>(0.44) |                   |                       | 0.50**<br>(0.23)   |                    |
| Salary dif.*increases    |                    |                  |                   | 1.00***<br>(0.46) |                       |                    | 0.62**<br>(0.27)   |
| Salary dif.*decreases    |                    |                  |                   | 0.24<br>(0.74)    |                       |                    | -0.071<br>(0.41)   |
| Sal. dif.*low*increases  |                    |                  |                   |                   | 1.24***<br>(0.62)     |                    |                    |
| Sal. dif.*high*increases |                    |                  |                   |                   | 0.36<br>(0.48)        |                    |                    |
| Sal. dif.*high*decreases |                    |                  |                   |                   | 0.22<br>(0.74)        |                    |                    |
| Appearing first          |                    |                  | 0.58***<br>(0.13) | 0.57***<br>(0.13) | 0.56***<br>(0.13)     | 0.38***<br>(0.075) | 0.38***<br>(0.075) |
| Pair fixed effects       | yes                | yes              | yes               | yes               | yes                   | yes                | yes                |
| Postal code f.e.         | no                 | yes              | yes               | yes               | yes                   | yes                | yes                |
| N                        | 248                | 248              | 248               | 248               | 248                   | 384                | 384                |

\* p < 0.10, \*\* p < 0.05, \*\*\* p < 0.01. Clustered standard errors (by pair) in parentheses. Columns (1)-(5) are Poisson model where  $\exp(\beta) - 1$  is reported (which is the percentage effect). Columns (6)-(7) are log-linear models where the independent variable is  $\log(\text{saves}+0.1)$

Table 19: Effect of wage change on number of viewed: Edinburgh and Glasgow pairs

|                          | Poisson regression |                   |                    |                    |                    | Log-linear regression |                    |
|--------------------------|--------------------|-------------------|--------------------|--------------------|--------------------|-----------------------|--------------------|
|                          | (1)                | (2)               | (3)                | (4)                | (5)                | (6)                   | (7)                |
| Salary difference (in %) | 0.72***<br>(0.36)  | 0.73***<br>(0.36) | 0.87***<br>(0.30)  |                    |                    | 0.60**<br>(0.24)      |                    |
| Salary dif.*increases    |                    |                   |                    | 0.84***<br>(0.29)  |                    |                       | 0.47*<br>(0.25)    |
| Salary dif.*decreases    |                    |                   |                    | 1.84*<br>(1.62)    |                    |                       | 1.18*<br>(0.64)    |
| Sal. dif.*low*increases  |                    |                   |                    |                    | 0.89***<br>(0.35)  |                       |                    |
| Sal. dif.*high*increases |                    |                   |                    |                    | 0.66*<br>(0.48)    |                       |                    |
| Sal. dif.*high*decreases |                    |                   |                    |                    | 1.84*<br>(1.62)    |                       |                    |
| Appearing first          |                    |                   | 0.50***<br>(0.075) | 0.50***<br>(0.075) | 0.50***<br>(0.075) | 0.41***<br>(0.078)    | 0.41***<br>(0.078) |
| Pair fixed effects       | yes                | yes               | yes                | yes                | yes                | yes                   | yes                |
| Postal code f.e.         | no                 | yes               | yes                | yes                | yes                | yes                   | yes                |
| N                        | 318                | 318               | 318                | 318                | 318                | 384                   | 384                |

\*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ . Clustered standard errors (by pair) in parentheses. Columns (1)-(5) are Poisson model where  $\exp(\beta) - 1$  is reported (which is the percentage effect). Columns (6)-(7) are log-linear models where the independent variable is  $\log(\text{views}+0.1)$

Figure 13: Mean number of views (with 95% confidence interval)

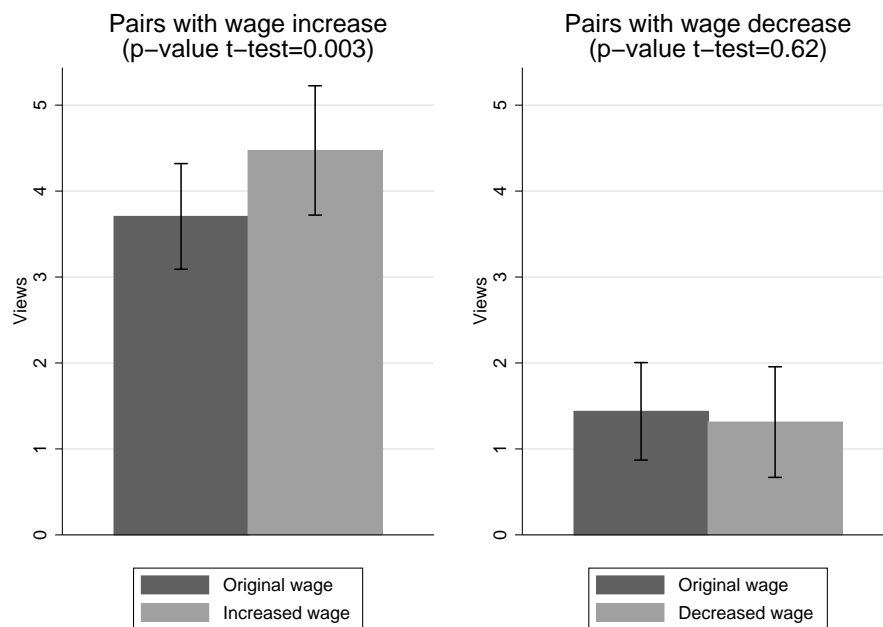


Figure 14: Cronbach alpha's for the 16 vacancy sets

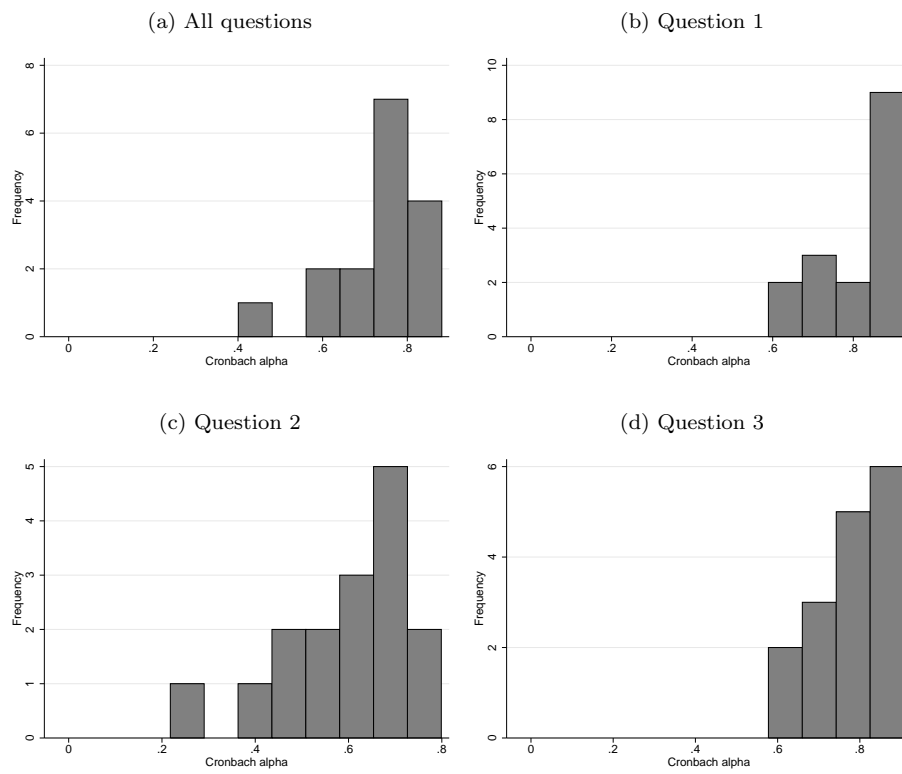
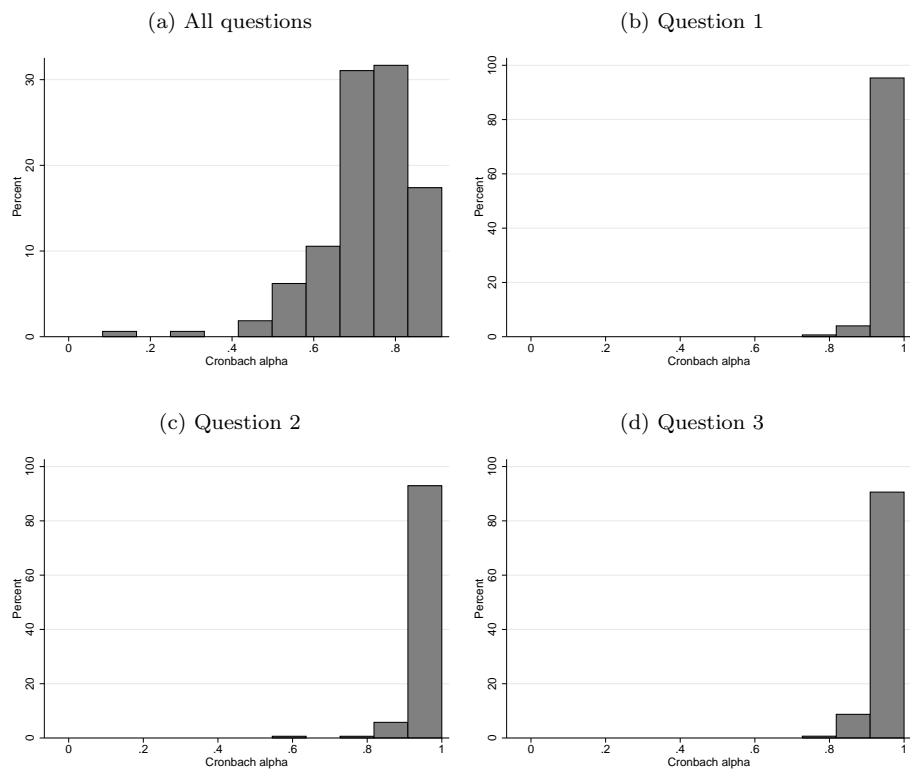


Figure 15: Cronbach alpha's for the 161 vacancy pairs



## **Supplemental Online Appendix - Instructions and Consent Forms**

**OA.1    Consent form**



# **Consent Form for Participants: “How Do Unemployed Search for Jobs?”**

**Thank you for your willingness to consider taking part in this study. Please read the information below carefully. By signing the consent form below, you indicate that you have understood the purpose of the study, you have been made aware of your rights and you have agreed with the terms and conditions of the study.**

## **Purpose of the study**

The study is undertaken to understand better how people search for jobs. The study aims to observe how people search for real jobs. The goal is to document parts of the job search process.

## **How will this work?**

The study will be conducted over a period of 12 weeks and you are asked to take part to one weekly session of 2 hours taking place at a pre-agreed time slot. You will be asked to come to our computer facilities, located at the School of Economics, 31 Buccleuch Place, EH8 9JT Edinburgh. There will be a maximum of 30 participants present at the same time in the facilities. The research team aims to provide an environment that is conducive to the job search of participants and hopes that participants will attend for the duration of the study or up to the point you find a job.

You will be able to spend most time each week to search for job vacancies. These job vacancies are obtained from two sources:

- Our main data source is the vacancy database of Universal Jobmatch and coincides with those used at Jobcentre Plus.
- Additionally, our database includes a small number of vacancies (no more than 2 per 100 vacancies) that is added for research purposes. These “research vacancies” are included to understand better which types of vacancies people are interested in even if these are not currently offered. If you express interest in such a vacancy, you will be immediately informed that this is a research vacancy before you start any application.

We will track the pages you consult, what vacancies you are looking at and consider applying to. This information will never be linked to any of your personal information such as your name and address, which will be stored separately. Your personal information will never be given out to anyone and will be accessible only to selected members of the research team.

You will also be asked some survey questions about your job search in the past week and your wellbeing. In the initial week, we will also ask a number of questions about your background and unemployment history. Six month after the end of your participation we will send you a survey about your labour market experience and your well-being.

Note that we ask all participants to stay for the full 2 hours in the laboratory. But if you do not want to search for jobs anymore, we provide some alternative ways in which you can use the computer and internet facilities.

If you are unable to participate to a session, please inform us as soon as possible (under [jobsearch@ed.ac.uk](mailto:jobsearch@ed.ac.uk) or 0131 6508324). The research team will attempt to provide additional slots in case a participant misses his time slots for justified reasons (e.g., job interviews, illness).

### Important notes

- Participation to this study is entirely voluntary. You should by no means feel compelled to participate. You can also withdraw from the study at any time if you wish to do so.
- Since the study is to gain understanding in how people search for jobs, the research team holds no particular view on how individuals should search for jobs. Thus, you should search for jobs in the same way as you would normally do.
- The study is conducted by the research team, and no personalized information is shared with any other organization. Therefore, no information will be shared with Job Centre Plus or the Department of Work and Pensions. If you would like to obtain a record of your search activities, e.g. to use for discussion with your case worker, you can obtain a printed record to take along at the end of each session.
- You should be aware that **participation in this study does not provide any additional benefits**, and in particular it does not provide particular help in job search. In particular, you **should follow your usual job search strategy**, such as for example looking at other job vacancies beyond those provided in our database, searching from home via the internet, and contacting friends and acquaintances. You should not take the time within the study as an indication of the appropriate time to spend on searching for a job.
- All the data collected during your time in our computer facility is anonymous. Your search activities will not be matched to your identity in any way. You will be attributed a randomly generated number at the first session and all data records will be matched to that number.
- We will ask you for a telephone number that we can use to contact you. We will only contact you to remind you of the time slot you have been allocated to and to inform you of any changes in schedule. Of course the telephone number will not be matched to the data we collect in the laboratory.
- You have the right to withdraw entirely from the study (i.e. ask us to delete all the data records associated with you) at any point during the study.
- The impersonal data collected will be used for research purposes (and ONLY for research purposes). Personal data will never be given out, and will be eliminated after the study is completed. The results of the study will be published in peer-reviewed scientific journals.

## **Compensation**

You will be compensated for your efforts of coming to and participating in each session in our computer facility with a compensation of £12.50 per visit (2 hours) to the laboratory. Additionally, if you participated in all four sessions in the first four weeks you are entitled to a £50 clothing voucher for job market attire as compensation for arranging the visit every week. The same holds for weeks 5 to 8 and for weeks 9 to 12.

## **Eligibility**

Participants have to be at least 18 years of age, permanent residents of the UK and living in Edinburgh (or within a distance of 5 miles from Edinburgh). You should be seeking for a job for a period of 4 weeks or less at the start date of the study.

## **Signature**

If any of the material above is unclear to you, or if you have any doubts and would like clarification, please consult a member of the research team before proceeding.

If you are willing to take part in this study, please sign the consent form below:

**I certify that I voluntarily participate in this research study. I certify that I read and understood the information above, and am eligible for taking part in this study.**

-----  
(please print your name)

-----  
(please sign)

-----  
(place and time of signature)

## OA.2 Lab instructions

## **UNIVERSITY JOB SEARCH STUDY: INSTRUCTIONS**

**Please do not start using the computer before we indicate you to do so.**

**We will read these instructions aloud at the start of the first session.**

### **INTRODUCTION**

Welcome and thank you for coming here today. Before we explain how each session will work, we would like to raise your attention to the following:

- **Health and Safety:** There will always be one person from the research team in the computer room. There is one toilet on this floor that you are free to use. In case of fire, please do follow the signs for fire exit. The main exit is through the staircase you have used to come up here.
- **No smoking:** Smoking is not allowed in this building.
- **Silence:** Since there are many of you in the room, we would appreciate if you would keep silent, so that everyone can concentrate on their computer activity.
- **Mobile phones:** Mobile phones must either be switched off or be on “silent” during each session. We would appreciate if you leave it on only if you are expecting an important phone call. And if you do receive a phone call, please leave the room and take the call outside (in the staircase).
- **Food and drinks** are not allowed in this room.
- **Questions:** Please do not hesitate to call us if you have a question.

### **WHAT IS THE STUDY ABOUT?**

The goal of the study is to understand how people search for jobs. Importantly, we hold no preconceptions regarding how people *should* search for jobs. We designed this study to find out what people usually do and what strategies are most successful. At the moment, we do not know what these are. We are interested in finding out common patterns in search strategies, and kindly ask you to search exactly in the same way as you normally would.

### **WHAT WILL HAPPEN IN EACH SESSION**

**When you come in, you will be assigned to a computer station. We may provide specific instructions at the beginning of the session, so please do wait for us to indicate the start of the session. We will now describe how each session will proceed.**

#### **1. LOGIN**

You have received a unique login number and password that you can use to login on the website here and also from home. You will be able to access your records using this login information.

## 2. SURVEY

Each weekly session will start with a **short survey**, asking questions about your past week and job search. After filling the survey, you will be re-directed towards the job search engine's main page.

For the first session, we will ask you to fill in a longer survey asking you questions about your background, qualifications and job search experience so far. You will only need to answer this initial survey once, in this session. It should take 20 minutes to fill in this initial survey.

## 3. THE JOB SEARCH ENGINE

We have designed our own job search engine. It allows you to search through all UK vacancies that are also recorded in Universal Jobmatch.

We ask you to search for jobs using this search engine only for a minimum of 30 minutes.

You can search using various criteria (keywords, occupations, location, salary, preferred hours). Importantly, you do not have to specify all of these. You just need to fill at least one of them.

If you specify more than one criterion, it is important to note that the computer will search for vacancies that satisfy all the criteria at the same time. For example, if you enter a keyword and you also select an occupation, it will search for vacancies that match both at the same time. Vacancies that match the keyword but not the occupation will not be shown.

Within some categories you can fill in more than one field. For example, within "occupations" you can specify up to two of them. If you do fill in two occupations, the computer that match either the first OR the second occupation. Vacancies that match one occupation but not the other will still be shown. You can also specify more than one pay range. This allows you to specify, for example, the hourly wages and the yearly wages that you are willing to accept. If you only specify hourly wages, it will not show vacancies that only specify yearly wages.

If you fill in your preferred hours, for example full time work, it will only list vacancies where the employer ticked a box that it is full-time work. Vacancies where the employer did not explicitly state that it is full-time work will not be shown.

If you leave a field empty, the computer will not use that criterion to restrict your search.

# Search for Jobs

You should spend at least 30 minutes searching for jobs in the lab, after which you will be able to view / print / apply for your saved vacancies and use the rest of the computer, you have been searching for 30 minutes.

Search for jobs by entering one or more search terms below.

### General

Keywords

Keywords (e.g. nurse)

Occupations

Select a category

Select a category then an

Select a category

Select a category then an

choose up to 2 occupations or categories

Hours

Select desired hours

### Location and Salary

Location

Enter city or postcode

radius

Salary

min to max

Select a

min to max

Select a

choose up to 2 salary ranges

☒ Include jobs with no salary information

Once you have defined your search criteria, you can press the search button at the bottom of the screen and a list of vacancies fitting your criteria will appear. You can click on each individual vacancy to get more information about it. You can then either

- **Save the job (if you are interested in applying)**
- **Do not save the job (if you are not interested)**

**If you save the job**, the computer will keep a record of the vacancy. You will be able to see all records of all saved vacancies at the end of the session.

**If you do not want to save the job and want to go back to the search results**, we will first ask you a few questions about why you are not interested in the job. Your answers are very important to us.

You can modify your search criteria at any point and launch a new search.

Note that we have also created a small number of vacancies ourselves (about 2% of the database), which are there for research purposes only. This is to learn whether you would find these vacancies attractive and would consider applying to them if they were available. We kept them to a minimum not to disturb your search. These vacancies will appear as all the other vacancies and may appear in your search results. But we will inform you at the end of the 30 minutes of any vacancy that may not be real. You will be able to see the list of your saved vacancies immediately after the 30 minutes are over, and we will indicate if any of them was an artificial one.

We may try alternative interfaces for the job search engine in the coming weeks. We will inform you if we do so and will explain the changes at that point in time.

#### **4. FREE USE OF THE FACILITIES (after 30 minutes)**

We will let you know when the first 30 minutes are over. You will then be free to use the computer for other purposes. You can of course keep searching using our job search engine, or you can do other things, such as write your CV, write a letter, or even send e-mails. You can use the facilities for up to 2 hours.

If you do not wish to continue searching or use the computer for other purposes, you are free to leave.

#### **END OF THE SESSION**

We can print a record of your job search for the day (just call us once you have finished), but only if that is your wish. You are free to show these records to your adviser at the Job Centre. They informed us that this would count as a proof of search activity.

Compensation: In general, you will receive a total of £11 as a compensation for your travel and meal expenses. This time, as you will soon discover in the initial survey, we do offer you the possibility of investing part of this compensation in this initial session. This is not compulsory. But if you do choose an investment option, your earnings will then be a function of what investment you have chosen.

Please collect your compensation from the registration room. You will get an envelope and be asked to sign a receipt. Note that the Job Centre has agreed that these £11 are a compensation for expenses and are not an income.

### **IMPORTANT NOTES**

#### **LOG IN FROM HOME OR FROM ANOTHER COMPUTER**

You will be able to use our search engine from home or from another computer as well. You just need to log in on the website and use your login information. You will be able to see all the vacancies you saved and will be able to retrieve all the relevant information about them.

Note that as indicated in the consent form, all records saved are anonymous. These will not be matched to your names at any point.

#### **YOUR COMMITMENT**

Note that it is very important for us that you come back every week and search in our facilities, unless of course you have found a job. If for one reason or the other you do have to cancel your session in a given week, please let us know as soon as possible. We will either try to reallocate you to another slot or ask you to search from home in that particular week. If you have found a job, please do let us know. This is of course of key importance for our study.

Also, importantly, you will receive a £50 clothing voucher for each four consecutive weeks you come. The first voucher will be distributed in the fourth week, that is, three weeks from now. The second voucher will be distributed in the eighth week and the third voucher in the twelfth week.

Thank you very much for your attention. If you have any questions, please raise your hand and we will come to you.



### **OA.3 Vacancy perceptions survey**

## VACANCY SURVEY

Thank you for participating to this survey. We will show you 20 job advertisements and ask you to answer questions about these ads. After that, we will ask you a few questions about your background characteristics.

### **Preamble**

Please confirm that you are eligible to participate to the study (click all that applies):

1. I am currently living in Edinburgh
2. I am not a student
3. I am a registered participant of the BLUE subject pool

*[Participants will be shown 20 vacancies in total, one vacancy at a time, and will be asked to answer the following questions]*

1. Given the skill and experience requirements described in the job announcement (if any), how good would you expect an applicant needs to be in order to be considered for this job?
  - a. Very much above average
  - b. Above average and higher
  - c. Average and higher
  - d. Below average and higher
  - e. Very much below average and higher
2. For someone with the skill and experience requirements described in the job announcement (if any), how much competition would you expect for this job relative to other jobs in the same profession and area?
  - a. Very much above average
  - b. Above average
  - c. Average
  - d. Below average
  - e. Very much below average
3. For someone with the skill and experience requirements described in the job announcement (if any), how would you expect the overall (non-monetary) working conditions of this job to be? Examples of non-monetary working conditions are working hours, career prospects, demands associated with the job, health and safety, etc.
  - a. Much better than average
  - b. Better than average
  - c. Average
  - d. Worse than average
  - e. Much worse than average
4. What is your gender?
  - a. Female
  - b. Male

5. How old are you? [text]
6. What is your current occupation?
  - a. Employed part or full time
  - b. Self employed
  - c. Unemployed and not looking for work
  - d. Unemployed and looking for work
  - e. Retired
  - f. Student
  - g. Other
7. Are you currently looking for work?
  - a. Yes
  - b. No
8. What is your unique BLUE id?
9. What is your e-mail address (that was used to send the survey link)?

#### **OA.4 Example vacancy pair**

Note that the visualizations below have been generated from the underlying data of the vacancies. Thus, this is not exactly how they appeared to the job seekers. Of course the id-numbers were not shown to the job seekers.

id: 1940173

id2:102278128

## **Job Title: Room Attendant**

**Location:** Edinburgh (EH23DT)

**Skills requirements:** Punctual,Attention to detail,Efficient

**Salary:**

**min:** £9.66 (Per Hour)

**max:** £9.66

**Contract:** Full time

Room attendant required. Should be dependable, quality focussed and able to provide good customer service. Duties include: maintaining hotel rooms by cleaning, dusting, vacuuming, and polishing; providing linen services; other cleaning activities as required.

id: 1940172

id2:102278128

## **Job Title: Room Attendant**

**Location:** Edinburgh (EH75DW)

**Skills requirements:** Punctual,Attention to detail,Efficient

**Salary:**

**min:** £6.90 (Per Hour)

**max:** £6.90

**Contract:** Full time

**Job Purpose:**

Maintains hotel rooms by cleaning, dusting, vacuuming, and polishing; providing linen services.

**Duties:**

\* Maintains cleaning schedule priorities by following room assignment list; servicing rooms requesting early cleaning first. Skills/Qualifications:

Dependability, Quality Focus, Customer Service

id: 1870132

id2:102290576

## **Job Title: Welder**

**Location:** Edinburgh (EH141AR)

**Skills requirements:**

**Salary:**

**min:** £11.90 (Per Hour)

**max:** £12.60

**Contract:** Full time

Temporary Assignment - Immediate start. We are looking for experienced fabricator/ welders for our client. Candidates applying for this role must have experience of MIG/TIG welding, and be able to set up and run machines in a fabrication environment. You must also have a good level of English and be able to read drawings and instructions.

Successful candidates must have an engineering background.

id: 1870133

id2:102290576

## **Job Title: Welder**

**Location:** Edinburgh (EH31DT)

**Skills requirements:**

**Salary:**

**min:** £8.50 (Per Hour)

**max:** £9.00

**Contract:** Full time

Position available for an experienced fabricator/ welders.

Candidates applying for this role must have experience of MIG/TIG welding, and be able to set up and run machines in a fabrication environment. A good level of English and the ability to read drawings and instructions is also necessary.

Successful candidates must have an engineering background. (This is a temporary assignment, with immediate start)