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Differences in employment histories between employed and unemployed job seekers

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Non-Technical Summary

While looking for a job, unemployed people have to compete not only with other unemployed people, but also with employed job seekers. Job search theory suggests that employed workers look for jobs that pay a higher wage than their current job, while the unemployed look for jobs that offer acceptable wages (at which the unemployed are indifferent between accepting the job and continuing to search). Most models assume that all job seekers are the same, and they only differ in their labour force status and in the intensity and effectiveness of their search. Nevertheless, there is lack of empirical evidence that employed and unemployed job seekers have similar characteristics.

From previous research using the British Labour Force Survey (LFS) we know that employed people who engage in on-the-job search tend to be in worse jobs than employed individuals who are not searching, and that there are significant differences in the characteristics of employed and unemployed job seekers, for example, in terms of qualification levels. However, it is possible that differences between employed and unemployed job seekers in job preferences and search methods used are due to different employment experiences or other unobserved differences, which may influence both their labour market status and their job preferences, search methods and other observed factors.

In this paper we go one step further and combine data from the LFS with the British Household Panel Survey from 1993 to 2007 to investigate whether differences between employed and unemployed job seekers persist when also differences in (un)employment histories and unobserved characteristics are taken into account. Even after controlling for all these factors we find substantial differences between employed and unemployed job seekers, especially in terms of qualification levels and past employment histories. Our results are consistent with workers becoming locked in a sequence of unemployment and bad jobs – a 'low-pay no-pay' cycle. Some people leave unemployment into a 'bad' job from which they will look for a 'good' job, but they have a low probability of entering a good job and high probability of losing the bad job and returning to unemployment. Others, who have comparatively worse individual characteristics, might never find a job at all.

Differences in employment histories between employed and unemployed job seekers*

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Abstract

We use the British Household Panel Survey (BHPS) to analyse whether employed and unemployed job seekers are substitutes by comparing their individual characteristics and past (un)employment and job histories. Since the BHPS does not directly collect information on job search activities of employed workers, we combine it with the British Labour Force Survey to assign a probability that employed respondents in the BHPS engage in on-the-job search. Even after controlling for individual heterogeneity we find important differences between employed and unemployed job seekers, both in their qualification levels and past employment histories.

Keywords: unemployment; on-the-job search; employment histories
JEL Classification: J29, J60

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1. Introduction

While looking for a job, unemployed people have to compete not only with other unemployed people, but also with employed job seekers. According to search theories employed workers look for better paying jobs while the unemployed seek jobs that offer wages exceeding their reservation wage (Burdett and Mortensen 1998). In theoretical job search models, employed and unemployed job seekers typically apply for the same jobs (Burdett and Mortensen 1998; van den Berg and Ridder 1998). As potential employers do not observe the productivity of job applicants they may use previous or current unemployment as a signal of low productivity. Therefore all else equal employers prefer applicants who are employed (Atkinson et al. 1996; Eriksson and Gottfries 2005).

Both the theoretical and empirical literatures suggest that employed job seekers have a negative impact on the probability of the unemployed finding a suitable job (Burgess 1993; Eckstein and van den Berg 2007). Despite this, there is a lack of direct evidence on whether employed and unemployed job seekers are similar, and therefore substitutes for each other. The recruiting literature, which focuses on employers' perceptions of their job applicants, suggests that there might be important differences between unemployed and employed job applicants (e.g. Atkinson et al. 1996). From the labour supply side, Longhi and Taylor (2010) use the British Labour Force Survey (LFS) to compare employed and unemployed job seekers from a cross-sectional perspective and find that there are substantial differences between these two groups in terms of individual characteristics, preferences over the type of job sought, and job search methods used. This suggests that employed and unemployed job seekers may not be competing for the same jobs. However, this analysis was constrained by the lack of information in the LFS on past employment histories; it is possible that differences between employed and unemployed job seekers in job preferences and search methods used are due to different employment experiences. Furthermore, the analysis was unable to control for unobserved differences between job seekers which may be correlated with both their labour market status and their job preferences, search methods and other observables. Our contribution is to extend the work of Longhi and Taylor (2010) by investigating whether differences between employed and unemployed job seekers persist when also controlling for differences in (un)employment histories and unobserved heterogeneity.

The literature on unemployment persistence suggests that current employment is strongly related to past unemployment (e.g. Arulampalam et al. 2000; Gregg 2001), even

when allowing for observed and unobserved differences between individuals. Such persistence in unemployment indicates that the unemployed and employed will have very different job and employment histories, which need to be incorporated into any comparison between employed and unemployed job seekers. Furthermore, employed and unemployed job seekers may differ in other unobservable ways. For example one might speculate that, among job seekers, those who are more likely to be unemployed at any point in time are those who are less flexible in terms of the jobs they find acceptable, either because they have higher reservation wages, or because they are less flexible in terms of other job characteristics (e.g. occupation, permanency, etc.). By using data from the British Household Panel Survey (BHPS) we are able to identify differences in past (un)employment and job histories of employed and unemployed job seekers, and to account for unobserved individual heterogeneity.

A disadvantage of the BHPS, however, is that it does not directly identify people who search on-the-job. Therefore we also make a methodological contribution by using information from the LFS to construct models of employed job search which we then use to estimate the probability that employed respondents in the BHPS engage in on-the-job search. This allows us to identify a group of employed job seekers in the BHPS whose employment histories can be compared with those of the unemployed. This approach maximises the advantages of each data set.

Even after controlling for individual heterogeneity substantial differences between employed and unemployed job seekers remain, especially in terms of qualification levels and past employment histories. Our results are consistent with workers becoming locked in a sequence of unemployment and bad jobs – a 'low-pay no-pay' cycle – consistent with previous empirical research (Böheim and Taylor 2002; Stewart 2007). Some people leave unemployment into a 'bad' job from which they will look for a 'good' job, but they have a low probability of entering a good job and high probability of losing the bad job and returning to unemployment. Others, who have comparatively worse individual characteristics, might never find a job at all.

2. Data

Our main analysis is based on the BHPS, a panel of households living in the UK, in which each member of the household is interviewed annually. The data collection started in 1991; the most recent wave available to date refers to 2007. For our purposes, the BHPS has two

advantages over the LFS. The first is that it collects job and employment histories, allowing us to identify differences in previous employment experiences between employed and unemployed job seekers. The second is that it is a panel dataset, allowing us to account for unobserved differences across individuals in estimation. Although it includes a large quantity of information on individual and job characteristics, as well as household contextual information, like many datasets the BHPS collects data on job search activity only from people who are currently unemployed and not from those who are in employment. As we do not directly observe on-the-job search in the BHPS, we use data from the LFS to predict the probability that BHPS respondents engage in on-the-job search.

The LFS is a nationally representative household survey focussing on employment status, education, and job characteristics. It asks a series of questions on job search to all respondents, not only to the unemployed but also to employed people and to those classified as temporarily inactive. Following Longhi and Taylor (2010), we define job seekers – whether employed or unemployed – as those who say they are looking for a job as an employee; have been looking for work in the last four weeks; and mention at least one method of job search.[1] As shown in Figure 1, the LFS indicates that between 1992 and 2009 the proportion of employed workers engaging in on-the-job search ranges from 5 to 7.5 percent.

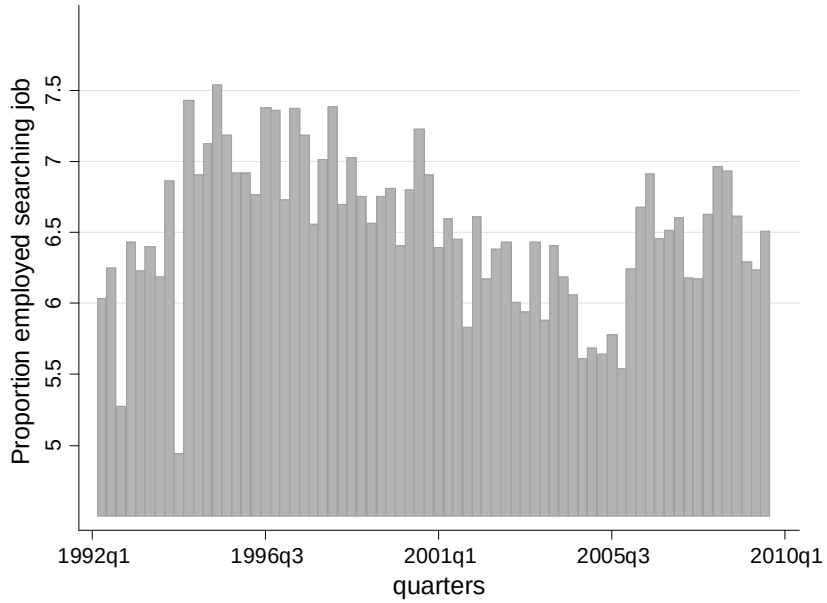

Figure 1: Proportion of employed workers engaging in on-the-job search
Source: LFS 1992–2009.

[1] In contrast to Longhi and Taylor (2010), however, we only focus on workers looking for a new job, excluding the small proportion of workers looking for an additional job.

We use this information, together with job characteristics, to construct a model of engaging in on-the-job search which we then use to predict which employed BHPS respondents are searching for a new job.[2] Clearly, this step of the analysis only uses job characteristics that are available – and comparable – in both datasets. Current wages are likely to be a key determinant of engaging in on-the-job search (see Longhi and Taylor 2010), and this is only available in the LFS from 1993 onwards. Therefore our analysis is restricted to the period 1993–2007.

The BHPS collects retrospective information on job and (un)employment spells that individuals experience between two waves of data (or in the previous 12 months). We use this to identify the incidence and duration of unemployment and economic inactivity spells that respondents have experienced in the previous 12 months. By following the same individuals over time, we can construct labour market histories that cover the whole sample period (or at least the periods in which respondents are interviewed). We also use this information to identify recent changes in occupation. Changes in occupations are defined as job changes which also involve a change in Standard Occupational Classification at the 2-digit level, without an intervening spell of non-employment (see also Longhi and Brynin 2010).

We also use this information to identify workers who moved between jobs without intervening spells of non-employment, and can assume that such workers were engaging in on-the-job search at the time of the previous interview. This is an alternative way of identifying on-the-job search, although it is an underestimate as it excludes all unsuccessful job seekers. We use information on job-to-job moves to test the robustness of our main results.

3. Method

3.1. Identifying employed job seekers in the BHPS

Our first task is to identify employed job seekers in the BHPS. As there is no question that asks whether employed people are searching for a new job, we do this by predicting who, among employed BHPS respondents, are most likely to engage in on-the-job search using

[2] Although the LFS has a small rotating panel component, where people are interviewed for up to five successive quarters, for our analysis we use only data from the last (fifth) interview, when questions on earnings are asked.

information on job search collected in the LFS. Using the LFS, Longhi and Taylor (2010) show that job characteristics, such as wages or whether the job is temporary, are important determinants of on-the-job search. Given the random, nationally representative nature of both data sets, it seems reasonable to assume that the relationship between on-the-job search and job characteristics estimated using the LFS sample can also be applied to respondents in the BHPS sample. We therefore estimate a probit model for engaging in on-the-job search using the LFS sample and then use the estimated regression coefficients to predict the probability that employed workers in the BHPS sample engage in on-the-job search. The probit model is estimated separately for men and women and conditional on being employed, where 0 = not searching and 1 = searching for a new job, via the latent variable y_{ij}:

$$y_{ij} = X'_{1i}\,\beta_j + \varepsilon_{ij} \qquad (1)$$

where ε_{ij} are i.i.d. and follow a multivariate normal distribution; *i* represents individuals and *j* represents choices. Hence, the probability of observing individual *i* in state *q* is the probability that $y_{iq} > y_{ij}$ for each $j \neq q$.

Explanatory variables include only characteristics of the current job: dummies for whether the job is temporary, part-time, in the public sector, and for occupations, job tenure and its square, gross weekly wages, and hours of work. The model also includes one variable aggregated at the regional level, the proportion of job seekers who are employed in each quarter and region, which captures local labour market conditions that are likely to influence the decision to engage in on-the-job search (e.g. Pissarides 1994; Longhi and Taylor 2010). Dummies for Government Office Regions, year and quarter are also included.[3]

We use the estimated regression coefficients from model (1) to predict the probability that each employed respondent in the BHPS engages in on-the-job search. Given that the proportion of employed workers engaging in on-the-job search is around six percent and varies little over the business cycle (Longhi and Taylor 2010), for each year of the sample we

[3] The exclusion of individual characteristics from the model does not reduce its predictive power, and the descriptive statistics of employed job seekers in the two data sets (LFS and BHPS) are more similar when individual characteristics are excluded. In terms of job characteristics, it might be argued that job tenure is endogenous in this context as individuals who have been in the job longer are in a better match and so less likely to search, while those in poor matches will have searched and found better matches. However, for this analysis endogeneity is not an issue since the purpose of this model is to predict who in the BHPS is more likely to engage in on-the-job search, rather than identifying causality. Furthermore, excluding job tenure has no impact on the results: models excluding job tenure lead to the same classification of workers between searching and not searching for a new job.

identify employed searchers in the BHPS as those six percent of respondents with the highest probability of engaging in on-the-job search.

3.2. The impact of employment histories on job search

Having identified the group of employed job seekers, we use BHPS data to compare the individual characteristics and past (un)employment and job histories of employed and unemployed job seekers. We model the employment status of job seekers, and account for individual heterogeneity by estimating a random effects logit model. In doing so we relax the typical (and restrictive) assumption of independence between observed characteristics and unobservables by including the within-individual means of the time-varying covariates among the explanatory variables (Mundlak 1978).[4] Hence, we model the probability that the job seeker is either employed ($j = 0$) or unemployed ($j = 1$) at time t via the latent variable z_{ij}:

$$z_{itj} = X'_{2it}\,\gamma_j + \alpha_i + \xi_{itj} \qquad (2)$$

where α_i are the individual-specific random effects, and the random errors ξ_{ij} are i.i.d. and follow a logistic distribution. The probability of observing individual i in status q at time t is the probability that $z_{itq} > z_{itj}$ for each $j \neq q$. Explanatory variables in X_2 include age, household structure and education, dummies for region and year, plus a set of variables summarising the previous (un)employment and job history of the job seeker. Among these we have dummies for whether the job seeker had an unemployment or an inactivity spell in the previous 12 months (which we label 'recent') distinguishing between spells that were shorter and longer than 3 months; dummies for earlier unemployment or inactivity spells that lasted longer than three months; and dummies for recent and earlier occupational change. These allow us to identify whether employed and unemployed job seekers differ in terms of their unemployment experiences and their occupational stability. The rationale behind the choice of these variables is related to the persistence of unemployment. It is reasonable to expect that shorter unemployment and inactivity spells might have a smaller impact than longer spells on the current probability of being an unemployed rather than employed job seeker, and that earlier spells have a smaller impact than more recent spells. We also assume

[4] A fixed effects logit model produces results very similar to those from the random effects model shown, but has the disadvantage of not directly estimating the impact of important time-invariant characteristics such as education. Hence, the results of the fixed effect logit model are not shown, but are available on request.

that only earlier spells that lasted more than three months have an impact on the current situation.

We identify employed job seekers on the basis of the probability that an employed worker engages in on-the-job search at a certain point in time rather than on questions regarding job search activities. Therefore on-the-job search is measured with error. At the extreme, none of the people we identify as employed job seekers may engage in on-the-job search, and our models would simply compare employment histories of employed and unemployed people, and previous research has highlighted strong causal relationships between past and current unemployment (e.g. Arulampalam et al. 2000). Therefore differences between employed and unemployed job seekers may be overestimated if employed job seekers are more similar than the employed who do not search to unemployed people. We run some sensitivity analyses and test the robustness of our results against different definitions of employed job seekers. One of these identifies job seekers within the BHPS as people who will move from job to job within the following 12 months without an intervening employment interruption (and who therefore must have engaged in some form of on-the-job search).

4. Results

4.1. Identifying employed people searching on-the-job

The impact of job characteristics on the probability of engaging in on-the-job search, estimated using the LFS, is shown in Table 1. The table suggests that having a temporary rather than a permanent job is one of the most important factors motivating people to search while employed, increasing the probability of engaging in on-the-job search by 4.5 percentage points for women and 4.8 for men. Having a part-time job seems to deter women from engaging in on-the-job search, as suggested by Longhi and Brynin (2010), although it reduces the probability by less than one percentage point. For women, part-time employment might be a choice more than a constraint, and most women working part-time might not want a full-time job (Böheim and Taylor 2004). This argument is supported by the finding that working more hours per week has a small positive impact on the probability of women engaging in on-the-job search. Longer job tenure and higher wages also deter people from engaging in on-the-job search. Finally, a higher proportion of job seekers in the region who are employed – as opposed to unemployed – has a positive impact on on-the-job search. All these results are consistent with those reported by Longhi and Taylor (2010).

Table 1: Determinants of on-the-job search (LFS 1993–2007)

0 = employed not searching 1 = employed searching	(1) Men		(2) Women	
	Coefficients	Marginal effects	Coefficients	Marginal effects
Job temporary	0.437***	0.048***	0.416***	0.045***
	(0.025)	(0.003)	(0.024)	(0.003)
Part-time	0.047	0.005	-0.075***	-0.008***
	(0.039)	(0.004)	(0.024)	(0.003)
Gross weekly pay (hundreds)	-0.041***	-0.005***	-0.048***	-0.005***
	(0.004)	(0.000)	(0.006)	(0.001)
Years of job tenure / 10	-0.277***	-0.031***	-0.319***	-0.034***
	(0.026)	(0.003)	(0.030)	(0.003)
Years of job tenure / 10 squared	-0.017	-0.002	0.024*	0.003*
	(0.010)	(0.001)	(0.014)	(0.001)
Public sector	-0.006	-0.001	-0.024	-0.003
	(0.018)	(0.002)	(0.016)	(0.002)
Usual hours per week / 10	0.007	0.001	0.077***	0.008***
	(0.009)	(0.001)	(0.010)	(0.001)
Proportion job seekers who are employed (%)	0.008***	0.001***	0.006**	0.001**
	(0.003)	(0.000)	(0.003)	(0.000)
Pseudo R^2	0.052		0.034	
Observations	119398		94053	

Probit model. Standard errors in parenthesis are clustered by quarters x regions; other explanatory variables: dummies for occupations (pre- and post- 2000), regions, year, and quarter. * Significant at 10%, ** Significant at 5%, *** Significant at 1%

We now use these estimated regression coefficients to predict who, among employed BHPS respondents, is most likely to engage in on-the-job search. The individual probability of engaging in on-the-job search varies over time, not only because of potential changes in the characteristics of the job, but also because of the macroeconomic climate captured in the model by time dummies and the proportion of job seekers that are employed by quarter and region. These capture differences over time and regions in the overall propensity to engage in on-the-job search, which are related to exogenous macroeconomic events.

The predicted probabilities of respondents engaging in on-the-job search range from almost zero to a maximum of 27%, with a median of 4.5%. The distribution of these probabilities is shown in Figure 2. Such low predicted probabilities are not surprising, given that the LFS data indicates that only six percent of employed people engage in on-the-job search. Therefore for each year of BHPS data we rank men and women according to their predicted probability of being an employed job seeker, and categorise as employed job seekers the six percent of workers with the highest probability of engaging in on-the-job

search. Hence, the threshold probability used to identify those searching on-the-job varies by year, and ranges from 8 percent to 11 percent. Table 2 shows how the threshold varies between 1993 and 2007, together with the number of BHPS respondents who are then classified as employed workers engaging and not engaging in on-the-job search.

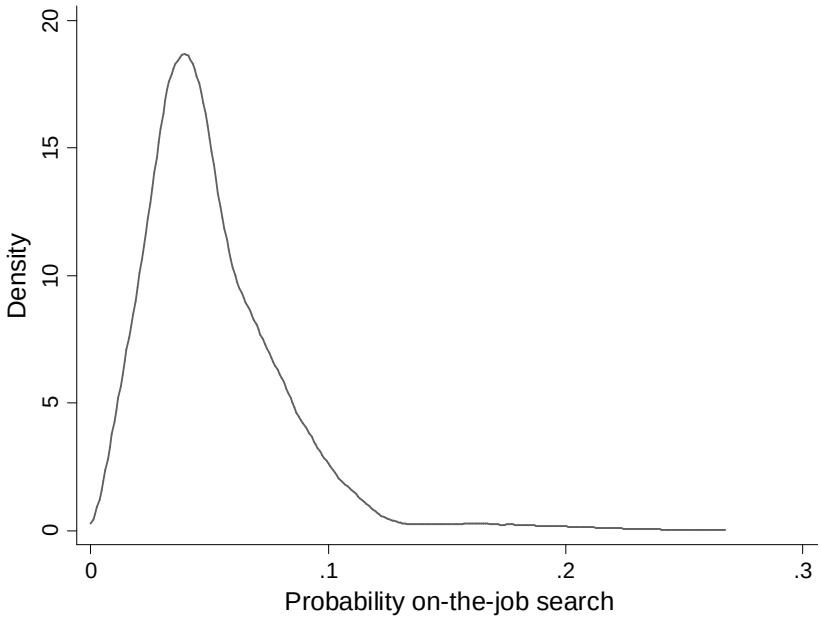

Figure 2: Distribution of the probability of engaging in on-the-job search (BHPS respondents)

Table 2: Threshold probability of engaging in on-the-job search (BHPS 1993–2007)

Year	Threshold Probability (%)	Employed not searching (observations)	Employed searching (observations)	Unemployed (observations)
1993	9.14	3838	246	546
1994	10.30	3919	251	508
1995	10.70	3878	248	392
1996	11.32	4081	261	393
1997	11.14	4654	298	408
1998	9.86	4650	297	365
1999	9.90	6388	408	588
2000	10.77	6362	407	568
2001	9.50	6352	406	514
2002	9.42	5637	360	424
2003	8.86	5514	353	458
2004	8.77	5343	342	371
2005	8.29	5284	338	407
2006	9.22	5379	344	409
2007	8.74	5130	328	322

Table 3a for men, and Table 3b for women, compare the individual characteristics of employed people searching and not searching in the LFS with those that we define as employed and searching and non-searching within the BHPS. For comparison, the individual characteristics of the unemployed in the BHPS are also included. These descriptive statistics refer to the samples only, and are therefore unweighted. The tables indicate that the average characteristics of men and women identified as employed job seekers and non-seekers in the two surveys are similar. For example employed job seekers are on average younger than non-seekers and are less likely to be married. Consistent with Longhi and Taylor (2010), the table also indicates that in the BHPS sample unemployed people have lower levels of education than employed people; this is especially true for men. Almost all the differences between BHPS groups are statistically significant.

Table 3a: Individual characteristics: BHPS and LFS 1993–2007 (men)

	Employed men not searching		Employed men searching		Unemployed men
Dataset:	LFS	BHPS	LFS	BHPS	BHPS
age	39.13	38.67	34.17	31.12	34.12
Married	0.605	0.749	0.473	0.471	0.486
Children 0-15	0.380	0.401	0.377	0.299	0.391
Degree	0.190	0.173	0.244	0.189	0.088
Higher qualification	0.108	0.336	0.116	0.258	0.186
GCE, A levels and lower	0.608	0.382	0.578	0.472	0.431
Other or no qualification	0.095	0.109	0.063	0.082	0.296
Recent unemployment spell <= 3m		0.019		0.120	0.053
Recent unemployment spell > 3m		0.018		0.112	0.096
Recent inactivity spell <= 3m		0.005		0.026	0.023
Recent inactivity spell > 3m		0.016		0.115	0.092
Recent occupational change		0.055		0.183	0.086
Earlier unemployment spell > 3m		0.037		0.115	0.149
Earlier inactivity spell > 3m		0.032		0.181	0.131
Earlier occupational change		0.092		0.175	0.084

Table 3b: Individual characteristics: BHPS and LFS 1993–2007 (women)

	Employed women not searching		Employed women searching		Unemployed women
Dataset:	LFS	BHPS	LFS	BHPS	BHPS
age	38.06	37.95	33.70	30.50	33.33
Married	0.579	0.718	0.404	0.505	0.419
Children 0-15	0.397	0.405	0.376	0.356	0.409
Degree	0.158	0.162	0.235	0.263	0.094
Higher qualification	0.138	0.298	0.136	0.228	0.181
GCE, A levels and lower	0.578	0.428	0.560	0.459	0.477
Other or no qualification	0.127	0.113	0.068	0.050	0.248
Recent unemployment spell <= 3m		0.019		0.147	0.053
Recent unemployment spell > 3m		0.016		0.090	0.058
Recent inactivity spell <= 3m		0.009		0.062	0.027
Recent inactivity spell > 3m		0.053		0.277	0.123
Recent occupational change		0.062		0.209	0.083
Earlier unemployment spell > 3m		0.027		0.064	0.084
Earlier inactivity spell > 3m		0.095		0.361	0.174
Earlier occupational change		0.095		0.129	0.081

In Tables 3a and 3b we also make an initial comparison of previous experiences of employment and economic inactivity between employed and unemployed job seekers, and employed people who do not engage in on-the-job search using BHPS data. This indicates that employed job seekers are most likely to have experienced unemployment or inactivity spells in the previous 12 months; these spells have also been slightly longer (note that this table includes long term unemployed). Employed job seekers are also most likely to have had occupational changes in the past perhaps indicating a less stable employment trajectory. Unemployed people are most likely to have experienced earlier unemployment spells, and least likely to have experienced previous occupational changes. Unemployed people generally seem to have experiences that lie between those of employed people not searching and employed people searching for a new job. In the next section we supplement these bivariate descriptive statistics with more complete multivariate econometric models.

4.2. Differences in (un)employment histories among job seekers

Table 4 presents results from models exploring the impact of observed and unobserved individual heterogeneity and employment histories on being an unemployed rather than employed job seeker. The numbers presented are odds ratios, so an estimated effect of less than (more than) one indicates that the characteristics reduces (increases) the probability of a job seeker being unemployed. We initially estimate a logit model pooling observations over

the years, thus ignoring the panel nature of the BHPS data. The results, shown in column (i) of Table 4, are consistent with previous research. Married people are less likely than single people to be unemployed rather than employed job seekers, while men with dependent children are more likely to be unemployed rather than employed job seekers. Furthermore, we find that the probability of being an unemployed rather than employed job seeker is lower for the more highly educated. This is consistent with studies of recruitment behaviour, who find that one of the reasons why the unemployed do not get a particular job is that they do not meet the job requirements in terms of qualification and experience levels (e.g. Gorter et al. 1993; Behrenz 2001). The question, however, remains about the extent to which these differences are due to differences in unobserved characteristics across individuals.

The models in column (ii) of Table 4 present the results of the random effect logit models. Although some of the impacts of the individual characteristics (such as marital status) lose their statistical significance, that of the level of education remains. Therefore although time invariant unobserved individual characteristics do seem to play a role in the probability of being an unemployed rather than employed job seeker, qualifications play a role over and above such unobserved characteristics. At this point we could speculate that the impact of education is related to the lower probability that highly qualified people have of experiencing unemployment. We examine this in column (iii) of Table 4, which also includes information on employment histories. However a comparison of the estimates in columns (ii) and (iii) reveals that the impact of qualifications is generally robust to allowing for differences in previous labour market trajectories.

The impacts of previous labour market experience indicate that past experiences of unemployment reduce the probability that the job seeker is unemployed rather than employed: those who had an unemployment spell in the past are more likely to currently be an employed rather than unemployed job seeker. This is consistent with the idea that there is some turnover in unemployment: the unemployed are able to find a job, but then keep searching while in the new job. Those with no unemployment experience are likely to be employed people who are not searching (see also below and Table 3). Table 4 also shows that the impact of longer unemployment spells is larger than the impact of shorter unemployment spells, especially for women, and that earlier spells have a smaller impact than recent ones, as we might expect. A recent inactivity spell increases the probability that the job seeker is unemployed rather than employed, at least for men. This may indicate that men move from economic inactivity into unemployment and then from unemployment into a (bad) job in which they keep searching for a new (good) job. Once again, longer spells have

larger impacts than shorter spells. However earlier spells of inactivity reduce the probability of being unemployed for both men and women: job seekers who had an inactivity spell more than one year ago are more likely to be employed rather than unemployed. At least for men, recent occupational changes increase the probability that the job seeker is unemployed rather than employed, thus suggesting an unstable career path.

Table 4: Determinants of being an unemployed rather than employed job seeker: BHPS 1991–2007

	(i) Logit model		(ii) Random effect Logit model		(iii) Random effect Logit model	
	Men	Women	Men	Women	Men	Women
Age	1.027	0.968	0.724*	0.759	0.748	0.765
	(0.019)	(0.031)	(0.137)	(0.356)	(0.145)	(0.383)
Age square	1.000	1.001	1.000	0.998	0.999	0.997
	(0.000)	(0.000)	(0.001)	(0.002)	(0.001)	(0.002)
Married	0.665***	0.684***	0.862	0.507	0.822	0.533
	(0.057)	(0.078)	(0.191)	(0.210)	(0.184)	(0.232)
Children 0-15	1.506***	0.966	1.503**	1.226	1.526**	1.265
	(0.107)	(0.104)	(0.261)	(0.486)	(0.270)	(0.539)
First or higher degree	0.270***	0.157***	0.165***	0.055***	0.151***	0.057***
	(0.033)	(0.036)	(0.033)	(0.022)	(0.030)	(0.024)
Other higher qualification	0.377***	0.316***	0.250***	0.157***	0.258***	0.153***
	(0.043)	(0.068)	(0.044)	(0.054)	(0.045)	(0.057)
GCE, A levels and lower	0.434***	0.341***	0.306***	0.188***	0.318***	0.168***
	(0.045)	(0.069)	(0.049)	(0.060)	(0.051)	(0.058)
Recent unemployment spell <=3m					0.439***	0.482**
					(0.075)	(0.171)
Recent unemployment spell >3m					0.451***	0.239***
					(0.066)	(0.102)
Recent inactivity spell <=3m					1.726*	2.604*
					(0.485)	(1.442)
Recent inactivity spell >3m					2.451***	2.094*
					(0.561)	(0.909)
Recent occupational change					1.394**	1.151
					(0.201)	(0.397)
Earlier unemployment spell >3m					0.621***	0.903
					(0.088)	(0.378)
Earlier inactivity spell >3m					0.607**	0.343**
					(0.132)	(0.148)
Earlier occupational change					1.039	0.954
					(0.159)	(0.334)
Log likelihood	-3735	-1388	-3512	-1335	-3411	-1292
Observations	6030	2256	6030	2256	6030	2256

Odds ratios from (random effects) logit models. Standard errors in parenthesis are clustered by individuals in the logit model; other explanatory variables: dummies for regions and year plus means of time-varying covariates over time. * Significant at 10%, ** Significant at 5%, *** Significant at 1%

Given the role played by qualifications in shaping the probability that the job seeker is unemployed rather than employed, we have re-estimated the models separately by qualification level to verify whether differences between employment histories still play a role when we compare workers with the same qualification level. We do not show the results here, as they confirm the main findings highlighted in Table 4. For all qualification levels previous unemployment significantly reduces the probability of being an unemployed rather than employed job seeker. Earlier economic inactivity also reduces this probability while recent inactivity increases it. Occupational changes have little impact.

4.3. Sensitivity of the results

The validity of our results relies crucially on the ability to accurately identify employed people in the BHPS who engage in on-the-job search. Failure to do so would result in models that simply compare the unemployed with the employed. As robustness checks, we therefore compare results using different strategies to identify on-the-job search. The results are shown in Table 5a for men and 5b for women. For comparison, the first column of the table reports the same models shown in the last two columns of Table 4, i.e., those in which the comparison group – employed job seekers – are defined as the six percent of employed people in the BHPS with the highest probability of engaging in on-the-job search.

In column (ii) of the tables we present results from changing the threshold separating employed people not searching from those searching on the job from 6 to 15 percent. Hence, we classify as employed job seekers those 15 percent of employed BHPS respondents with the highest probability of engaging in on-the-job search. We then show the results from moving the threshold from 15 to 100 percent, thus comparing all employed people to the unemployed (column (iii)).

A comparison of the estimates across these columns indicates that, in the most part, the odds ratios on individual characteristics do not change much from column (i) to column (ii), but change significantly from column (ii) to column (iii). The impact of qualifications changes only marginally when moving from column (i) to column (ii), but becomes much smaller in column (iii), especially for men. The differences between the coefficients of the qualification dummies are all statistically significant for men, while for women only the difference between the coefficients of the 'degree' dummy is statistically significant. Models (ii) and (iii) also produce statistically different coefficients on the dummies for recent unemployment spells and recent occupational change for men; and on the coefficients of the earlier unemployment spells for women. Overall, these results support our way of predicting

on-the-job search, as including in the analysis employed people not engaging in on-the-job search reduces the observed differences between unemployed and employed job seekers.

Table 5a: Determinants of being an unemployed rather than employed job seeker; sensitivity analysis (men)

	(i) 6% with highest probability on-the-job search	(ii) 15% with highest probability on-the-job search	(iii) All employed people (100%)	(iv) Job-to-job moves (BHPS)
Age	0.748	0.808	0.697***	0.656***
	(0.145)	(0.110)	(0.079)	(0.026)
Age square	0.999	1.001*	1.003***	1.001**
	(0.001)	(0.001)	(0.000)	(0.000)
Married	0.822	0.783	0.719***	0.719**
	(0.184)	(0.124)	(0.090)	(0.107)
Children 0-15	1.526**	1.404***	1.113	1.298**
	(0.270)	(0.182)	(0.113)	(0.158)
First or higher degree	0.151***	0.144***	0.248***	0.295***
	(0.030)	(0.023)	(0.035)	(0.042)
Other higher qualification	0.258***	0.240***	0.321***	0.382***
	(0.045)	(0.032)	(0.037)	(0.046)
GCE, A levels and lower	0.318***	0.326***	0.413***	0.461***
	(0.051)	(0.040)	(0.044)	(0.050)
Recent unemployment spell <=3m	0.439***	0.531***	0.751**	0.687**
	(0.075)	(0.073)	(0.094)	(0.100)
Recent unemployment spell >3m	0.451***	0.479***	0.655***	0.692***
	(0.066)	(0.056)	(0.068)	(0.089)
Recent inactivity spell <=3m	1.726*	1.840***	2.358***	1.833**
	(0.485)	(0.421)	(0.491)	(0.463)
Recent inactivity spell >3m	2.451***	2.746***	3.081***	4.714***
	(0.561)	(0.498)	(0.519)	(1.003)
Recent occupational change	1.394**	1.332***	1.692***	1.951***
	(0.201)	(0.148)	(0.165)	(0.222)
Earlier unemployment spell >3m	0.621***	0.629***	0.687***	0.426***
	(0.088)	(0.068)	(0.066)	(0.055)
Earlier inactivity spell >3m	0.607**	0.741*	0.833	0.901
	(0.132)	(0.130)	(0.134)	(0.179)
Earlier occupational change	1.039	0.975	0.923	1.347**
	(0.159)	(0.110)	(0.092)	(0.162)
Log likelihood	-3411	-5060	-6586	-4390
Observations	6030	14601	43653	11949

Odds ratios from random effects logit models. Standard errors in parenthesis; other explanatory variables: dummies for regions and year plus means of time-varying covariates over time. * Significant at 10%, ** Significant at 5%, *** Significant at 1%

Table 5: Determinants of being an unemployed rather than employed job seeker; sensitivity analysis (women)

	(i) 6% with highest probability on-the-job search	(ii) 15% with highest probability on-the-job search	(iii) All employed people (100%)	(iv) Job-to-job moves (BHPS)
Age	0.765	1.068	0.657***	0.655***
	(0.383)	(0.260)	(0.090)	(0.027)
Age square	0.997	1.000	1.003***	1.002***
	(0.002)	(0.001)	(0.001)	(0.001)
Married	0.533	0.667*	0.704***	0.694***
	(0.232)	(0.164)	(0.090)	(0.093)
Children 0-15	1.265	0.731	0.928	0.772**
	(0.539)	(0.175)	(0.110)	(0.094)
First or higher degree	0.057***	0.142***	0.334***	0.423***
	(0.024)	(0.030)	(0.049)	(0.064)
Other higher qualification	0.153***	0.333***	0.424***	0.528***
	(0.057)	(0.062)	(0.053)	(0.069)
GCE, A levels and lower	0.168***	0.494***	0.517***	0.639***
	(0.058)	(0.085)	(0.059)	(0.075)
Recent unemployment spell <=3m	0.482**	0.921	1.294*	1.011
	(0.171)	(0.216)	(0.195)	(0.163)
Recent unemployment spell >3m	0.239***	0.439***	0.496***	0.645**
	(0.102)	(0.104)	(0.078)	(0.110)
Recent inactivity spell <=3m	2.604*	1.563	2.079***	2.002***
	(1.442)	(0.558)	(0.445)	(0.457)
Recent inactivity spell >3m	2.094*	2.473***	2.708***	3.778***
	(0.909)	(0.680)	(0.443)	(0.704)
Recent occupational change	1.151	1.429*	1.564***	2.103***
	(0.397)	(0.302)	(0.180)	(0.259)
Earlier unemployment spell >3m	0.903	0.846	0.550***	0.438***
	(0.378)	(0.209)	(0.079)	(0.074)
Earlier inactivity spell >3m	0.343**	0.473***	0.618***	0.598***
	(0.148)	(0.125)	(0.099)	(0.106)
Earlier occupational change	0.954	1.308	1.028	1.757***
	(0.334)	(0.273)	(0.120)	(0.230)
Log likelihood	-1292	-2530	-4934	-3320
Observations	2256	5031	43866	10523

Odds ratios from random effects logit models. Standard errors in parenthesis; other explanatory variables: dummies for regions and year plus means of time-varying covariates over time. * Significant at 10%, ** Significant at 5%, *** Significant at 1%

Finally, it seems reasonable to assume that employed people who move between jobs without any intervening spell of non-employment were searching while in their previous job. Therefore an alternative way to identify employed job seekers is to use job-to-job moves with no intervening non-employment spells. Although job-to-job moves can be identified from the BHPS, this only identifies those who are successful in their search (i.e. people who

subsequently experience a job-to-job move). This might be a highly selected group of all employed people who engage in on-the-job search. The models comparing successful employed job seekers to unemployed people are shown in column (iv) of Tables 5a and 5b, and the results are more consistent with those in column (iii) rather than those in columns (i) and (ii). The similarity of the estimates in columns (iii) and (iv) suggests that job-to-job moves might not be a good way to identify employed people engaging in on-the-job search; at least when interviews are one year apart.

5. Conclusions

Our aim in this paper is to compare (un)employment histories of employed and unemployed job seekers in Great Britain. Although data on such histories is available from the British Household Panel Survey, this contains no information on on-the-job search. Therefore we use estimates from job search models based on LFS data to identify employed respondents in the BHPS who are most likely to engage in job search activity. We find substantial differences between employed and unemployed job seekers. On average employed job seekers have higher levels of education than unemployed job seekers, and different past employment histories. Overall results suggest that unemployed people transit into 'bad' jobs from which they keep looking for a 'good' job to exit unemployment. Job seekers who are employed might have accepted job offers which were not ideal, and are likely to engage in on-the-job search when in the new job. However, job seekers who search for a new job also seem to be in unstable jobs, with few chances to find a 'good' job and therefore to stop searching. Such people might be locked in a sequence of unemployment and bad jobs (a low-pay no-pay cycle), while others, with comparatively worse individual characteristics, might never find a job at all.

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