A new career in a new town. Job search methods and regional mobility of unemployed workers[☆,☆☆]

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Abstract

This paper investigates the effect of job search methods on regional mobility of unemployed workers. Data from the British Household Panel Survey are used to estimate a competing-risks unemployment duration model differentiating between exits to local and non-local employment. Non-local exits are associated to residential move across Local Authority Districts. Use of personal contacts and use of advertisements are found to enhance the probability to find job locally, but not the probability to find non-local job. Conversely, direct approach to employers is conducive to non-local employment but not to local employment. Employment agencies have no impact on either exits.

Keywords: job search, search methods, regional labour markets, regional mobility.

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1. Introduction

Regional labour mobility can compensate for disparities between regional labour markets (Blanchard and Katz, 1992). This adjustment mechanism is hindered in European countries (Decressin and Fatas, 1995; Jimeno and Bentolila, 1998; Puhani, 2001) relative to the US (Blanchard and Katz, 1992) by institutional characteristics, notably rigidities in the labour market (Bertola, 1999; Hassler et al., 2005) and in the housing market (Hughes and McCormick, 1987; Bover et al., 1989; Oswald, 1996, 1997, 1999; Partridge and Rickman, 1997; Nickell and Layard, 1999), that limit within-country mobility. Indeed mobility across EU NUTS2 regions is as low as 1%, that is half as much as across the United States (Bonin et al., 2008). Acknowledging the potential of labour mobility as an equilibrating factor, the European Commission has given strong emphasis to mobility in its employment strategies since the Lisbon strategy (European Commission, 2001), and more recently in Horizon 2020 (European Commission, 2010).

Survey evidence for the EU suggests that one of the key hurdles to regional mobility is related to worries about finding a suitable job (Bonin et al., 2008). Although suitable job options can be available outside the region, incentives to search and move in distant labour markets can be limited if information about job opportunities is localized.

A large body of literature has documented the importance of social relationships in the job matching process (Ioannides and Loury, 2004; Topa, 2011). Evidence from survey data consistently report that a large fraction of job matches are created through friends and relatives, and hence this channel is considered very effective for finding job. However, the widespread use of social contacts may hinder regional mobility, since social contacts can be localized and used in place of alternative methods, potentially leading to national jobs or to better job matches (Bentolila et al., 2010). This insight is corroborated by evidence that personal contacts are less important in the US (Blau and Robins, 1990) and in the UK (Frijters et al., 2005; Battu et al., 2011; Bachmann and Baumgarten, 2013), where regional mobility is higher than the EU average. In a UK-specific study, Manning and Petrongolo (2011) find that the likelihood of accepting jobs in another area is very low even for short distances, suggesting that labour markets are quite "local". The aforementioned evidence poses concerns about the geographic enclosure of labour markets and raises interest for a joint investigation of the job search process and mobility.

Theoretical models of job search show that unemployed people redistribute search effort from national to local search to avoid costs of relocation (Dohmen, 2005; Munch et al., 2006; Coulson and Fisher, 2009; Rouwendal and Nijkamp, 2010; Morescalchi, 2016). Models incorporating the choice of search methods suggest that individuals decide on the amount of effort to allocate to each method by taking into account associated costs and benefits (Holzer, 1988; Weber and Mahringer, 2008). Several empirical studies have investigated the returns to search methods in terms of the job finding rate, wages, job tenure or others (Holzer, 1988; Blau and Robins, 1990; Osberg, 1993; Böheim and Taylor, 2001; Addison and Portugal, 2002; Frijters et al., 2005; Weber and Mahringer, 2008; Bentolila et al., 2010; Pellizzari, 2010; Battu et al., 2011; Caliendo et al., 2011; Bachmann and Baumgarten, 2013). However no studies have taken into consideration the geographic dimension of search methods so far. The present paper fills this gap by investigating the effect of search methods on regional mobility of unemployed workers.

Data from the British Household Panel Survey (BHPS) for the period 1996-2008 are used to estimate a competing-risks model for the duration of unemployment. Exploiting information on Local Authority Districts (LAD), exits to employment are decomposed between exits to local employment and exits to non-local employment. Exits to non-local jobs are defined as employment inflows associated to cross-LAD residential move. Exits to local jobs are defined residually. The following five search methods are considered in the BHPS: (i) Direct Approach to Employers (DAE); (ii) advertisements (ADS); (iii) Employment Agency (EA); (iv) social contacts (SOCNET); (v) search as self-employed (SEMP).

By establishing a link between search methods and regional mobility of unemployed workers, this paper contributes to existing knowledge about the labour market functioning in two key ways. First, it offers a new perspective to assess efficiency in the selection of search methods. In this context efficiency requires that less mobile workers allocate relatively more (respectively, less) effort to methods that are conducive to local (respectively, non-local) employment. This line of research is relevant to the literature on housing tenure and labour market outcomes. Theoretical models show that higher mobility costs of homeowners have negative impact on search intensity and on the job finding rate, as a result of opposite effects in local and non-local labour markets (Munch et al., 2006; Morescalchi, 2016). Although (outright) homeowners are consistently found to use fewer search methods than renters (Morescalchi, 2016), most microeconometric studies find that homeowners have no longer, or even shorter, unemployment spells than renters (Goss and Phillips, 1997; Coulson and Fisher, 2002; Flatau et al., 2003; Munch et al., 2006; Van Vuuren, 2009; Battu et al., 2008; Morescalchi, 2016). As an explanation of diverging unemployment outcomes, Morescalchi (2016) provides evidence for the UK suggesting that homeowners are more efficient in the selection of search methods. Indeed, homeowners are found to use relatively more often ADS, and renters to use relatively more often the Public Employment Service (PES), whereas PES is associated to relatively longer unemployment spells. Therefore the present analysis can inform whether this selection of methods is efficient in a regional perspective. According to results in Morescalchi (2016), this would be the case if ADS was relatively conducive to local employment, and PES was relatively conducive to non-local employment.

Second, the present paper offers insights for policy interventions in the job search process aiming to weaken impediments to regional mobility. This appears of interest in light of the relevance attributed to this issue by the European Commission. Furthermore, the present analysis evaluates whether employment agencies play a significant role in the matching process and in particular whether they can be effective in enhancing regional labour mobility. This is of particular interest since the European Commission envisions a more comprehensive role for employment agencies, in particular PES, in the implementation of the European employment strategy (European Commission, 2010, p. 7).

This paper has the following structure. Section 2 describes related literature; namely Section 2.1 reviews the literature on job search methods, while Section 2.2 relates this paper to literature on search and regional mobility. Section 3 describes the data. Section 4 describes the econometric methodology employed for estimating the competing-risks unemployment duration model, and Section 5 provides the results. Section 6 concludes.

2. Related literature

The present paper is related to two strands of literature. The first one investigates the impact of job search methods on labour market outcomes of unemployed people. The second one focuses on the impact of mobility constraints on job search and finding in local vis-à-vis non-local labour markets. The tho strands are discussed in the following sections.

2.1. Search methods and labour market outcomes

Theoretical models of search incorporating the choice of search methods suggest that individuals decide on the amount of effort to dedicate to each method by taking into account associated costs, in terms of time and money, and benefits, in terms of quantity and quality of offers (Holzer, 1988; Weber and Mahringer, 2008). Using data from the EU-LFS for the years 2006–2008, Bachmann and Baumgarten (2013) show that the weighted percentage of unemployed people using a specific method is 65% for public employment office, 21% for private employment agency, 52% for direct applications, 61% for personal contacts, 42% for inserting/answering advertisements, 68% for studying advertisements, and 17% for test interview and examinations. These shares exhibit some variation across EU countries, with the UK having remarkably below-average share for friends and relatives (50%) and remarkably above-average share for inserting/answering advertisements (59%) and for studying advertisements (82%).[1]

The effects of search methods on labour market outcomes of unemployed people have been investigated empirically quite extensively. Table 1 summarizes results for a selection of survey-based studies, focusing on the effect of any of the five methods considered in the present study, namely EA, SOC-NET, DAE, ADS, SEMP. This leads to exclude those studies grouping methods into categories, for

[1] Personal contacts are found to be less important in the UK also by Frijters et al. (2005) and Battu et al. (2011).

which the effect of individual methods cannot be grasped. A distinction between Public Employment Service (PES) and Private Employment Agency (PEA) is also included whenever possible.

The choice of search methods can be measured in three possible ways. If the individual is currently unemployed, he is asked to report the search methods used, either selecting multiple methods (i) or only the main one (ii). If the individual is currently employed, he is asked to report retrospectively the method through which he found the present job when he was unemployed. This is labeled in Table 1 as the successful method (iii). The effect of each method can be compared against the alternative of either not using that specific method, or using another baseline method.

Table 1 shows that the interest has been primarily on the effect on the probability to find a job, on wage, and to a lesser extent on job tenure and others. As concerns the probability to find job, DAE stands out as the most effective method. Indeed it is consistently found to have positive effects in all the eight studies considering exits to employment. However, the effect of DAE on wage is mixed: it is positive in only one case (Green, 2012), while it is non-significant in three studies (Böheim and Taylor, 2001; Weber and Mahringer, 2008; Longhi and Taylor, 2011) and even negative in one (Addison and Portugal, 2002).

Evidence on the effect of ADS on the probability to find job is available for seven studies in Table 1. In three cases, ADS is found to have no effect on the probability to find job (Gregg and Wadsworth, 1996; Böheim and Taylor, 2001; Addison and Portugal, 2002). In the other four cases ADS is compared with employment agencies, and it is found to be more effective than PES in three cases (Frijters et al., 2005; Longhi and Taylor, 2011; Morescalchi, 2016), but no more effective than EA in one case (Battu et al., 2011). Moreover, Holzer (1988) finds that ADS increases the probability to receive a job offer.

Table 1 shows also that the interest of this literature has focused primarily on the effects of SOCNET and PES, that are considered as opposite examples of a very informal and very formal method (Van den Berg and Van der Klaauw, 2006). This section proceeds by reviewing in turn the literature for SOCNET and PES. The effect of SEMP is investigated in only two studies in Table 1 and hence it is not considered relevant in the present review.

The literature on the impact of social networks on labour market outcomes is particularly rich, and it is not restricted to survey evidence. Evidence from survey data consistently report that a large fraction of job matches are created through friends and relatives, and hence this channel is often considered to enhance employment inflows (Ioannides and Loury, 2004; Topa, 2011). Table 1 shows that among the ten studies considering the job finding or job offer as outcomes, positive effects of SOCNET are roughly as frequent as non-significant effects. Also, in the four UK studies comparing SOCNET with PES or EA, the effect is positive in two cases (Frijters et al., 2005; Longhi and Taylor, 2011) and non-significant in other two cases (Battu et al., 2011; Morescalchi, 2016). Therefore, although SOCNET is documented to be useful for finding job in some specific cases, it is not always effective, and it does not seem to be as effective as DAE. Indeed, among the nine studies considering SOCNET as well as DAE, six studies provide evidence that DAE is effective while SOCNET is not in at least one case (Osberg, 1993; Gregg and Wadsworth, 1996; Böheim and Taylor, 2001; Addison and Portugal, 2002; Battu et al., 2011; Morescalchi, 2016), and only one study finds that SOCNET is more effective (Holzer, 1988).

Evidence on the effect of SOCNET on wage is mixed. Table 1 shows that the effect of SOCNET on wage is positive in one study (Green, 2012), non-significant in three studies (Böheim and Taylor, 2001; Weber and Mahringer, 2008; Longhi and Taylor, 2011), and negative in two studies (Addison and Portugal, 2002; Bentolila et al., 2010). Moreover, using a large dataset of European households Pellizzari (2010) finds that the wage effect of social contacts has high cross-country variation.

Besides survey evidence, another strand of literature has investigated the impact of social networks in the labour market by explicitly modeling the mechanisms through which information about job opportunities/candidates is transmitted. Two main transmission mechanisms have been pointed out in this literature: referrals of network members by firm's employees (Dustmann et al., 2015; Brown et al., 2014) and interactions among potential employees (Topa, 2001; Calvo-Armengol and Jackson, 2004, 2007; Galeotti and Merlino, 2014). In the first case, employees obtaining jobs through referrals by firm's employees are predicted to earn higher wages and have longer tenure, because their match-specific productivity is less uncertain. In the second case, individuals with larger social networks, and in particular with larger number of employed contacts, are predicted to have higher job finding rates because they can receive information about more job opportunities.[2] Predictions of these models have been tested typically with administrative data and by using various measures of network connections, such as neighbourhood (Bayer et al., 2008; Hellerstein et al., 2011, 2014; Schmutte, 2015), ethnicity (Beaman, 2012; Dustmann et al., 2015), family (Kramarz and Nordström Skans, 2014), firm (Cingano and Rosolia, 2012), military service (Laschever, 2009), and friendship connections (Cappellari and Tatsiramos, 2015). Evidence from this literature generally reports that network connections enhance the employment probability and job stability, but have mixed effects on wage as well.[3]

Evidence on the effect of PES on the probability to find job, either alone or combined with PEA, is available for eight studies in Table 1. A positive effect is found by Gregg and Wadsworth (1996), and by Osberg (1993) only for long-term unemployed in two samples out of six, while two studies find no effect (Böheim and Taylor, 2001; Addison and Portugal, 2002), and four studies find a negative effect relative to other methods (Frijters et al., 2005; Battu et al., 2011; Longhi and Taylor, 2011; Morescalchi, 2016). Moreover, Holzer (1988) finds no effect on the probability to receive a job offer. Therefore, PES seems

[2]This prediction rests on the assumption that, while employed workers share information about job opportunities with unemployed workers in their network, unemployed workers keep the information for themselves.

[3]See Loury (2006), Pellizzari (2010) and Bentolila et al. (2010) for explanations of the mixed results for the wage effect of SOCNET.

to be the least effective method in enhancing exits from unemployment. Similarly bad performance is found for wages (Böheim and Taylor, 2001; Addison and Portugal, 2002; Weber and Mahringer, 2008; Longhi and Taylor, 2011; Green, 2012). PES can be compared to PEA in only three studies, pointing out similar job finding performance in two cases (Osberg, 1993; Gregg and Wadsworth, 1996), and a relative effectiveness of PEA in one case (Morescalchi, 2016).

Although PES is often found to be ineffective for unemployed workers, it may be possible that PES is less effective because used at the last resort (Green, 2012), when alternative search channels are not available (Bachmann and Baumgarten, 2013) or have been already exhausted (Osberg, 1993). Moreover, PES is typically approached by low quality workers, for whom it can be as efficient as other channels (Weber and Mahringer, 2008).

Taking stock of the literature reviewed in this section, it appears that unemployed people tend to select search methods somehow efficiently (Holzer, 1988; Weber and Mahringer, 2008). SOCNET and PES are the two most popular methods and they are also associated to low search costs. Indeed, SOCNET can provide relevant information through informal contacts, while PES can offer a personalized service free of charge. However, while SOCNET is often found to enhance chances to escape unemployment, PES stands out as the least effective method. Relying on PES could be anyway efficient for those individuals who have limited chances to find a job with alternative methods. DAE and ADS can be associated to higher costs of search since they require active steps to gather information on jobs or to get in contact to employers, which can be associated to time as well as pecuniary costs. Therefore, although DAE stands out as the most effective method to find job, it is less used.

The present paper contributes to this literature by examining the productivity of search methods for local and non-local jobs. The regional separation offers a new perspective to assess efficiency in the selection of search methods. Individuals with higher costs of mobility dedicate more (respectively, less) effort in search for local (respectively, non-local) jobs Morescalchi (2016). Therefore, efficiency requires that they allocate more (respectively, less) effort to methods that are more conducive to local (respectively, non-local) employment. This line of research is relevant to the literature on job search and regional mobility, which is introduced in the following section.

2.2. Search and regional mobility

Regional mobility is typically incorporated in theoretical models of job search by allowing for two distinct labour markets, a local one and a non-local one (Van den Berg and Gorter, 1997; Dohmen, 2005; Coulson and Fisher, 2009; Van Vuuren, 2009; Rouwendal and Nijkamp, 2010; Munch et al., 2006; Morescalchi, 2016). Accepting a job offer in the non-local labour market requires costly relocation, while no costs are incurred for accepting local jobs. A general result from these models is that unemployed workers set higher reservation wages for non-local jobs since they want a compensation for mobility costs.

These models are used to predict differences in labour outcomes among unemployed workers with different mobility costs, typically homeowners and renters. Higher mobility costs imply that homeowners have higher search intensity and higher probability to find job locally, but lower search intensity and lower probability to find job with a move in a distant area (Munch et al., 2006; Morescalchi, 2016). Morescalchi (2016) has recently demonstrated that the second effect prevails, yielding an overall negative impact of homeowership on search intensity and on the job finding rate. The result that homeowners should experience longer unemployment spells due to barriers to mobility is known in the literature as "Oswald's hypothesis" (Oswald, 1996, 1997, 1999).

The existing empirical evidence has provided some support to the predictions that homeowners should exit unemployment less rapidly for non-local jobs and more rapidly for local jobs (Munch et al., 2006; Battu et al., 2008; Van Vuuren, 2009). However, in contrast with "Oswald's hypothesis", most microeconometric studies have found that exits from unemployment are overall not slower, or even faster, for homeowners (Goss and Phillips, 1997; Coulson and Fisher, 2002; Flatau et al., 2003; Munch et al., 2006; Van Vuuren, 2009; Battu et al., 2008; Morescalchi, 2016). This evidence is in contrast not only with theoretical predictions, but also with evidence on job search intensity, since Morescalchi (2016) finds that (outright) homeowners use fewer search methods than renters, suggesting that they search indeed less intensively. Therefore Morescalchi (2016) has investigated the choice of search methods as an explanation of diverging unemployment outcomes between homeowners and renters. He finds that homeowners use relatively more often newspapers advertisements, and that renters use relatively more often public employment offices, whereas the latter search method is associated with relatively longer unemployment spells. Therefore, the combined evidence that homeowners use fewer search methods, but that they select those associated to higher returns, seems to suggest that they search more efficiently.

However, no evidence exists so far informing whether search methods are selected efficiently also from a spatial point of view. In the context of the choice of search methods, mobility costs increase (respectively, reduce) relative expected benefits associated to methods that are more conducive to local (respectively, non-local) employment. Specifically, homeowners (respectively, renters) should dedicate relatively more effort to search methods that are more productive in terms of local (respectively, non-local) employment. Therefore it is of interest to investigate the productivity of search methods for local vis-à-vis non-local jobs. According to results in Morescalchi (2016), one would expect that newspapers and advertisements are more conducive to local employment, and that public employment offices are more conducive to non-local employment.

3. Data

The dat set used is the British Household Panel Survey (BHPS), a nationally representative longitudinal survey collecting yearly interviews for about 10,000-15,000 individuals. The BHPS started in 1991 and ran until 2008 for a total of 18 waves. Thereafter the BHPS became part of a new longitudinal study called Understanding Society.

The BHPS is a rich data set containing detailed information on labour market histories. Each individual is asked to report information on the current labour market spell at the time of interview, as well as on all previous spells back to one year before. From these data a complete sequence of unemployment spells recorded to the nearest calendar month was constructed. Unemployment spells are defined as a series of unemployment monthly episodes ending up in a transition to job or out of labour force. In case unemployment is observed in the last interview available, the spell is right censored since the end date cannot be observed.

Among uncensored unemployed spells two types of spells can be identified. First, spells ongoing at any wave's time of interview and completed before the next interview. The end date of these spells is taken from the list of recalled spells in the later interview. Second, unemployment spells started and completed within two subsequent interviews. The end and start date of these spells can be taken from the list of recalled spells in the latest wave. However, information on job search methods and other characteristics is not available for these spells since it is recorded only for the current spell at the time of interview. Therefore, similarly to Battu et al. (2008), these shorter spells have to be dropped from the sample.

For any unemployment spell recorded at the time of interview, the individual is asked to report on the search methods used in the last four weeks. The unemployed can select any out of five methods, namely whether he/she (i) applied directly to an employer (DAE); (ii) studied or replied to advertisements (ADS); (iii) contacted a private employment agency or Job Centre (EA); (iv) asked friends or contacts (SOCNET); (v) took steps to start own business (SEMP). Information about job search methods of unemployed people is present in the BHPS since 1996, therefore only unemployment spells from wave 6 onwards are used in the present paper. Unfortunately, evidence on the effect of public employment service can be only partial in the present analysis, since the data do not allow distinguishing between private and public employment agencies. Evidence from the UK LFS reveals that public agencies are used three times more often than private ones (Bachmann and Baumgarten, 2013), suggesting that public agencies can be a major determinant of the combined effect.

In data with repeated measurement of spells, artificial spells can arise by discrepancies in what an individual recalls at a certain interview, and what was recorded at the previous interview. Following Upward (1999), and similarly to Battu et al. (2008) and Monchuk et al. (2014), these seam effects are dealt with in this paper by applying the principle that information recorded closest to a certain event is the most reliable. Namely, the following three general rules have been used: (i) if the earliest spell recalled by the individual at wave t starts on or before the date of interview in $t-1$, and labour force status has changed, the spell is considered a new one and the start date is set equal to the following month; (ii) if the earliest spell recalled by the individual at wave t starts on or before the date of interview in $t-1$, and labour force status is the same, the spell is considered the same; (iii) the start date of the unemployment spell is derived from the earliest interview in the spell.

In order to investigate the geographical scope of search methods, exits to job are decomposed between exits to local jobs and to non-local jobs (Munch et al., 2006; Battu et al., 2008; Monchuk et al., 2014). Exits to non-local jobs are defined as exits associated to a residential move in a distant area occurring around the date of exit. The identification of long-range moves is based on information recorded by the BHPS about the change of address in the last 12 months and the region of residence. Regional mobility is defined as a change in Local Authority District (LAD) as in Battu et al. (2008). The UK is divided in 434 LADs according to the boundaries definition in the present data.[4]

A time window of 12 months before and 12 after the entry into job is used to define long-range job-related moves. An interval of 12 months after the entry into employment is chosen in line with Munch et al. (2006) and Battu et al. (2008), allowing for the fact that some workers first start a new job and then search for a new permanent residence. 12-month before the start of the new job is the same interval as in Battu et al. (2008) but larger than the one used by Munch et al. (2006) who consider 52 weeks. By using narrower intervals of 9 or 6 months before entry into job, the number of cross-LAD moves shrinks by 2.9% and 11.7% respectively; results remain largely similar in both cases (see Appendix B).

Exits to local jobs are defined residually as exits non associated to cross-LAD moves. This category comprises exits associated to either no move or within-LAD move.

Finally, since including ongoing spells would over-represent long duration spells (Lancaster, 1990), only spells starting after September 1995 are used in the analysis (Battu et al., 2008). After deleting cases with missing values in variables used in estimation, the resulting sample of unemployment spells is summarized in Table 2. Of the total 1,611 unemployment spells observed, 137 (8.5%) end with exit to non-local job, 908 (56.4%) with exit to local job, 244 (15.1%) with exit out of the labour force, and 322 (20%) are right censored.

Table 2 reports also summary statistics calculated at the last month and by type of exit. Looking at the five search methods, ADS is the most used in total (77.7%), EA is the second most used (73.4%), DAE and SOCNET are used by a similar fraction of unemployed ($\sim$ 68%), while SEMP is used only by a small fraction (8.4%). By comparing the two job inflows it can be noticed that

[4] The boundaries definition of LADs is the one in place before the local government changes of 2009. In 2000 the population of LADs was on average 135,682, ranging between 2,100 (Isles of Scilly) and 985,100 (Birmingham). Population estimates are drawn from NOMIS (www.nomisweb.co.uk).

individuals exiting to non-local employment are on average younger, more educated, more likely to be women, more likely to have no dependent children, more likely to be private renter but less likely to be social renter, and finally they have similar marital status but with higher probability to have non-working spouse. Therefore individuals relocating to a distant area are observed with somehow better labour market characteristics, which is in turn consistent with a lower average spell duration, being 6.4 months against 10 months.

4. Econometric Model

In order to identify search methods conducive to local or non-local employment, an unemployment duration model with competing risks is estimated. Three competing risks, or unemployment exits, are modeled against the probability of remaining unemployed, namely (i) exit to non-local job (involving a cross-LAD residential move), (ii) exit to local job (involving a within-LAD move or no move), and (iii) exit out of the labour force.

Unemployment spells have an underlying continuous process but the data are interval-censored since the exact exit date is not observed within months. Following Monchuk et al. (2014) and Morescalchi (2016), hazards are treated as intrinsically discrete by employing a multinomial logit model with data organized in person-month form (Allison, 1982). In case intervals are relatively short or interval-hazards are relatively small, the multinomial logit model provides a close approximation of interval-censored duration models in which the underlying (continuous) hazard is constant within intervals (Jenkins, 2005, p. 105). A continuous competing risks model is also estimated for comparison.

A parsimonious parametric baseline hazard is used to model temporal dependence. The logarithm of duration is used in analogy with the continuous time Weibull model. Results with alternative baseline specifications are also reported.

This approach rests on the assumption that risks are conditionally independent, that is the risk of any event is not related to the risk of any other event after conditioning on the included covariates. This assumption has been relaxed in the related literature by exploiting repeated spells for the same individuals (Munch et al., 2006; Battu et al., 2008). In the present data only $\sim 15\%$ of individuals are observed with multiple unemployment spells. Therefore the reliability of the assumption is sustained by the use of a rich set of control variables.

The set of control variables includes human capital characteristics (age, education, gender, previous occupation), household characteristics (marital status, spouse's economic activity, children, housing tenure), receipt of unemployment benefit, and indicators accounting for macro-economic effects at the national (year and quarter dummies), regional (region dummies) and local level (claimant inflows and outflows for LADs). These variables are assumed constant within spells, except age, time indicators, and claimant flows, which vary within the spell on a monthly basis.

In order to estimate the impact of search methods on the competing risks, a set of dummies corresponding to the five methods is included in the specification.

5. Results

Table 3 reports estimates of the competing-risks unemployment duration model. The first three columns report the effects on the hazards to, respectively, non-local job, local job, and out of labour force (OLF), relative to the baseline state of remaining unemployed. The last column reports the effect on the hazard to non-local job considering exit to local job as a baseline. Exponentiated β-s have the usual interpretation as relative-risks ratios.

Results show that SOCNET and ADS have positive impact on the probability to find job locally. Specifically, use of SOCNET enhances the likelihood to leave unemployment for a local job by $(\exp(0.406) - 1) \cdot 100 = 50.1\%$, and ADS enhances it by $(\exp(0.199) - 1) \cdot 100 = 22\%$. No significant effects are found on exit to non-local employment for both methods. Looking at the last column of Table 3, the percentage effect on the hazard to non-local employment vis-à-vis local employment is $(\exp(-0.516) - 1) \cdot 100 = -40.3\%$ for SOCNET and $(\exp(-0.511) - 1) \cdot 100 = -40\%$ for ADS. These results suggest that SOCNET and ADS are much more conducive to local employment than employment requiring relocation in a distant area, but the effect on local jobs is stronger for SOCNET.

Opposite results are found for DAE, with a positive (mildly) significant effect on the hazard to non-local employment and no significant effect on the hazard to local employment. The comparison between the two exits suggests that unemployed using DAE are $(\exp(0.508) - 1) \cdot 100 = 66.2\%$ more likely to exit unemployment for a non-local job relative to a local job. Concerning the other two search methods, namely EA and SEMP, significant effects are not found for any of the hazards considered.

The coefficients on the unemployment duration show that, as the time spent unemployed increases, the probability to find a non-local job decreases, although the effect is not significant, while the probability to find a local job increases. The unemployment duration has also a positive effect on the probability to drop off search as the third column in Table 3 suggests. Estimates with alternative specifications of the time dependence are reported in Appendix B as robustness checks (see Tables 4–6). The effects of the search methods are not sensitive to modeling the baseline hazards either with a quadratic function of time (t = months unemployed), or with a cubic function of time, or with a piecewise constant baseline. However these alternative specifications provide more evidence on the relationship between the hazards and the unemployment duration. For example, the hazard to non-local employment is highest between the 2nd and 9th month of unemployment (see Table 6). Moreover, the hazard to local employment increases with the unemployment duration until a certain level and then starts reducing (see Table 4 and Table 6).

Additional robustness checks for the results in Table 3 have been performed by using either different time windows to identify moves, or a continuous-time competing-risks model. These checks are reported in Appendix B (see Tables 7–9). Results are largely unaffected also in these cases.

The rest of this section describes results for the other variables reported in Table 3. Age has a negative and roughly monotonic effect on both transitions to non-local and local employment. There are two explanations for this result. First, older workers are less capable to adapt to new jobs requiring a skill adjustment. Second, unemployment can be more acceptable for them since they should have accumulated larger wealth. Moreover the negative effect of age is stronger for transitions to non-local jobs as the the last column of Table 3 suggests. The effect is significant for unemployed aged 35 or above. This result is consistent with older workers having stronger family ties and attachment with the local community and hence a higher reservation wage for non-local jobs.

Having educational qualifications increases the probability to find job either locally or non-locally relative to the baseline of no qualifications. For non-local jobs, the effect increases monotonically with the level of qualification and it is significant for the two highest categories (i.e. Nursing & other qualifications, and First degree or above). For local jobs, the strongest effects are found for the two lowest categories (i.e. O Levels and A Levels). By comparing the two hazards, it is found that the probability to find job in a distant area is positively an monotonically affected by the level of qualification. This result is consistent with the insight that more educated workers tend to earn higher wages and hence the returns to mobility are more likely to exceed the costs.

Gender does not have any significant effect on the probability to find local job, as well as on mobility. However unemployed females are more likely to drop off the labour market. Having children aged 15 or below in the household reduces the likelihood to move for a job, and even more if compared to local job, but none of these effects are significant.

Having a working partner increases the probability to find a local job against both alternatives of being single or having a non-worker partner. The latter result contradicts the "added worker hypothesis", which would predict an increase in the employment probability for an individual whose partner has lost the job. However it is not unusual to find rejections of this hypothesis, or even opposite results such as in the UK (Dex et al., 1995). Among various arguments raised in the literature to support the rejection, the main one is that means-tested unemployment benefits may generate disincentives to work for the spouse of the unemployed person (see Cooke, 1987, for a review). Table 3 suggests also that having a non-working partner increases the chance to relocate for a job relative to the probability of remaining unemployed as well as of finding a local job. Rather than a validation of the added worker hypothesis, this result seems driven by the fact that having a working partner inhibits mobility to avoid household separation.

Housing tenure dummies show that, relative to private renters, homeowners are less likely to enter employment with a move but more likely to find a job locally. These findings confirm the theoretical predictions of search models with spatial mobility (see Section 2.2). Moreover, social renters are found to stay unemployed longer than homeowners regardless of the type of job entry. This is a well-known result in the UK literature on social housing (Hughes and McCormick, 1981, 1987, 2000; Battu et al., 2008). The result that social renters are less prone to move for a job than homeowners is usually explained with a lock-in effect originating by strong disincentives to residential move.[5]

Receiving unemployment benefit reduces the probability to find either non-local or local jobs, but the effect is significant only in the latter case. A negative but non-significant impact on the probability of a job-related move is similarly found by Tatsiramos (2009), using UK data from the European Community Household Panel (ECHP) for the years 1994 to 2001. Unemployment benefit is expected to have a negative effect on both local and non-local job-finding rates by rendering unemployment relatively more valuable and hence increasing the reservation wage in both cases. However this effect can be contrasted for non-local jobs by an opposite force in case unemployment benefits relax the financial constraint induced by mobility costs (Tatsiramos, 2009). Although this latter channel seems supported by the non-significant coefficient on the hazard to non-local job, the almost null impact on the relative hazard suggests that it may not be very important.

The rates of flows into and out of the local claimant stock capture changes in the conditions of the local labour market. An increase in the inflow rate can correspond to a reduction in the probability to find a local job as well as to an increase in the share of non-employed people who seek actively for a job. Consistently, it is found to reduce the hazard to local job and to increase the hazard to OLF. The impact on the hazard to non-local job is positive but not significant signaling that unemployed may not react immediately by moving to non-local jobs. Conversely, an increase in the claimant outflow rate is expected to capture an increase in the probability to find a local job as well as a reduction in the share of job-seekers. Consistently, it is found to increase the hazard to local job as well the hazard to OLF. The impact on the hazard to non-local job is positive but not significant suggesting that an increase in the local claimant outflow corresponds only modestly to unemployed people moving for non-local jobs.

6. Conclusions

This paper has investigated the effect of job search methods on regional mobility of unemployed workers. A competing-risks model for the duration of unemployment has been estimated using data from the British Household Panel Survey for the period 1996-2008. Exploiting information on Local Authority Districts (LAD), exits to employment are decomposed between exits to a local job and

[5]Disincentives to mobility of social renters can derive from below-market rent, long waiting lists, security of tenure and restricted transferability within social housing.

exits to a non-local job. Exits to a non-local job are defined as employment inflows associated to a cross-LAD residential move, while exits to a local job are defined residually.

Results show that personal contacts (SOCNET) and advertisements (ADS) enhance the probability to find a job locally, but have no effect on the probability to find a job outside the local labour market. Conversely, direct approach to employers (DAE) enhances exits to non-local employment, but has no effect on local employment. Employment agencies (EA) are found to be ineffective for both employment inflows.

The findings of this paper enrich existing evidence on the effect of job search methods on unemployment exits by establishing a link with regional mobility. This novel approach contributes to existing knowledge about the labour market functioning in two key ways. Firstly, the distinction between local and non-local employment inflows offers a new perspective to evaluate efficiency in the selection of search methods. With regional mobility, efficiency requires that workers with higher mobility costs allocate relatively more (respectively, less) effort to methods that are conducive to local (respectively, non-local) employment. Therefore the present results suggest that less mobile workers should use relatively more often SOCNET and ADS, while more mobile workers should use relatively more often DAE.

These conclusions have specific relevance for the literature on the role of housing tenure in the labour market. In a study investigating the impact of mobility costs of homeownership for the UK, homeowners are found to use relatively more often ADS, and renters are found to use relatively more often Public Employment Service (PES), whereas the latter method is associated to longer unemployment spells (Morescalchi, 2016). The search process of (outright) homeowners has been considered more efficient because they are found to escape unemployment more rapidly, while using fewer search methods. The results of the present analysis complement this evidence by suggesting that homeowners are more efficient in the allocation of effort between local and non-local search. Indeed they concentrate their efforts in a channel (ADS) that is found to lead to local jobs. This result is consistent with theoretical predictions suggesting that homeowners set relatively lower reservation wage as well as higher search intensity for local jobs in order to avoid costly relocation (Munch et al., 2006; Morescalchi, 2016). Moreover the distinction between search methods conducive to local vis-à-vis non-local jobs provides an explanation for the recurring empirical finding that homeowners exit unemployment overall more rapidly than renters.

Secondly, the findings of this paper provide a guidance to policy makers for interventions in the job search process aiming to weaken impediments to regional mobility. This is of particular interest since in recent years the European Commission has promoted regional mobility as a key driver of the labour market adjustment. Given that personal contacts account for a large fraction of job matches and are largely used by unemployed workers, evidence of a strong geographic confinement in employment inflows suggests that personal contacts can exacerbate low mobility figures in Europe. This insight is corroborated by evidence that in the UK and US personal contacts are relativity less used and mobility is higher. Therefore these results point to policies aiming to weaken the relative importance of family and social ties in the search process (Bentolila et al., 2010). The following two instruments are supported by the present evidence (Bonin et al., 2008): (i) a nationwide placement system allowing PES to monitor job vacancies throughout the country; (ii) instruments promoting integration of mobile workers and their families, such as supporting the job search of spouses.

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Tables

Table 1

Survey evidence on the effect of job search methods of unemployed people

article	outcome	sample	choice	PES	PEA	EA	SOCNET	ADS	DAE	SEMP
Holzer (1988)	job offer	unem. m. (16-23 yo)	multiple	0	n/a	n/a	+	+	0	n/a
Osberg (1993)	finding job	st unem. f. (81, 83, 86)	multiple	0, 0, 0	0, 0, 0	n/a	0, 0, 0	n/a	0, +, 0	n/a
	finding job	lt unem. f. (81, 83, 86)	multiple	0, 0, +	0, 0, n/a	n/a	0, 0, 0	n/a	0, 0, +	n/a
	finding job	st unem. m. (81, 83, 86)	multiple	0, 0, 0	0, +, 0	n/a	-, +, 0	n/a	0, +, 0	n/a
	finding job	lt unem. m. (81, 83, 86)	multiple	-, +, 0	n/a, 0, 0	n/a	0, 0, 0	n/a	+, +, +	n/a
Gregg and Wadsworth (1996)	finding job	unem. m.	multiple	+	+	n/a	+	0	+	n/a
	finding job	unem. f.	multiple	+	+	n/a	0	0	+	n/a
Böheim and Taylor (2001)	finding job	unem. m.	multiple	n/a	n/a	0	0	0	+	0
	wage	empl. m.	multiple	n/a	n/a	0	0	+	0	0
Addison and Portugal (2002)	finding job	unem.	multiple	0	n/a	n/a	0	0	+	+
	wage	empl.	successful	- base=other	n/a	n/a	- base=other	0 base=other	- base=other	n/a
	job duration	empl.	successful	+ base=other	n/a	n/a	0 base=other	0 base=other	- base=other	n/a
Frijters et al. (2005)	finding job	unem. white UK born	main	base	n/a	n/a	+ base=PES	+ base=PES	+ base=PES	n/a
Weber and Mahringer (2008)	wage	empl.	successful	base	n/a	n/a	0 base=PES	0 base=PES	0 base=PES	n/a
	job duration	empl.	successful	base	n/a	n/a	0 base=PES	0 base=PES	+ base=PES	n/a
Pellizzari (2010)	wage	empl.	successful	n/a	n/a	n/a	+ AT, BE, NL	n/a	n/a	n/a
	wage	empl.	successful	n/a	n/a	n/a	0 DK, FR, DE, IE, LU, ES	n/a	n/a	n/a
	wage	empl.	successful	n/a	n/a	n/a	- FI, GR, IT, PT, UK	n/a	n/a	n/a
	wage	empl.	successful	n/a	n/a	n/a	0	n/a	n/a	n/a
Bentolila et al. (2010)	finding job	empl. (< 35 yo)	successful	n/a	n/a	n/a	+	n/a	n/a	n/a
	wage	empl. (< 35 yo)	successful	n/a	n/a	n/a	-	n/a	n/a	n/a
	finding job	empl. 1st job (< 35 yo)	successful	n/a	n/a	n/a	+	n/a	n/a	n/a
	wage	empl. 1st job (< 35 yo)	successful	n/a	n/a	n/a	-	n/a	n/a	n/a
Battu et al. (2011)	finding job	m. in wa	main	n/a	n/a	base	0 base=EA	0 base=EA	+ base=EA	n/a
	seniority	m. in wa	main	n/a	n/a	base	0 base=EA	+ base=EA	+ base=EA	n/a
Longhi and Taylor (2011)	finding job	unem. m.	main	base	n/a	n/a	+ base=PES	+ base=PES	+ base=PES	n/a
	finding job	unem. f.	main	base	n/a	n/a	+ base=PES	+ base=PES	+ base=PES	n/a
	wage	empl. m.	main	base	n/a	n/a	0 base=PES	0 base=PES	0 base=PES	n/a
	wage	empl. f.	main	base	n/a	n/a	0 base=PES	0 base=PES	0 base=PES	n/a
Green (2012)	wage	empl.	successful	base	n/a	n/a	+ base=PES	0 base=PES	+ base=PES	n/a
Morescalchi (2016)	finding job	m. hoh	main	base	+ base=PES	n/a	0 base=PES	+ base=PES	+ base=PES	n/a

Notes: Longhi and Taylor (2011) consider also the effect on temporary contract and whether working-hours are in line with preferences.Symbols, abbreviations and acronyms: "+"=positive and significant effect; "0"=non-significant effect; "-'=negative and significant effect; "n/a"=not available; "PES'=Public Employment Service; "PEA'=Private Employment Agency; "EA'=Employment Agencies (public or private); "SOCNET"=Friends and relatives; "ADS"=Newspapers and advertisements; "DAE"=Direct Approach to Employers; "SEMP"=taken steps to start own business;"unem."=unemployed; "empl."=employed; "f."=females; "m."=males; "st"=short-term; "lt"=long-term; "hoh"=heads of household; "wa"=working age; "yo"=years old; "fe"=fixed-effects; "AT"=Austria; "BE"=Belgium; "NL"=Netherlands; "LFS"=Labour Force Survey; "MCSUI"=Multi-City Study of Urban Inequality; "NLSY"=National Longitudinal Survey of Youth; "BHPS"=British Household Panel Survey; "ECHP"=European Community Household Panel; "SEUP"=Survey of Employment and Unemployment Patterns.

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article	country	dataset	period	estimation method
Holzer (1988)	US	NLSY	1981	probit
Osberg (1993)	Canada	LFS	1981, 1983, 1986	logit
	Canada	LFS	1981, 1983, 1986	logit
	Canada	LFS	1981, 1983, 1986	logit
	Canada	LFS	1981, 1983, 1986	logit
Gregg and Wadsworth (1996)	UK	LFS	1992	probit
	UK	LFS	1992	probit
Böheim and Taylor (2001)	UK	BHPS	1996-1999	probit selection model
	UK	BHPS	1996-1999	selection model
Addison and Portugal (2002)	Portugal	LFS	1992-1996	duration model
	Portugal	LFS	1997	grouped regression
	Portugal	LFS	1994-1997	duration model
Frijters et al. (2005)	UK	LFS	1997-2002	duration model
Weber and Mahringer (2008)	Austria (Styria region)	ad-hoc survey	1997	OLS
	Austria (Styria region)	ad-hoc survey	1997	OLS
Pellizzari (2010)	EU countries	ECHP	1994-1999	individual fe
	EU countries	ECHP	1994-1999	individual fe
	EU countries	ECHP	1994-1999	individual fe
	US	NLSY	1996-2000	individual fe
Bentolila et al. (2010)	US (Atlanta, Boston, Los Angeles)	MCSUI	1992-1994	OLS
	US (Atlanta, Boston, Los Angeles)	MCSUI	1992-1994	OLS
	EU (13 pooled countries)	ECHP	1995-2001	OLS
	EU (13 pooled countries)	ECHP	1995-2001	OLS
Battu et al. (2011)	UK	LFS	1998-2001	logit
	UK	LFS	1998-2001	logit
Longhi and Taylor (2011)	UK	LFS	1992-2009	probit
	UK	LFS	1992-2009	probit
	UK	LFS	1992-2009	OLS
	UK	LFS	1992-2009	OLS
Green (2012)	Australia	SEUP	1994-1997	selection model
Morescalchi (2016)	UK	LFS	1999-2009	duration model

Table 2
SUMMARY STATISTICS FOR UNEMPLOYMENT SPELLS

	Total spells		Non-local job		Local job		OLF		Unemployed	
Number of spells	1,611		137 (8.5%)		908 (56.4%)		244 (15.1%)		322 (20%)	
Number of individuals	1,369		121		788		232		322	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Duration in months	9.718	10.772	6.394	6.877	9.953	10.026	11.217	12.408	9.332	12.437
DAE	0.684	0.465	0.781	0.415	0.673	0.469	0.602	0.490	0.736	0.441
EA	0.734	0.442	0.759	0.429	0.739	0.439	0.697	0.461	0.736	0.441
SOCNET	0.680	0.466	0.628	0.485	0.713	0.453	0.615	0.488	0.661	0.474
ADS	0.777	0.417	0.752	0.434	0.794	0.405	0.758	0.429	0.752	0.433
SEMP	0.084	0.277	0.102	0.304	0.093	0.290	0.053	0.225	0.075	0.263
Age 16–24	0.430	0.495	0.489	0.502	0.379	0.485	0.439	0.497	0.540	0.499
Age 25–34	0.221	0.415	0.321	0.469	0.211	0.409	0.193	0.395	0.227	0.419
Age 35–44	0.158	0.365	0.080	0.273	0.187	0.390	0.148	0.355	0.118	0.323
Age 45–64	0.191	0.393	0.109	0.313	0.222	0.416	0.221	0.416	0.115	0.319
Female	0.381	0.486	0.431	0.497	0.344	0.475	0.557	0.498	0.332	0.472
Unemployment benefit	0.567	0.496	0.540	0.500	0.573	0.495	0.488	0.501	0.621	0.486
No qualifications	0.259	0.438	0.131	0.339	0.252	0.435	0.275	0.447	0.323	0.468
O Levels or equivalent	0.236	0.425	0.197	0.399	0.243	0.429	0.213	0.410	0.252	0.435
A Levels of equivalent	0.140	0.347	0.161	0.368	0.146	0.354	0.123	0.329	0.124	0.330
Nursing & other quals.	0.227	0.419	0.263	0.442	0.242	0.429	0.221	0.416	0.174	0.380
First degree or above	0.137	0.344	0.248	0.434	0.116	0.320	0.168	0.375	0.127	0.334
Single	0.601	0.490	0.584	0.495	0.577	0.494	0.615	0.488	0.668	0.472
Working partner	0.256	0.437	0.219	0.415	0.287	0.453	0.270	0.445	0.174	0.380
Non-working partner	0.142	0.349	0.197	0.399	0.135	0.342	0.115	0.319	0.158	0.366
Children 0-15 years	0.218	0.413	0.139	0.347	0.243	0.429	0.217	0.413	0.183	0.387
Homeowner	0.546	0.498	0.569	0.497	0.590	0.492	0.574	0.496	0.388	0.488
Social renter	0.310	0.460	0.120	0.330	0.320	0.470	0.310	0.460	0.380	0.490
Private renter	0.140	0.350	0.310	0.460	0.090	0.290	0.120	0.320	0.230	0.420
Claimant inflow rate	24.50	6.21	25.82	6.70	24.53	6.08	24.66	6.07	23.72	6.39
Claimant outflow rate	25.80	7.19	26.67	7.43	25.57	6.84	26.94	7.50	25.21	7.69

Notes: Summary statistics refer to the last month of the unemployment spell. Additional variables used in estimation are dummies for region, previous occupation, calendar quarter and year. See Appendix A for description of the variables.

Table 3
Unemployment Duration Competing-risks Model Estimates

	Non-local job			Local job			OLF			Non-local job (base is Local job)		
	β		SE	β		SE	β		SE	β		SE
DAE	0.424	*	0.231	-0.084		0.079	-0.234		0.147	0.508	**	0.246
EA	0.124		0.210	0.067		0.084	0.108		0.157	0.057		0.224
SOCNET	-0.110		0.191	0.406	***	0.083	0.046		0.142	-0.516	**	0.208
ADS	-0.311		0.222	0.199	**	0.097	0.177		0.182	-0.511	**	0.244
$SEMP$	0.074		0.297	-0.150		0.126	-0.491		0.313	0.224		0.319
Age 25–34	-0.373		0.263	-0.240	**	0.112	-0.292		0.226	-0.134		0.287
Age 35–44	-1.306	***	0.423	-0.158		0.129	-0.348		0.245	-1.148	***	0.441
Age 45–64	-1.572	***	0.381	-0.316	***	0.117	-0.268		0.224	-1.256	***	0.398
Female	-0.107		0.218	-0.084		0.084	0.694	***	0.148	-0.024		0.233
Unemployment benefit	-0.285		0.208	-0.281	***	0.087	-0.497	***	0.163	-0.004		0.223
O Levels	0.344		0.339	0.291	***	0.109	0.009		0.204	0.053		0.351
A Levels	0.509		0.370	0.293	**	0.124	0.048		0.246	0.216		0.387
Nursing & other quals.	0.739	**	0.337	0.065		0.119	-0.014		0.208	0.674	*	0.353
First degree or above	0.913	***	0.340	0.123		0.135	0.478	*	0.268	0.790	**	0.364
Working partner	0.189		0.291	0.206	**	0.104	0.234		0.198	-0.016		0.312
Non-working partner	0.809	***	0.258	-0.178		0.126	-0.372		0.244	0.987	***	0.284
Children 0–15 years	-0.496		0.322	0.027		0.110	0.103		0.204	-0.523		0.340
Social renting	-0.863	***	0.297	-0.215	**	0.096	-0.214		0.178	-0.648	**	0.306
Private renting	0.834	***	0.222	-0.242	*	0.127	-0.023		0.224	1.076	***	0.257
(log) Claimant inflow rate	0.640		0.624	-0.517	**	0.255	-2.439	***	0.506	1.157	*	0.667
(log) Claimant outflow rate	0.588		0.522	1.103	***	0.209	2.669	***	0.470	-0.515		0.555
(log) Months unemployed	-0.027		0.088	0.120	***	0.038	0.165	**	0.068	-0.147		0.094
Number of observations							15,655					

Notes: *** significant 1%, ** significant 5%, * significant 10%. Discrete time competing-risks are modeled by a multinomial logit with data in person-month form. See Table 2 for summary statistics in the last month of the spell. Reported coefficients are impacts on the competing hazards against the baseline outcome of remaining unemployed, except in the last column. Exponentiated β-s have the usual interpretation as relative-risks ratios. Standard errors clustered at the individual level are reported. Additional variables included in estimation but not reported are dummies for region, previous occupation, calendar quarter and year. See Appendix A for description of the variables.

Appendices

A. Description of variables

This section lists and describes the variables used in estimation.

- Housing tenure. Categorical variable identifying homeowners, social renters, and private renters. Homeowners form the baseline category in estimation.
- Age. 4 age bands are used: 16–24, 25–34, 35–44, 45–64. Age 16–24 is the baseline category.
- Gender. Dummy identifying females.
- Unemployment benefit. Dummy identifying whether the individual has received unemployment benefit or income support as an unemployed person in the last year.
- Highest education. Categorical variable identifying the highest educational qualifications. There are five possible states: No qualifications; O Levels or equivalent; A Levels of equivalent; nursing and other qualifications; first degree or above (including teaching). No qualifications is the baseline category.
- Marital status. Categorical variable identifying three possible states: single; married (or living as a couple) with spouse without job; married (or living as a couple) with spouse in employment. Single is the baseline category.
- Children. Dummy indicating whether the individual has own children under age of 16 in household.
- Claimant flows. Two continuous variables are used to capture flows into and out of claimant status. They vary by LAD and month. The series are drawn from NOMIS (www.nomisweb.co.uk).
- Last occupation. Occupational categories of last job. They are created using the 1990 Standard Occupational Classification (SOC), with the following possible 10 states: managers and administrators; professional, associate professional and technical occupations; clerical and secretarial occupations; craft and related occupations; personal and protective service occupations; sales occupations; plant and machine operatives; other occupation; no previous job.
- Region. Nine regions defined as Yorkshire and Humberside, and North East; North-West; Midlands; East Anglia; South East; South West; Wales; Scotland; Northern Ireland.
- Time variables. Year and calendar quarter dummies.

B. Robustness Checks

This section reports a number of robustness checks for the results reported in Table 3. Namely, Table 4–6 report results by using different baseline hazards to model temporal dependence, such as a quadratic function of time (t = months unemployed), a cubic function of time, or a piecewise constant baseline, respectively. Table 7–8 report results considering a shorter time window to identify cross-LAD moves, with an interval before exit to job of nine or six months instead of twelve months, respectively. Finally, Table 9 reports results using a continuous-time competing-risks model.

Table 4

Unemployment Duration Competing-risks Model Estimates — Other Baseline Hazard (I)

	Non-local job			Local job			OLF			Non-local job (base is Local job)		
	β		SE	β		SE	β		SE	β		SE
DAE	0.424	*	0.228	-0.081		0.077	-0.236		0.146	0.505	**	0.244
EA	0.118		0.208	0.061		0.081	0.104		0.156	0.057		0.223
SOCNET	-0.127		0.189	0.401	***	0.080	0.035		0.141	-0.528	**	0.206
ADS	-0.313		0.221	0.193	**	0.094	0.170		0.179	-0.506	**	0.244
SEMP	0.069		0.294	-0.149		0.124	-0.483		0.312	0.218		0.317
Age 25–34	-0.347		0.262	-0.206	*	0.108	-0.275		0.225	-0.141		0.286
Age 35–44	-1.268	***	0.421	-0.125		0.125	-0.325		0.244	-1.143	***	0.440
Age 45–64	-1.506	***	0.374	-0.267	**	0.114	-0.238		0.223	-1.239	***	0.393
Female	-0.112		0.217	-0.075		0.081	0.692	***	0.147	-0.038		0.233
Unemployment benefit	-0.268		0.204	-0.276	***	0.084	-0.479	***	0.163	0.008		0.220
O Levels	0.318		0.337	0.275	***	0.105	0.003		0.203	0.043		0.350
A Levels	0.482		0.366	0.279	**	0.120	0.039		0.244	0.202		0.384
Nursing & other quals.	0.731	**	0.332	0.059		0.115	-0.017		0.206	0.673	*	0.350
First degree or above	0.878	***	0.336	0.111		0.130	0.464	*	0.265	0.767	**	0.361
Working partner	0.166		0.289	0.175	*	0.101	0.230		0.198	-0.009		0.311
Non-working partner	0.802	***	0.255	-0.182		0.121	-0.367		0.243	0.984	***	0.281
Children 0–15 years	-0.476		0.321	0.042		0.107	0.104		0.201	-0.519		0.341
Social renting	-0.838	***	0.291	-0.201	**	0.093	-0.206		0.176	-0.638	**	0.300
Private renting	0.822	***	0.220	-0.248	**	0.124	-0.029		0.222	1.070	***	0.255
(log) Claimant inflow rate	0.603		0.623	-0.532	**	0.254	-2.448	***	0.506	1.135	*	0.666
(log) Claimant outflow rate	0.591		0.522	1.100	***	0.209	2.669	***	0.471	-0.509		0.555
t	-0.021		0.030	0.026	**	0.011	0.016		0.017	-0.047		0.032
t^2	0.000		0.001	-0.001	**	0.000	0.000		0.000	0.001		0.001
Number of observations						15,655						

Notes: *** significant 1%, ** significant 5%, * significant 10%. See notes to Table 3.

Table 5
Unemployment Duration Competing-risks Model Estimates — Other Baseline Hazard (II)

	Non-local job			Local job			OLF			Non-local job (base is Local job)		
	β		SE	β		SE	β		SE	β		SE
DAE	0.426	*	0.228	-0.075		0.077	-0.233		0.146	0.502	**	0.245
EA	0.117		0.208	0.061		0.081	0.106		0.156	0.056		0.223
SOCNET	-0.128		0.189	0.402	***	0.080	0.036		0.141	-0.530	**	0.206
ADS	-0.315		0.221	0.191	**	0.094	0.168		0.179	-0.506	**	0.243
SEMP	0.069		0.294	-0.169		0.125	-0.500		0.313	0.238		0.316
Age 25–34	-0.355		0.262	-0.207	*	0.108	-0.280		0.226	-0.148		0.285
Age 35–44	-1.270	***	0.421	-0.120		0.125	-0.321		0.244	-1.150	***	0.440
Age 45–64	-1.515	***	0.375	-0.269	**	0.114	-0.237		0.223	-1.246	***	0.393
Female	-0.122		0.219	-0.083		0.082	0.688	***	0.148	-0.039		0.234
Unemployment benefit	-0.277		0.204	-0.289	***	0.086	-0.484	***	0.163	0.013		0.221
O Levels	0.321		0.337	0.281	***	0.106	0.009		0.202	0.040		0.350
A Levels	0.491		0.367	0.306	**	0.120	0.065		0.245	0.185		0.385
Nursing & other quals.	0.743	**	0.333	0.073		0.115	-0.003		0.207	0.670	*	0.352
First degree or above	0.880	***	0.337	0.122		0.131	0.481	*	0.266	0.758	**	0.361
Working partner	0.162		0.290	0.163		0.101	0.218		0.198	-0.001		0.311
Non-working partner	0.803	***	0.255	-0.192		0.121	-0.379		0.244	0.995	***	0.281
Children 0–15 years	-0.479		0.323	0.045		0.108	0.110		0.201	-0.524		0.342
Social renting	-0.836	***	0.292	-0.200	**	0.092	-0.204		0.176	-0.636	**	0.301
Private renting	0.823	***	0.220	-0.246	*	0.126	-0.029		0.223	1.070	***	0.255
(log) Claimant inflow rate	0.584		0.623	-0.549	**	0.255	-2.455	***	0.505	1.132	*	0.666
(log) Claimant outflow rate	0.587		0.522	1.102	***	0.209	2.661	***	0.470	-0.515		0.555
t	0.032		0.047	0.116	***	0.019	0.087	**	0.034	-0.084	*	0.050
t^2	-0.003		0.003	-0.006	***	0.001	-0.004	**	0.002	0.002		0.003
t^3	0.000		0.000	0.000	***	0.000	0.000	**	0.000	0.000		0.000
Number of observations							15,655					

Notes: *** significant 1%, ** significant 5%, * significant 10%. See notes to Table 3.

Table 6
Unemployment Duration Competing-risks Model Estimates — Other Baseline Hazard (III)

	Non-local job			Local job			OLF			Non-local job (base is Local job)		
	β		SE	β		SE	β		SE	β		SE
DAE	0.407	*	0.228	-0.079		0.076	-0.250	*	0.142	0.486	**	0.245
EA	0.133		0.208	0.057		0.080	0.096		0.152	0.076		0.223
SOCNET	-0.137		0.189	0.408	***	0.080	0.039		0.138	-0.545	***	0.207
ADS	-0.305		0.224	0.195	**	0.093	0.137		0.173	-0.500	**	0.246
SEMP	0.051		0.293	-0.161		0.124	-0.505		0.311	0.212		0.315
Age 25–34	-0.328		0.260	-0.186	*	0.107	-0.217		0.219	-0.142		0.283
Age 35–44	-1.276	***	0.428	-0.101		0.124	-0.267		0.237	-1.175	***	0.447
Age 45–64	-1.494	***	0.374	-0.239	**	0.113	-0.145		0.216	-1.255	***	0.393
Female	-0.132		0.219	-0.071		0.080	0.715	***	0.144	-0.062		0.235
Unemployment benefit	-0.292		0.203	-0.290	***	0.084	-0.504	***	0.159	-0.002		0.219
O Levels	0.291		0.337	0.270	**	0.105	-0.009		0.198	0.020		0.351
A Levels	0.458		0.369	0.292	**	0.119	0.012		0.241	0.166		0.387
Nursing & other quals.	0.733	**	0.333	0.065		0.114	-0.008		0.200	0.668	*	0.352
First degree or above	0.859	**	0.336	0.114		0.129	0.456	*	0.256	0.745	**	0.361
Working partner	0.149		0.290	0.147		0.100	0.179		0.192	0.003		0.312
Non-working partner	0.825	***	0.257	-0.186		0.119	-0.339		0.234	1.011	***	0.282
Children 0–15 years	-0.483		0.322	0.053		0.106	0.140		0.196	-0.536		0.342
Social renting	-0.851	***	0.291	-0.194	**	0.091	-0.170		0.172	-0.657	**	0.300
Private renting	0.831	***	0.219	-0.250	**	0.124	-0.022		0.220	1.081	***	0.253
(log) Claimant inflow rate	0.558		0.623	-0.540	**	0.256	-2.445	***	0.514	1.097		0.666
(log) Claimant outflow rate	0.586		0.527	1.101	***	0.210	2.690	***	0.478	-0.515		0.559
Months unemployed 2–3	0.789	**	0.341	0.743	***	0.151	1.007	***	0.290	0.045		0.366
Months unemployed 4–6	0.836	**	0.335	0.539	***	0.156	0.640	**	0.305	0.297		0.356
Months unemployed 7–9	0.630	*	0.380	0.698	***	0.165	0.272		0.352	-0.068		0.401
Months unemployed 10–12	0.192		0.490	0.774	***	0.175	0.944	***	0.344	-0.581		0.509
Months unemployed 13–18	-0.496		0.548	1.017	***	0.167	0.832	**	0.334	-1.512	***	0.561
Months unemployed 19–24	0.820		0.591	0.720	***	0.205	1.022	***	0.387	0.100		0.624
Months unemployed 25–36	-0.075		0.781	0.328		0.233	0.955	**	0.379	-0.403		0.806
Months unemployed 37–48	-12.79	***	0.402	0.200		0.303	0.079		0.626	-12.99	***	0.465
Months unemployed > 48	0.696		1.089	-0.030		0.442	0.130		0.737	0.726		1.175
Number of observations							15,655					

Notes: *** significant 1%, ** significant 5%, * significant 10%. See notes to Table 3.

Table 7

Unemployment Duration Competing-risks Model Estimates — Exits to Non-local Job Can Happen 9 Months Before and 12 Months After Exit

	Non-local job			Local job			OLF			Non-local job (base is Local job)		
	β		SE	β		SE	β		SE	β		SE
DAE	0.389	*	0.231	-0.078		0.079	-0.234		0.147	0.467	*	0.246
EA	0.099		0.210	0.070		0.084	0.109		0.157	0.029		0.224
SOCNET	-0.125		0.193	0.407	***	0.082	0.045		0.142	-0.532	**	0.210
ADS	-0.338		0.224	0.202	**	0.097	0.177		0.182	-0.540	**	0.245
SEMP	0.130		0.297	-0.157		0.126	-0.491		0.313	0.286		0.318
Age 25–34	-0.427		0.264	-0.231	**	0.111	-0.292		0.226	-0.196		0.287
Age 35–44	-1.387	***	0.445	-0.154		0.129	-0.348		0.245	-1.233	***	0.462
Age 45–64	-1.627	***	0.403	-0.313	***	0.117	-0.269		0.224	-1.314	***	0.419
Female	-0.146		0.221	-0.079		0.084	0.694	***	0.148	-0.067		0.236
Unemployment benefit	-0.313		0.214	-0.278	***	0.087	-0.497	***	0.163	-0.035		0.230
O Levels	0.306		0.336	0.293	***	0.108	0.009		0.204	0.013		0.348
A Levels	0.504		0.370	0.291	**	0.124	0.048		0.246	0.213		0.387
Nursing & other quals.	0.659	*	0.341	0.074		0.119	-0.014		0.208	0.585		0.357
First degree or above	0.943	***	0.338	0.115		0.135	0.478	*	0.268	0.828	**	0.363
Working partner	0.248		0.294	0.200	*	0.103	0.234		0.198	0.048		0.314
Non-working partner	0.797	***	0.260	-0.174		0.125	-0.372		0.244	0.971	***	0.285
Children 0–15 years	-0.500		0.324	0.026		0.110	0.103		0.204	-0.526		0.341
Social renting	-0.817	***	0.296	-0.219	**	0.096	-0.214		0.178	-0.598	**	0.304
Private renting	0.837	***	0.230	-0.226	*	0.125	-0.023		0.224	1.063	***	0.261
(log) Claimant inflow rate	0.699		0.635	-0.518	**	0.254	-2.439	***	0.506	1.217	*	0.676
(log) Claimant outflow rate	0.545		0.528	1.105	***	0.208	2.668	***	0.470	-0.560		0.560
(log) Months unemployed	-0.041		0.090	0.121	***	0.038	0.165	**	0.068	-0.162	*	0.095
Number of observations						15,655						

Notes: *** significant 1%, ** significant 5%, * significant 10%. See notes to Table 3.

Table 8

Unemployment Duration Competing-risks Model Estimates — Exits to Non-local Job Can Happen 6 Months Before and 12 Months After Exit

	Non-local job			Local job			OLF			Non-local job (base is Local job)		
	β		SE	β		SE	β		SE	β		SE
DAE	0.385		0.243	-0.078		0.078	-0.235		0.147	0.463	*	0.257
EA	-0.025		0.217	0.087		0.083	0.108		0.157	-0.112		0.230
SOCNET	-0.018		0.203	0.393	***	0.081	0.046		0.142	-0.411	*	0.218
ADS	-0.379		0.232	0.203	**	0.096	0.177		0.182	-0.581	**	0.253
SEMP	-0.054		0.325	-0.131		0.125	-0.492		0.313	0.077		0.344
Age 25–34	-0.405		0.276	-0.220	**	0.110	-0.292		0.226	-0.185		0.298
Age 35–44	-1.280	***	0.459	-0.166		0.128	-0.347		0.245	-1.114	**	0.474
Age 45–64	-1.567	***	0.418	-0.323	***	0.116	-0.268		0.224	-1.244	***	0.433
Female	-0.132		0.231	-0.083		0.083	0.694	***	0.148	-0.049		0.244
Unemployment benefit	-0.417	*	0.222	-0.265	***	0.087	-0.498	***	0.163	-0.152		0.237
O Levels	0.224		0.347	0.298	***	0.108	0.008		0.204	-0.073		0.357
A Levels	0.399		0.377	0.306	**	0.123	0.048		0.246	0.094		0.392
Nursing & other quals.	0.502		0.355	0.088		0.118	-0.015		0.208	0.414		0.371
First degree or above	0.793	**	0.347	0.155		0.133	0.478	*	0.269	0.638	*	0.369
Working partner	0.072		0.313	0.226	**	0.102	0.234		0.198	-0.154		0.331
Non-working partner	0.485	*	0.276	-0.137		0.124	-0.374		0.244	0.623	**	0.297
Children 0–15 years	-0.341		0.339	0.004		0.110	0.104		0.204	-0.345		0.355
Social renting	-0.963	***	0.325	-0.216	**	0.096	-0.215		0.178	-0.747	**	0.333
Private renting	0.715	***	0.242	-0.151		0.121	-0.022		0.224	0.866	***	0.269
(log) Claimant inflow rate	0.634		0.665	-0.509	**	0.251	-2.441	***	0.506	1.143		0.703
(log) Claimant outflow rate	0.790		0.561	1.082	***	0.207	2.670	***	0.470	-0.292		0.590
(log) Months unemployed	-0.036		0.096	0.120	***	0.038	0.165	**	0.068	-0.156		0.101
Number of observations						15,655						

Notes: *** significant 1%, ** significant 5%, * significant 10%. See notes to Table 3.

Table 9
UNEMPLOYMENT DURATION COMPETING-RISKS MODEL ESTIMATES — CONTINUOUS TIME

	Non-local job			Local job			OLF			Non-local job (base is Local job)		
	β		SE	β		SE	β		SE	β		SE
DAE	0.456	**	0.217	-0.131	*	0.073	-0.326	**	0.138	0.558	**	0.224
EA	0.140		0.208	0.029		0.076	0.028		0.145	0.083		0.209
SOCNET	-0.237		0.191	0.339	***	0.074	0.004		0.133	-0.317	*	0.189
ADS	-0.412	*	0.215	0.176	**	0.088	0.109		0.163	-0.503	**	0.212
SEMP	0.039		0.298	-0.076		0.112	-0.461		0.306	0.013		0.300
Age 25–34	-0.188		0.243	0.052		0.099	-0.232		0.211	-0.179		0.246
Age 35–44	-1.070	**	0.435	0.255	**	0.107	-0.194		0.225	-1.143	***	0.427
Age 45–64	-1.231	***	0.357	0.053		0.100	0.004		0.193	-1.192	***	0.372
Female	-0.126		0.206	-0.022		0.075	0.722	***	0.142	-0.113		0.205
Unemployment benefit	-0.151		0.200	-0.184	**	0.078	-0.431	***	0.152	-0.055		0.205
O Levels	0.253		0.328	0.202	**	0.097	0.002		0.189	0.200		0.328
A Levels	0.391		0.358	0.227	**	0.115	0.075		0.230	0.304		0.352
Nursing & other quals.	0.790	**	0.321	0.153		0.100	0.099		0.194	0.646	**	0.318
First degree or above	0.868	***	0.326	-0.008		0.125	0.435	*	0.243	0.854	***	0.326
Working partner	0.168		0.279	0.084		0.095	0.170		0.184	0.097		0.283
Non-working partner	0.931	***	0.250	-0.127		0.112	-0.287		0.236	0.922	***	0.261
Children 0–15 years	-0.416		0.327	0.111		0.096	0.225		0.190	-0.423		0.325
Social renting	-0.926	***	0.293	-0.258	***	0.084	-0.253		0.165	-0.777	***	0.290
Private renting	0.406	*	0.215	-0.652	***	0.127	-0.365	*	0.220	0.720	***	0.216
(log) Claimant inflow rate	1.675	**	0.689	0.230		0.258	-0.689		0.441	1.330	**	0.643
(log) Claimant outflow rate	-0.362		0.522	0.229		0.220	0.752	*	0.411	-0.338		0.516
Number of observations							1,611					

Notes: *** significant 1%, ** significant 5%, * significant 10%. See notes to Table 3.