Marketplace Matching in Britain: Evidence from Individual Unemployment Duration Analysis

Eric Smith and Mienyun Kuo

University of Essex

Abstract

Using hazard estimation, the paper finds evidence that supports the stock-flow model of unemployment transitions. The paper first documents that the hazard rate exhibits a stepwise decrease after the first day of unemployment. Then the results from regression suggest that that the stock of unmatched traders on one side of the market will match with the flow of new traders on the other side. In particular, we consider if the previous employment duration of an unemployed worker affects his search behaviour. The findings here suggest that the workers with long-term employment history mainly match with the vacancy stock in the first month of unemployment while the workers with short-term employment history match with both the vacancy stock and the vacancy inflow.

1. Introduction

Search and matching models have become an accepted work-horse for analysing equilibrium unemployment and labour market transitions. To capture labour market frictions, these models generally posit an exogenous, black-box matching function that describes the number of potential matches between workers and firms and hence governs transitions out of unemployment.

Some studies have recently attempted to provide a more rigorous micro-foundation for this matching technology.[1] Stock-flow or marketplace matching not only provides one such micro-foundation it also gives rise to a number of empirical implications. The stock-flow search model (Coles and Smith, 1998) assumes that the information channels in a labour market are well established. Due to information channels, job seekers have complete information about the location of available vacancies and apply simultaneously to as many they like. Upon contact, the firm and the worker decide whether to form a match and start producing or resume search.[2] Those who remain unmatched and keep searching do so because there are no trading partners that are suitable for them among existing pool. Therefore, no job vacancy and unemployed worker who has been through one round of sampling will attempt to match later with a pre-existing job seeker or vacancy.

Given this assumption of full sampling within a matching period, the stock-flow approach has three empirical predictions which are different to those made in the random search literature. First, the stock of unmatched traders on one side of the market will match with the flow of new traders on the other side. Second, a trader's hazard rate should initially be high, and then become low if she/he fails to match with

[1] Urn-ball matching is an alternative strand.
[2] This non-random search framework has been extended in order to analyze price determination in a market equilibrium (Coles and Muthoo1998; Coles 1999), and also employment duration (Smith, 2003).

current stock of unmatched traders in the market. With no transaction delay, there should be a stepwise decrease in the hazard rate. Third, these exit rates depend on different variables at different stages of an agent's stay in the market. The probability that a new unemployed worker forms a match successfully depends positively only on the stock of vacancies in the market. However, the exit rate of an 'old' unemployed worker depends positively on the flow of new vacancies, negatively on the stock of unemployment (because of crowding out) and is independent of the stock of vacancies.

Although support for such behaviour exists, there as yet has not been a rigorous analysis of this effect using observations on individual work histories. This paper fills this void. Applying techniques developed to analyse survivor data, this paper uses individual unemployment histories from 1987-1996 to estimate re-employment probabilities. To allow for the proposed sampling effect over the duration of job search, a piece-wise hazard specification is adopted.

Like previous contributions (Coles and Smith, 1998; Gregg and Petrongolo, 1997; Coles and Petrongolo, 2002), the regression results demonstrate clear evidence of matching between the stock of vacancies and the short term or flow unemployed and between workers with longer spells of unemployment and the flow of new job opportunities. We also find that institutional details affect individual search behaviour. The unemployment benefits are counted on a weekly basis, and corresponding to it, there is a weekly cycle in the empirical hazard rates.

In addition to this improved evidence on the existence of stock-flow matching evidence, this paper also provides a new qualitative dimension to this evidence. It controls for a limited set of demographic characteristics and more interestingly, for prior employment duration. In the JUVOS unemployment data, it is possible to identify the duration since the individual last reported searching for work. A worker returning to unemployment from a short spell of employment has not allowed the vacancy stock to replenish itself through turnover, and hence does not encounter a large stock of new vacancies. Thereby, this worker is more likely to match with the flow of vacancies rather than the stock in the early stage of unemployment. To investigate this implication, the paper divides the data into two samples. One includes the unemployed workers whose previous employment duration is less than three months (defined as short-term employment duration), and the other includes the unemployed workers whose previous employment duration is longer than one year (defined as long-term employment duration).

The evidence controlling for prior employment spells again supports the stock-flow approach. The results demonstrate the unemployed workers with long employment spells prior to entering unemployment behave like stock-flow searchers as they only match with the stock of vacancies in the first month of unemployment. On the other hand, although the workers with short-term employment duration match with both vacancy stock and inflow in the first month being unemployed, their search behaviour is consistent with the stock-flow matching model in the sense that once all currently available vacancies have been scanned, they match with the flow of new vacancies.

The demographic results find here suggest that the reemployment probabilities decrease with age, and that the reemployment probabilities for female unemployed are higher than for male unemployed. This is consistent with the age effect and the gender divide established elsewhere, where the duration of long-term unemployment increases with age, and male workers have longer expected duration of long-term unemployment than female workers.

The organisation of this paper is as follows. Section 2 addresses the econometric methods. Section 3 describes the data and tackles the variables derived for the empirical modelling and the issues related to the sample selection. Our analysis of reemployment hazard rates using the hazard regression is reported in section 4, and section 5 concludes this paper. An appendix provides the supplementary tables and the details in the empirical modelling.

2. Modelling framework

Suppose a worker enters the labour market. Stock-flow or marketplace matching implies that the worker's hazard into employment is initially high while the worker looks through and attempts to match with existing job opportunities. Until the worker exhausts the existing pool of employment opportunities, this hazard is constant unless either the competition for jobs (essentially from those workers with short unemployment spells), the worker's willingness to accept employment, or the worker's ability to work changes in some way. In other words, the vacancy stock is the primary demand determinant of short unemployment spells as it affects the matching rate of initial phase of job search.

If the worker is unlucky during this early phase and fails to find an acceptable position from the existing opportunities, the matching process and hence the likelihood of finding employment changes dramatically. With no acceptable positions among the vacancy stock, the worker must now wait for new opportunities to match. Moreover, when a new job appears, all workers compete for this job. During the initial phase, a job seeker does not lose out on an employment opportunity to a worker who has already looked at and failed to match with a given job. However, eventually competition for employment will come from all workers, not just those with short unemployment spells who are looking at job vacancies. This change in circumstances implies that the worker's hazard rate exhibits a discrete jump once all employment opportunities have been examined. Moreover, the determinants of the hazard rate in this second phase differ fundamentally from those determining the matching probabilities early on.

To formalize this process, let h_i^τ be the discrete time hazard or probability of becoming employed for worker i given unemployment duration $\tau=1,2,3,...$. In general this hazard depends not only on the matching conditions – the stocks and flows of jobs and of unemployed denoted by v, V, u, U which vary with duration across workers (observations of individuals occur at different places and dates, which will be discussed in detail in the next section), but also on individual characteristics X_i which for simplicity are taken as fixed:

$$h_i^\tau = h^\tau(v, V, u, U; X_i) \qquad (1)$$

At the end of period τ, we observe if an unemployed worker i becomes employed or remains jobless. Define $y_{i,\tau} = 1$ if this transition occurs and zero otherwise. Using this observation as the dependent variable, the hazard for duration τ can then be estimated using familiar binary regression techniques.[3] Jenkins (1995) provides

[3] Specific functional forms emerge for this hazard for limiting cases of stock-flow matching. In particular, suppose all workers have the same probability, μ, of matching with a job, that there are no delays in trade and that all workers face the same market conditions. In this case, the immediate re-employment probability for a worker who enters unemployment depends (positively) only on the stock of vacancies available at entry[3]:

$$h_i^1(V) = 1 - (1 - \mu)^V$$

In contrast, for $\tau > 1$ the re-employment hazard depends on the flow rate of vacancies and the stock of unemployed

$$h_i^\tau = (v / U)[1 - (1 - \mu)^U] \quad \tau = 2, 3, 4, ...$$

Delays in consummating a match, worker heterogeneity, and changes in workers circumstances (e.g. in UI benefits) complicate matters. Among other things, the resulting hazard will subsequently depend on the way in which firms select among the acceptable, heterogeneous workers. To allow for such generality we adopt the reduced form approach. Atkinson and Micklewright (1991, p1708) argue that 'reduced form models provide a much greater degree of flexibility which can be used to handle important institutional details of benefit systems'. Although this paper does not directly consider these further details and discusses the implications of functional form specifications (see also the appendix). Given the large quantity of data available, we follow Jenkins (1995) and use the logistic model.

The primary aim here is to observe how the estimates of these regressions vary by τ and assess whether this pattern is consistent with stock-flow matching. Suppose that after a duration $\tau^* \geq 1$, the worker has examined and rejected all potential matches, that is, the worker reaches the end of the stock of vacancies at this duration.[4] For $\tau<\tau^*$, stock flow predicts that the hazard will depend primarily on V and to a lesser extend on v, u and only marginally, at best, on U. However, for $\tau>\tau^*$, V has no effect on h^τ unless the workers circumstances change causing the worker to accept previous unacceptable jobs. Such duration dependence may for example come from changing UI payments. Thus, the parameter estimates of the hazard for larger τ will be insignificant for the vacancy stock but positive for the vacancy flow.

Individual characteristics are also likely to affect the hazard. The previous work in this field suggests that old or male workers are less likely to match quickly. Marriage status is also likely to play a role, although unlike age and sex, this may have ambiguous effects on the hazard as τ increases. On one hand, family responsibilities are likely to make individuals put more effort in to finding a job, regardless of the perceived potential benefits. However, the additional financial support in a family environment could reduce the willingness to lower the reservation wage when looking for a job. The interaction term between marriage status and sex is also included. The

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institutional features, the relevant point is that reduced form models supply more flexibility in modelling search behaviour.

[4] In principle τ^* can depend on individual characteristics and the number of vacancies. Given that the data a recorded monthly, these considerations are ignored here.

hypothesis is that married men are under more pressure to find a job, compared with married women.

3. Data

3.1 Description

This paper uses British data on unemployment and vacancies, which come from two different sources. The vacancy data collected at Employment Exchanges/Jobcentres are extracted from the NOMIS database. The unemployment data supplied by the Unemployment Benefit Offices comes from the Joint Unemployment and Vacancies Operating Statistics System (JUVOS).

In the UK, the Travel-To-Work-Area (TTWA) is the standard measure of a self-contained labour market. Based on census figures, these are geographical regions that have a minimum of 3500 residents, at least 75% of the people working in the area live in it, and at least 75% of those living in the area also work there.

The U.K. Job Centre system is a network of government funded employment-service agencies, and there is at least one Job Centre in each TTWA. A Job Centre's services are free of charge to all users, both to firms posting vacancies and to job seekers. Besides that, all workers claiming unemployment-related benefits are required to register at the Job Centre.[5]

The vacancy data is a monthly time series, running from April 1987 to November 2000 for each TTWA. The data record the number of unfilled vacancies carried over from the previous accounting month, and the number of the notified or new vacancies

[5] Gregg and Wadsworth (1996) report that Job Centres are used by roughly 80-90 percent of the claimant unemployed, 25-30 percent of employed job seekers, and hence the count of unemployment benefit claimants differs very slightly from the alternative count of people who register at the Job centre seeking jobs.

within each accounting month.[6] The data also include the number of vacancies outflow in each accounting month, which provides information on the relation between vacancy inflow and vacancy outflow.

Figure 1: Monthly Vacancy stock, inflow and outflow in England and Wales, April 1987-November 2000. Source: Nomis. Data seasonally adjusted.

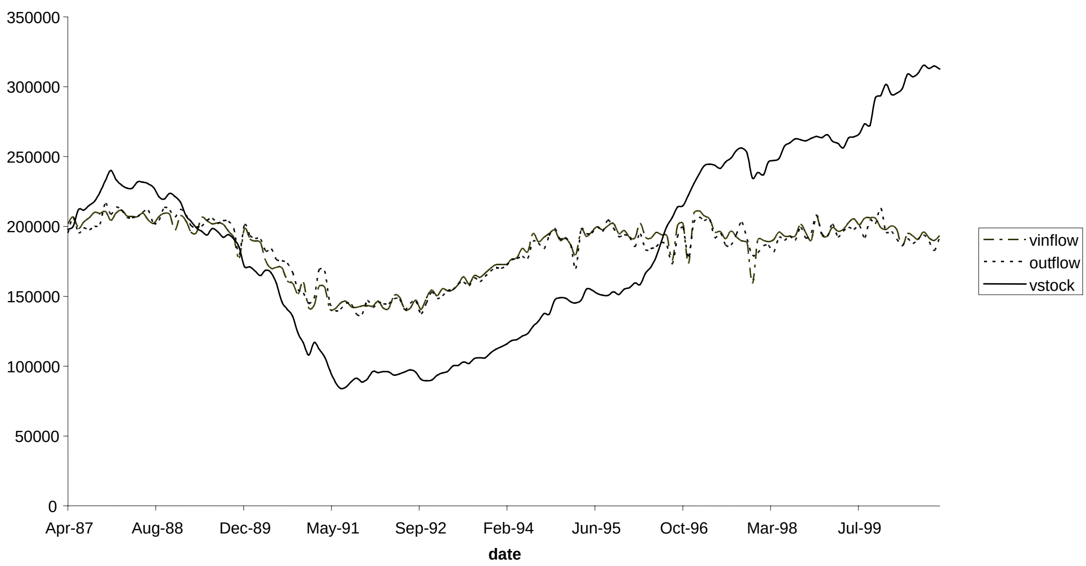


Figure 1 plots the aggregate series of vacancy stock, inflow and outflow from April 1987 to November 2000. The vacancy data extracted from the NOMIS databank are not seasonally adjusted, and to improve visual inspection of our data, the data series in Figure 1 are seasonally adjusted.[7] Figure 1 shows that the monthly vacancy outflow is very highly correlated with the inflow of new vacancies, and more weakly correlated with the vacancy stock. Correlation coefficients on raw data are 0.93 and 0.42 respectively. If only including the vacancies filled at the Job centre, the

[6] The dates on which the number of vacancies at Job Centre is counted are normally the first Friday of a month.
[7] To produce seasonally adjusted vacancy data, we run the regression on monthly dummy variables, and then add these estimated seasonal effects back to the vacancy data. In this procedure, the mean is preserved.

correlation between filled and new vacancy are around 10 times higher than that between vacancies filled and the vacancy stock (0.73 and 0.08 respectively).[8]

In the unemployment data, unemployment is defined as the number of people claiming unemployment-related benefits. All workers claiming state benefits are required to sign on at the unemployment benefit office as becoming unemployed and sign off as leaving unemployment. The flow of individuals signing on unemployment benefits is used to measure the number of the inflow of unemployment, and similarly the flow of individuals signing off is used to measure the number of the outflow of unemployment. Since this outflow is assumed to be into employment, any movements into states of non-participation are ignored.

The unemployment data are a five percent sample of all claims of unemployment-related benefits based on the claimant's National insurance number, which is known as the JUVOS cohort. The same five percent of National insurance numbers are selected each month so the individuals can be tracked in and out of period of unemployment. The JUVOS cohort file from March 1986 to December 2000 contains approximately 2.44 million claim records, and these relate to approximately 0.85 million claimants who have had at least one claim for unemployment-related benefits within the sample period.

The information on new claims, claim terminations and claim amendments is updated on a daily basis. For each relevant claim for unemployment benefits, the following details are recorded on the cohort file: (a) *Identification number* - this is unique personal identifier which replaces national insurance number in order to preserve confidentialality, (b) *Employment service local office code* – this identifies the Standard Statistical Region in which the office a claimant registers for benefits is

[8] The recorded vacancy outflow in the data includes not only the filled vacancies but also the cancelled vacancies.

located, (c) *Sex*, (d) *Marital status*, (e) *Date of birth,* (f) *Start of unemployment date,* and (g) *End of unemployment date.*

These claim details allow us to derive the variables of unemployment stock, unemployment inflow, and unemployment outflow. In particular, given the unique personal identifier, we can also calculate the number of times of entering into unemployment by workers and compute the duration of the previous employment for each claim. In the following, we describe the characteristics of the JUVOS cohort and the frequency of re-entering into unemployment. Then, we exam the flows into and out of the claimant count by weekday and monthday. The discussion of the time profile of unemployment follows.

- **Demographic characteristic**

Table 1 reports the age profile and the sex structure of the JUVOS cohort. Unemployment is concentrated on the youth; more than one third of the JUVOS cohort are aged less than 25. By sex, the male domination of unemployment is obvious; nearly 70 percent of the JUVOS cohort are male. Note much more female unemployed are young workers, compared with the male unemployed; around 45 percent of the female cohort are aged less than 25, and only around 36 percent of the male cohort are aged under 25. This is consistent with the sex structure of each age cohort. More young unemployed (aged less than 25) are female, compared with the other age cohorts; around 37 percent of the young cohort are female, and in general only around 28 percent of the other age cohorts are female.

Table 1: Age profile and sex structure of the JUVOS cohort

Age		Sex				Total	
		Female		Male			
		Freq.	Percent	Freq.	Percent	Freq.	Percent
Under25	Freq.	344303	44.72	592893	35.52	937196	38.43
	Percent	36.74		63.26		100.00	
25-34	Freq.	190210	24.71	467099	27.99	657309	26.95
	Percent	28.94		71.06		100.00	
35-44	Freq.	111423	14.47	277306	16.62	388729	15.94
	Percent	28.66		71.34		100.00	
Over44	Freq.	123895	16.09	331658	19.87	455553	18.68
	Percent	27.20		72.80		100.00	
Total	Freq.	769831	100.00	1668956	100.00	2438787	100.00
	Percent	31.57		68.43		100.00	

Table 2 reports the percentages of the young cohort (aged under 25), the early-middle-age cohort (aged 25-34), the late-middle-age cohort (aged 35-44), the elder cohort (aged 45 and over), and the sample as a whole with marriage status recorded in the data. Not surprisingly, many more young unemployed (aged less than 25) are single, compared with the other age cohorts, and the number of single unemployed decrease with age. Over 90 percent of the young cohort and more than half of the early-middle-age cohort are single. On the other hand, only about one quarter of the late-middle-age cohort and around 13 percent of the elder cohort are single. At the aggregate level, the single domination of unemployment is obvious as the unemployment is concentrated on the youth; more than half of the whole sample are single, and only around one third of the sample are married.

Table 2: Marriage status of the JUVOS cohort

	Young cohort	Early middle age cohort	Late middle age cohort	Elder cohort	All
Status	Percent	Percent	Percent	Percent	Percent
Single	90.93	55.17	25.14	13.35	56.31
Married	6.85	35.17	54.84	65.66	33.12
Widowed	0.01	0.09	0.53	2.48	0.58
Divorced	0.28	4.66	13.68	14.29	6.21
Separated	0.28	1.86	3.01	2.26	1.51
Cohabiting	0.65	1.30	1.00	0.54	0.86
Not known	1.00	1.76	1.79	1.40	1.41
Total	100.00	100.00	100.00	100.00	100.00

- **Re-entry to unemployment**

The number of times of each individual claimed unemployment benefits during the sample period is summarised in Table 3. The previous employment duration for each claim (except for the workers' first claim; this will be discussed in the next subsection) is summarised in Table 4.

Table 3 reports that around 42 percent of the JUVOS cohort have only one claim for the unemployment-related benefits, around 34 percent of the JUVOS cohort have claimed the benefits for two to three times, around 13 percent of the JUVOS cohort have claimed the benefits for four to five times, and around 10 percent of the JUVOS cohort have claimed the benefits more than five times. Table 4 states that nearly 70 percent of the previous employment duration is less than one year; more than one third of the previous employment duration is less than three months, and near one third of the previous employment duration is more than three months and less than nine months. These findings imply that many re-employed workers become unemployed again very quickly. This is consistent with the literature. Moylan et al (1982) find that of the British 1978 cohort, 40 percent of those who found a job within the first 12 months returned to unemployment within that period. Of this 40 percent, 36 percent had only one job in the year, 46 percent had two jobs, and the rest has three or more jobs (all within a year), as well as at least two periods of unemployment. The rate at which the 1987 cohort lost the first job they found was also very high: 41 percent of men finding a job within nine months became unemployed again within that period; of those who had least one job, 22 percent had two jobs and 8 percent had three or more jobs (Ehrens and Hedges 1990: 131 and Table 502).

Table 3: the times of individual claiming unemployment benefits

The number of times	Freq.	Percent	Cum.
1	199934	41.7	41.7
2	103757	21.64	63.34
3	60836	12.69	76.02
4	38151	7.96	83.98
5	24732	5.16	89.14
>=6	52086	10.86	100
Total	479496	100	

Table 4: the previous employment duration in each claim

Previous employment duration	Freq.	Percent	Cum.
0-3 months	345,589	34.04	34.04
4-6 months	166,342	16.38	50.42
6-9 months	103,138	10.16	60.58
9-12 months	91,317	8.99	69.57
more than 12 months	308,911	30.43	100
Total	1,015,297	100	

- **Weekday unemployment flows**

Table 5 reports the unemployment inflow and outflow by day of the week. Around 39 percent of the JUVOS cohort enter into unemployment on Monday, and this inflow drops dramatically to around 18 percent on Tuesday. After that, it generally decreases to around 12 percent on Friday. During the weekend, only about 3 percent of the JUVOS cohort flow into unemployment. On the other hand, the outflow from unemployment generally decreases from Monday to Thursday from around 19 percent to around 11 percent, and falls sharply to about 4 percent on Friday. However, more than one third of the JUVOS cohort leave unemployment on Saturday and Sunday. Clearly, there is a weekday pattern in the unemployment flows; a large amount of workers enter into unemployment on Monday, and also a large amount of workers leave unemployment on the weekend. This is quite odd as the outflow from unemployment shall be low on Saturday and Sunday, given the fact that most companies are closed during the weekend. This oddity will be explained when we obtain the empirical hazard rates.

Table 5: Unemployment inflow and outflow by weekdays

	Unemployment Inflow			Unemployment Outflow		
Weekdays	Sum	Percent	Cum	Sum	Percent	Cum
Monday	895054	38.50	38.50	454417	18.97	18.97
Tuesday	420152	18.07	56.57	411658	17.19	36.16
Wednesday	348212	14.98	71.54	350739	14.64	50.80
Thursday	310121	13.34	84.88	262795	10.97	61.77
Friday	286153	12.31	97.19	103890	4.34	66.11
Saturday	60074	2.58	99.77	636054	26.56	92.67
Sunday	5303	0.23	100.00	175639	7.33	100.00
Total	2325069	100.00		2395192	100.00	

- **Monthday unemployment flows**

Figures 2 and 3 plot the average unemployment inflow and outflow for each day of the month, respectively. The average inflow is high on the first day of the month, and drops sharply on the second day of the month. After this drop, the inflow decreases gradually to the end of the month. On the other hand, the outflow is initially high, gradually declines through the month, and dramatically rises at the end of the month. Clearly, there is also a monthday pattern in the unemployment flows; many more workers enter into unemployment in the beginning of a month, and many more workers leave unemployment at the end of a month.

Figure 2: Average mothday unemployment inflow

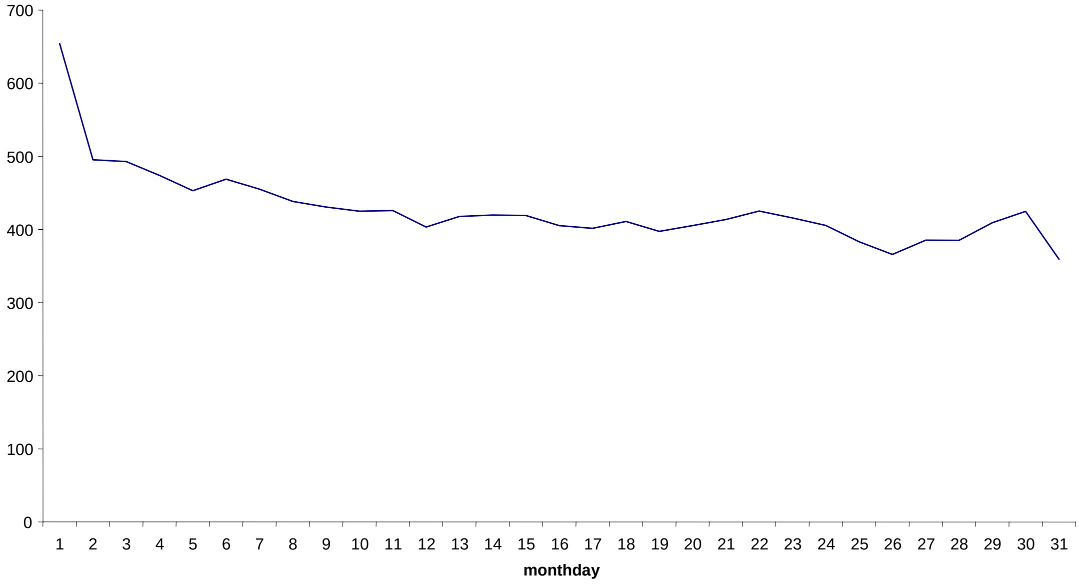
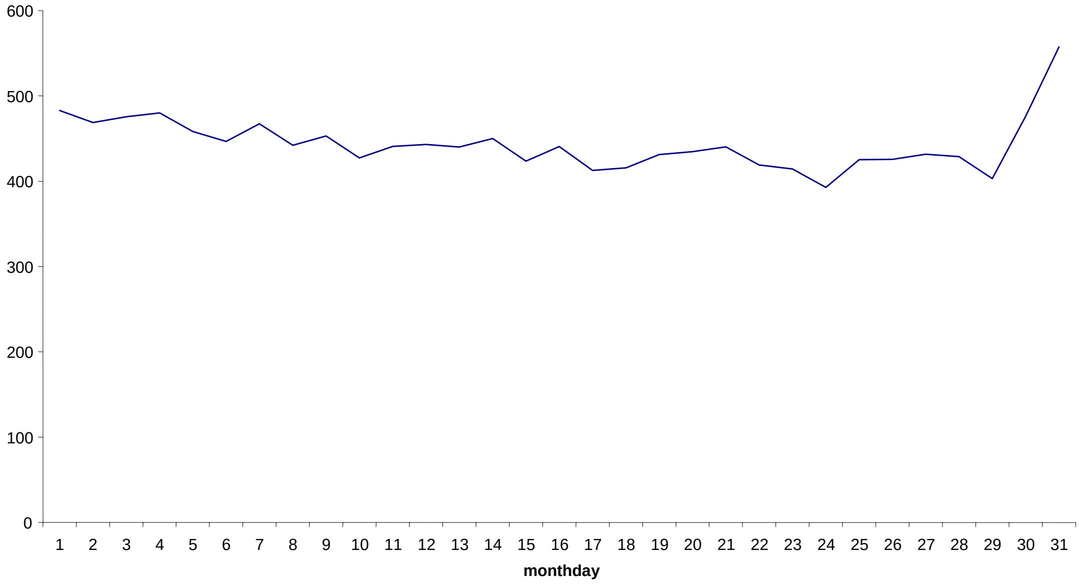


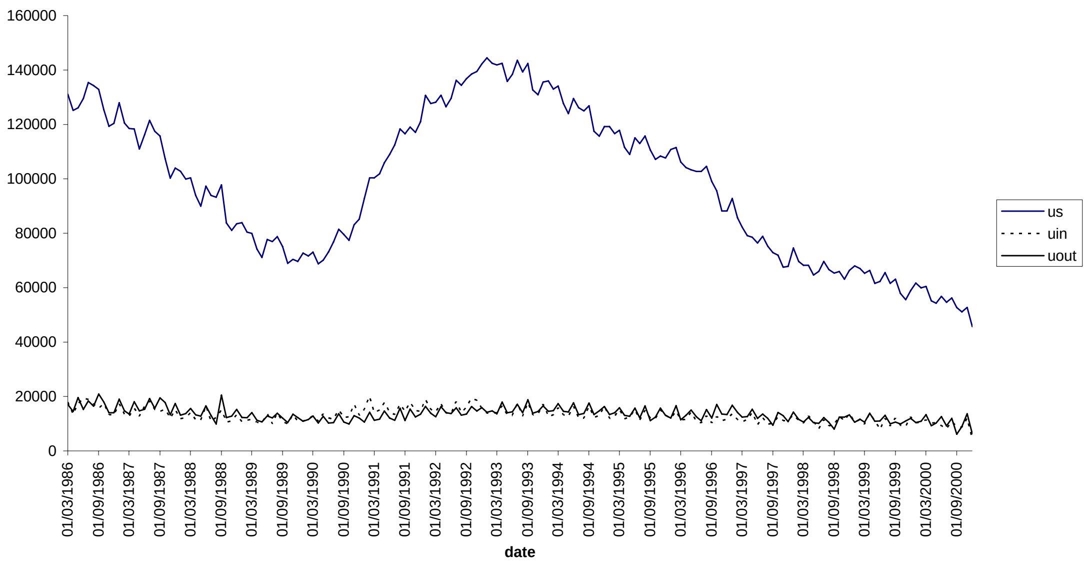
Figure 3: Average monthday unemployment outflow.



- **Time profile of unemployment**

Figure 4 plots the unemployment stock, inflow and outflow in England and Wales from March 1986 to December 2000. As there are monthly and weekly patterns in the unemployment flows, the data plotted in this figure are the monthly time series (i,e., the stock is the number of workers in unemployment in the beginning of each month, the inflow is the number of workers entering into unemployment within each month, and the outflow is the number of workers leaving unemployment in each month). To improve the visual inspection further, these series are seasonally adjusted. On the raw data, the correlation coefficient between the monthly inflow and the monthly outflow is 0.53, and the one between the monthly outflow and the stock in the relevant month is 0.48. Compare the average turnover rate with vacancies (the relevant monthly inflow/stock ratio), the average turnover rate for the unemployed is much lower than for vacancies. The figures are 0.16 and 1.12 respectively.

Figure 4: Monthly unemployment stock, inflow and outflow in England and Wales, March 1986 - December 2000. Source: JUVOS. Data seasonally adjusted.



3.2 Derived Variables

Although it is possible to construct daily individual unemployment histories, regional vacancy information is only available monthly. Vacancy data determine that time interval equals one month. Due to this limitation, the hazard within a month is treated as constant.

As noted above, the dependent variable - exit into a job - is observed as a binary variable, i.e., in the month τ, variable $y_{i,\tau}$ equals one if person i leaves unemployment, and equals zero otherwise. The explanatory variables for the associated hazard rate at duration τ, h_i^τ, are one of two types:

- The characteristics of the observation itself, including variables of age, age square, sex, marriage status, and the interaction term between marriage status and sex.
- The characteristics of the economic environment of the observation unit, including the variables of vacancy stock, vacancy inflow, unemployment stock and unemployment inflow (which all are measured in log form).

As far as the model specification is concerned, this distinction makes no difference. In practice, however, it makes a significant difference as the first type of variables is directly available in the JUVOS data, whereas the second type has to be collected separately (i.e., the vacancy data is extracted from the NOMIS databank) or counted from the data itself (i.e., unemployment stock and inflow) and then matched in by the spell month which an unemployed worker is in and also by the region where an unemployed worker lives.

More importantly, the first type of variables is fixed over calendar and survival time, whereas the second type of variable varies not only with the calendar time but also with duration. If a worker cannot find a job in the first month of being unemployed, the vacancy stock, vacancy inflow, unemployment stock, and unemployment inflow he or she faces in the second month of unemployment differs from the previous spell.[9] Note the stock of vacancies is defined as the number of unfilled vacancies at the start of the spell month, the flow of vacancies is defined as the number of new vacancies within the spell month, and similar definition is used for the stock and flow of unemployed workers.

3.3 Data related issues

There are three issues related to selecting the sample. First, although the unemployment data is updated on a daily basis, the vacancy data is observed monthly. Uncorrected, any regression results are potentially subject to mismeasurement. Unmatched job flows from the beginning of the month are part of the vacancy stock at the end of the month. Therefore, for individuals who enter into unemployment at the end of the month, the importance of stock effects is likely to be underestimated and the importance of the flow effect overestimated. Such mis-measurement becomes less of a problem for the people who enter into unemployment before the middle of the month. If a worker enters into unemployment in the first week of the month, it is much more likely that the worker enters first and the new vacancy is correctly counted as flow. To deal with this problem, our sample only selects the workers who enter into unemployment in the first week of each accounting month.

Secondly, the previous employment duration cannot be tracked down for each worker's first record in the data. To measure previous employment duration for each worker's first claim in the data, we use one year as the benchmark to assume that the workers who claim the unemployment benefits at the first time in the record had at least been employed for one year before entering into unemployment. As the

[9] Regional dummies are excluded as these effects are accounted for the regional unemployment stock, regional unemployment inflow, regional vacancy stock, and regional vacancy inflow. Monthly dummies which indicate what a spell month is are not included as the data we construct here is the cross-sectional data, and for the same reason, neither are yearly dummies.

unemployment data starts from March 1986, our sample includes the people entering into unemployment since April 1987.

Finally, there is a structural break in the unemployment data identified in our previous work.[10] Jobseeker's Allowance (JSA) is the current unemployment benefit fully operated from October 1996, which replaces Unemployment Benefit and Income support for unemployed jobseekers. Workers are entitled to claim Contribution-based Jobseeker Allowance (which replaces the Unemployment benefits) no longer than 26 weeks of unemployment instead of 52 weeks of unemployment, and once they have been unemployed more than 26 weeks, they can only claim or still receive Income-based Jobseeker allowance (which replaces the Income support for unemployed Jobseekers).[11] This discontinuity related to a change in rules affects the status of individuals in the claimant count without changing their labour market status. Although the data period covers up to November 2000, we do not include the people who enter into unemployment after March 1996 into the sample as the focus here is on the individual search behaviour and this discontinuity would result in serious bias in the estimation.

4. Results

We first present Kaplan-Meier estimates of empirical hazard functions for exits from unemployment to employment. These can be the interpreted as estimates of the

[10] The Employment Department identified three types of discontinuity to the claimant count; type (A) - involves a change in rules (entitlement to benefit etc) which affects the status of individuals in the daily count, without changing their labour market status, type (B) - an administrative change that necessitates a change to the method compiling the figure (for example, the move from a count of people registering at Jobcentres to a count of people claiming unemployment related benefits necessitated by the introduction of voluntary registration in Oct. 1982), and type (C) – a purely statistic change .

[11] In the JSA system, workers are allowed to claim Contribution-based and Income-based Jobseeker allowance at the same time in the first 26 weeks of unemployment, depending on their personal situations. In the previous system, they only can claim unemployment benefits in the first 52 weeks being unemployed, and if they have been unemployed more than 52 weeks, they can receive means-tested payments from the Income Support scheme which is much lower than unemployment benefits.

monthly re-employment probability estimates without accounting for heterogeneity across unemployed workers. The Kaplan-Meier unemployment hazard rates calculated here are for “representative” individuals, without explicit dependence on individual characteristics. Then, we report the estimates of multivariate hazard regressions of the hazard for the entire sample and the two sub samples.

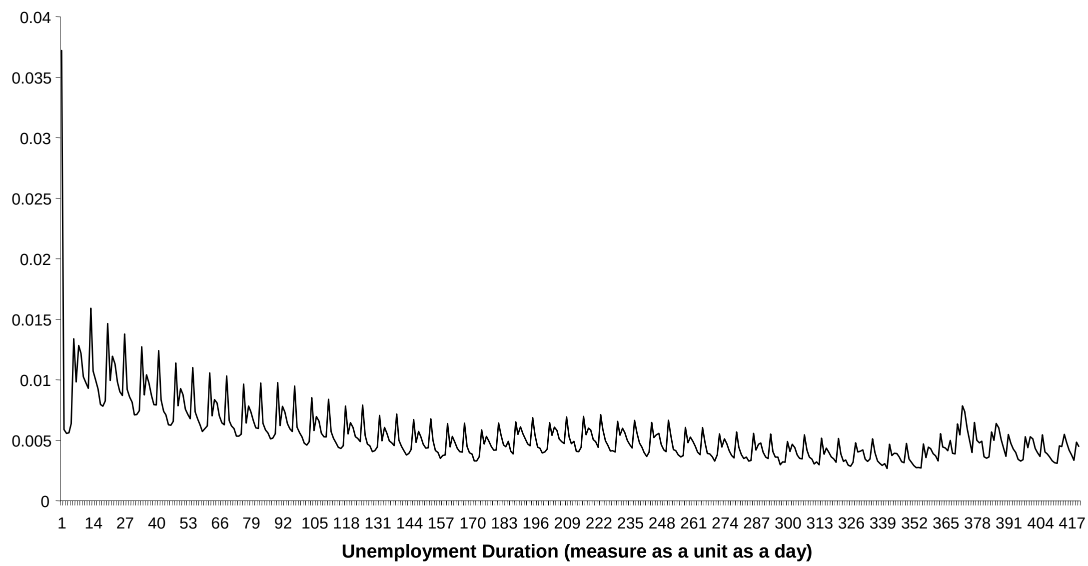
4.1 Empirical hazard estimates

As the JUVOS dataset is updated based on the daily information, the K-M reemployment probabilities of unemployed workers of daily spell can be easily calculated. Figure 5 plots the average hazard rates of daily unemployment spell. Surprisingly, the reemployment probabilities drop sharply after the first day of unemployment. The reemployment probability of getting a job in the first day of unemployment is approximately 3.73 percent, this probability drops to approximately 1.60 percent within the first week of unemployment, and falls gradually in general with unemployment duration thereafter.

This dramatic decline of the K-M unemployment hazard rates after the first day being unemployed strongly corresponds to the stock-flow search pattern in which there should be a stepwise decrease in the hazard rate without transaction delays. Of course, it is possible that some of these unemployed workers who find a job during the first day of unemployment are already hired by a firm before they enter into unemployment. It is also possible that people search before they sign on at Unemployment Benefit Office. Even so, the stock-flow search behaviour will be supported by the regression results which will be discussed in the next part of this section.

Note, Figure 5 also implies that there is a weekly cycle in the reemployment probabilities. The hazard rates in general have regular peak and drop every seven days. This corresponds to the weekday pattern observed in the unemployment outflow (Table 5). Recall that a large proportion of workers sign off unemployment benefits on Saturday, and a small proportion of workers sign off unemployment benefits on Friday and Sunday. The peak every seven days reflects the outflow on Saturday. Similarly, the drop prior to the peak reflects the outflow on Friday, and the drop after the peak reflects the outflow on Sunday. This weekly cycle is related to the institutional feature. Unemployment Benefits are counted on a weekly basis, and Saturday is the last day of the accounting week.[12] An unemployed worker may find a job at any day in a week, but sign off on leaving unemployment on the last day of the unemployment benefits accounting week.

Figure 5: Average reemployment probabilities of unemployed workers of daily duration.



[12] Sunday is the last day of the accounting week in the current benefit system (i.e., JSA).

4.2 Logistic hazard regression model estimates for entire sample

Table 6 reports the logistic regression estimates of re-employment probabilities by monthly unemployment duration. The estimates of the individual characteristics are shown in Appendix Table 6.A.

Table 6: Logistic hazard regression model of re-employment probability by monthly unemployment duration

unemployment duration	Vstock	vinflow	Ustock	uinflow	log likelihood	number of obs
0-1 month	0.308 (0.013)	0.068 (0.017)	-0.082 (0.006)	-0.090 (0.014)	-195919	354272
1-2 months	0.165 (*0.017*)	0.167 (*0.022*)	-0.070 (*0.007*)	-0.123 (*0.019*)	-123191	255882
2-3 months	0.150 (*0.020*)	0.279 (*0.026*)	-0.100 (*0.008*)	-0.042 (*0.023*)	-89392	202720
3-4 months	0.042 (*0.023*)	0.309 (*0.031*)	-0.046 (*0.010*)	-0.166 (*0.026*)	-67660	166276
4-5 months	0.039 (*0.028*)	0.236 (*0.036*)	-0.030 (*0.011*)	-0.194 (*0.031*)	-51507	140225
5-6 months	0.059 (*0.031*)	0.251 (*0.041*)	-0.008 (*0.013*)	-0.216 (*0.035*)	-41586	122296

Standard error in brackets
The estimates of the demographic effects are shown in Appendix table 6.A

For unemployment spell less than or equal to one month, the variables of vacancy stock and inflow are both positive and significant with the estimated parameter of the vacancy stock much higher than the vacancy inflow, around 0.31 and 0.07, respectively. On the other hand, for unemployment spell more than one month and less than or equal to two months, the variables of vacancy stock and inflow are also both positively significant. The estimated elasticity of the re-employment hazard with respect to the vacancy stock drops sharply to around 0.16, and in contrast, the estimated elasticity with respect to the vacancy inflow increases largely to around 0.17. These results clearly suggest that newly unemployed workers try to find a job from the current stock of vacancies, and those who fail to get employed search for a suitable job from the flow of new vacancies. This switch in the matching pattern provides strong support for the stock-flow search model.

For unemployment spells of 2-3 and 3-4 months, the flow of new vacancies has positive and significant impact on the re-employment probabilities, and the estimated elasticity jumps to around 0.30. On the other hand, the effect of vacancy stock is also positively significant for these unemployment spells, but the estimated elasticity decreases from around 0.15 to around 0.04. Although the vacancy stock has strong impact on the re-employment hazard of 2-3 months, the flow effect is much stronger than the stock effect. These results are consistent with the stock-flow search model in the sense that unemployed workers who fail to mach in the first place mainly match with the flow of new vacancies.

For unemployment spells of 4-5 and 5-6 months, the effect of vacancy inflow is positively significant, and the estimated elasticity is around 0.25. The effect of vacancy stock is insignificant for unemployment spell of 4-5 months, and positively significant for unemployment spell of 5-6 months, in which the estimated elasticity is around 0.06. Again, these results are consistent with the stock-flow search model where the matching probabilities of theses workers are supposed to be increased by the flow of vacancies

The crowding out effect by unemployed workers is clear. The unemployment stock and inflow, in general, have significant and negative impact on the reemployment probabilities. Note this effect is mainly from the inflow of unemployed workers.

Now, we turn our attention to the estimates for the other variables associated with personal characteristics. The age effect reported in Table 6.A is always negatively significant, and the sex effect is also always negatively significant, which suggests the reemployment hazard is higher for the workers who are younger or who are female. This is consistent with the demographic effects established elsewhere, where the expected unemployment duration increases with age (grouped into 18-24, 25-34, 35-44, and 45+), and female have shorter expected unemployment duration than male.

The marriage effect is ambiguous. The marriage effect is positively significant for unemployment spell of 0-1 month, and for the rest unemployment spells, the marriage effect is negatively significant. This ambiguous result is related to the two opposite effects of marriage. If married persons have family responsibilities, they are keener to find a job. On the other hand, if they can receive transfers from their spouses, the out-of-work utility raises. In contrast, the effect of the interaction term between sex and marriage is clear, and always has positive and significant impact on re-employment probabilities, which suggests married men have higher reemployment hazard, compared with single men, single women, and especially married women. Given the fact that family responsibilities are usually taken by husbands, this is not a surprising result. Most earlier studies have also found higher re-employment hazard for married men and attributed this to the greater pressure to get a job which greater needs might bring.

4.3 A comparison of employment durations

We now consider the way in which the previous employment duration affects the unemployment transition. In terms of the model specification summarised by equation (1), we condition on how long the workers had been employed before entering into unemployment. The unemployed workers with short-term employment duration are defined as the workers who had been employed less than three months before entering into unemployment, and the unemployed workers with long-term employment duration are defined as the workers who had been employed more than one year before entering into unemployment. Table 7 reports the ML estimates of the logistic hazard regression model of re-employment probabilities by monthly unemployment duration for the workers with short-term employment duration, and the estimates of the individual characteristics are shown in Appendix Table 7.A. Similarly, Table 8 reports the ML estimates for the workers with long-term employment duration, and the estimates of the individual characteristics are shown in Appendix Table 8.A.

- **Unemployment spell of 0-1 month**

For the unemployed workers with short-term employment duration, the vacancy stock and inflow both have significant and positive impact on the re-employment hazard of 0-1 month. The estimated parameter of vacancy stock is around 0.21, which is lower than the estimates reported in Table 6, and the estimated parameter of vacancy inflow is around 0.12, which is higher than the estimates reported in Table 5.3. Our interpretation is that most currently unfilled vacancies in the marked have already been sampled by the unemployed workers with short-term employment duration. In the stock-flow search framework, the vacancy stock is supposed to be on the long-side of the market, and hence it may have been in the market for a while. If a worker who left unemployment in the last three months enters into unemployment again, it is very likely that some current stock of vacancies had been sampled by him before, and thereby making the vacancy stock less viable. The information on how long the vacancies have been in the market, however, is not available.

On the other hand, for the unemployed workers with long-term employment duration, the effect of vacancy stock is positively significant, and the effect of vacancy inflow is insignificant. The estimated parameter of vacancy inflow is around 0.39, which is higher than the estimates reported in Table 6. This suggests that the unemployed workers with long-term employment duration are more representative of the stock-flow search model as they only match with the current vacancy stock in the first month of unemployment.

- **Unemployment spells of 1-2 and 2-3 months**

For the unemployed workers with short-term employment duration, the vacancy stock and inflow both have positive and significant impact on the reemployment hazard of 1-2 months. The estimated elasticity with respect to vacancy stock decreases to around 0.11, and the estimated elasticity with respect to vacancy inflow remains at the same level. Then, for the next unemployment spell, the effect of vacancy stock is not significant, and the effect of vacancy inflow is positively significant. The estimated elasticity with respect to the vacancy inflow rises to around 0.32. These results suggest that these workers are also stock-flow searchers in the sense that once they exhaust the existing pool of vacancies, they wait for a suitable job coming into the market.

For the unemployed workers with long-term employment duration, the vacancy stock and inflow both have positive and significant impact on the reemployment probability of 2-3 months. The estimated elasticity with respect to vacancy stock drops to around 0.22, and the estimated elasticity with respect to vacancy inflow rises to around 0.16. Then, for the next unemployment spell, the variables of vacancy stock and inflow are also both positively significant. The estimated elasticity with respect to vacancy stock decreases to around 0.16, and the estimated elasticity with respect to vacancy inflow increases to around 0.27. As the stock effect is decreasing with unemployment duration, and the flow effect is increasing with unemployment duration, these results further confirm that the unemployed workers with long-term employment duration are stock-flow searchers.

- **Unemployment spells of 3-4, 4-5, and 5-6 months**

For the unemployed workers with short-term employment duration, the variable of vacancy inflow is positively significant for these unemployment spells, and the variable of vacancy stock is insignificant. This is consistent with their search behaviour in the previous unemployment duration as they match with the flow of new vacancies, rather than the vacancy stock in this stage. Similarly, for the unemployed workers with long-term employment duration, the effect of vacancy inflow is positively significant for these unemployment spells, and the effect of vacancy stock is insignificant. This is also consistent with their search behaviour in the previous unemployment duration as their re-employment probabilities positively depend on the inflow of vacancies, and are independent of vacancy stock in these unemployment spells.

In particular, the estimated parameters of vacancy inflow for the workers with short-term employment duration in these unemployment spells are very close not only to the estimates for the workers with long-term employment duration, but also for the entire sample (reported in Table 6). This implies that the results obtained here are robust, as there seems to be no difference in the corresponding estimates for the workers with short-term and long-term employment duration, and the whole sample. To test the hypothesis that the coefficients of vacancy inflow in the same spell are equal among the entire sample and these two groups, the simple Wald test is a natural choice. The Wald statistic indicates there is actually no significant difference between these estimates, and therefore the robustness of our results is confirmed.

Table 7: Logistic hazard regression model of re-employment probability by monthly unemployment duration: workers with short-term previous employment duration.

unemployment duration	Vstock	vinflow	Ustock	uinflow	Log likelihood	number of obs
0-1 month	0.208 (0.028)	0.121 (*0.037*)	-0.108 (*0.012*)	-0.101 (*0.032*)	-42990	79456
1-2 months	0.113 (*0.035*)	0.110 (*0.046*)	-0.115 (*0.015*)	-0.045 (*0.040*)	-28543	59873
2-3 months	0.020 (*0.043*)	0.316 (*0.056*)	-0.065 (*0.018*)	-0.176 (*0.047*)	-20582	48514
3-4 months	-0.058 (*0.049*)	0.309 (*0.064*)	-0.033 (*0.020*)	-0.133 (*0.054*)	-16253	40638
4-5 months	-0.040 (*0.057*)	0.275 (*0.074*)	-0.051 (*0.023*)	-0.186 (*0.063*)	-12580	34658
5-6 months	0.028 (*0.064*)	0.256 (*0.083*)	-0.026 (*0.025*)	-0.218 (*0.071*)	-10381	30527

Standard error in brackets
The estimates of the demographic effects are shown in Appendix table 7.A

Table 8: Logistic hazard regression model of re-employment probability by monthly unemployment duration: workers with long-term previous employment duration.

unemployment duration	Vstock	vinflow	Ustcok	uinflow	Log likelihood	number of obs
0-1 month	0.386 (0.017)	0.017 (*0.023*)	-0.083 (*0.007*)	-0.060 (*0.019*)	-107604	188447
1-2 months	0.219 (*0.023*)	0.156 (*0.030*)	-0.052 (*0.010*)	-0.137 (*0.026*)	-64440	131539
2-3 months	0.159 (*0.028*)	0.268 (*0.036*)	-0.074 (*0.012*)	-0.082 (*0.031*)	-45720	102747
3-4 months	0.054 (*0.032*)	0.297 (*0.043*)	-0.036 (*0.014*)	-0.182 (*0.037*)	-33976	83551
4-5 months	0.066 (*0.039*)	0.218 (*0.052*)	-0.027 (*0.016*)	-0.174 (*0.044*)	-25495	70101
5-6 months	0.047 (*0.044*)	0.245 (*0.058*)	0.002 (*0.018*)	-0.175 (*0.050*)	-20469	61122

Standard error in brackets
The estimates of the demographic effects are shown in Appendix table 8.A

5 Conclusion

This paper not only computes daily unemployment hazard rates, but also uses a cross section of individual unemployment duration data to estimate re-employment probabilities. The K-M unemployment hazard rates conform with prediction of the stock-flow search model - it has a stepwise decrease. Moreover, it also shows that there is a weekly cycle in unemployment, and this is related to institutional feature. The evidence from the regression results also provides strong support for the stock-flow search theory in terms of matching between the unmatched stock on one side of the market with the flow on the other side of the market.

The demographic results suggest that the re-employment probability decreases with age, and that the reemployment probabilities are higher for female than for male. Moreover, these results also suggest that the reemployment probabilities for married men are higher than for married women.

Finally, regarding the previous employment duration, the results suggest that the unemployed workers with long-term employment duration are more like stock-flow searcher, and the search behaviour of the workers with short-term employment duration is consistent with the stock-flow matching model. These results provide yet more a strong support for the stock-flow search model.

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Appendix

Individual search behaviour: empirical modelling details

This material closely follows the exposition given in Jenkins (1995). The probability of observing an incomplete spell of length τ_i months for person i is given by the discrete survivor function

$$\prod_{j=1}^{\tau_i}(1-h_i^j) \qquad 1$$

whereas the probability of observing a completed spell of length τ_i months is given by

$$h_i^{\tau_i}\prod_{j=1}^{\tau_i-1}(1-h_i^j) \qquad 2$$

Hence the log-likelihood for a sample of n persons can be written as

$$\log L=\sum_{i=1}^{n}c_i\log(\frac{h_i^{\tau_i}}{1-h_i^{\tau_i}})+\sum_{i=1}^{n}\sum_{j=1}^{\tau_i}\log(1-h_i^j) \qquad 3$$

where c_i is an indicator variable equal to one if person i's spell is completed and equal to 0 if it is censored. Now define a new binary indicator variable $y_{i\tau}=1$ if person i gets a job in month τ, and $y_{i\tau}=0$ otherwise. Then, eq. (5.3) can be re-written as:

$$\log L=\sum_{i=1}^{n}\sum_{j}^{\tau_i}[y_{i\tau}\log h_i^j+(1-y_{i\tau})\log(1-h_i^j)] \qquad 4$$

This regression implicitly assumes that the coefficient estimates are constant within the unemployment state. However, the stock-flow search model suggests that the exit rates depend on different variables at different stages of an agent’s stay in the market. Using the piecewise technique, the log-likelihood for a sample of n unemployed workers who are at risk in the month τ is given by

$$\log L^{\tau} = \sum_{i=1}^{n} [y_{i\tau} \log h_i^{\tau} + (1 - y_{i\tau}) \log(1 - h_i^{\tau})] \qquad 5$$

This expression has exactly the same form as the standard likelihood function for a binary regression model. This model can be estimated by standard software applied to a re-organised data set in which each person contributes as many 'data rows' as he is observed at risk of exit from unemployment (Allison, 1982; Jenkins 1995, Jenkins and Garcia-Serrano, 2000). Note, the unit of observation is still the person rather than the person-month, but condition on this person is at risk in this period.

The discrete monthly re-employment hazard for person i who has been unemployed for τ months is parameterised as

$$h_i^{\tau} = \frac{1}{1 + \exp[-(\alpha + \beta' x_i)]} \qquad 6$$

where α is the constant term, x_i is a vector of independent covariates which potentially vary with time (see the discussion in Section 3.2) and β is a vector of parameters to be estimated.

Equation (6) is the logistic hazard specification, and has been used before by, for example, Nickell (1979), Narendranathan and Stewart (1993), and Bover et al. (1998). We choose it primarily as it makes estimation feasible using our very large data set. An alternative specification for the hazard is the complementary log-log one, which yields the discrete-time proportional-hazard model (Prentice and Gloeckler, 1978; Meyer, 1990). As h_i^{τ} is relatively small in practice, the logistic specification provides a very close approximation to this alternative model.[13] That is

[13] All estimates derived using stata 8.2. Estimation of the logistic models took between 5 to 60 minutes (depending on the number of covariates and the number of observations), whereas estimation of each proportional hazards cloglog model took about 3 hours.

$$Ln(h_i^{\tau}) \approx \alpha + x_i^{'}\beta \qquad 5.7$$

to a close approximation. Thus absolute differences in x imply proportional shifts in the hazard, and the estimated coefficient on a covariate which is measured in logarithms may be interpreted as the elasticity of the hazard with respect to that variable.

Table 6.A: Logistic hazard regression model of re-employment probability by monthly unemployment duration

Unemployment duration	Age	Age^2	Sex	Married	Sex*Married
0-1 month	-0.036 (0.002)	0.000 (0.000)	-0.237 (0.010)	0.091 (0.015)	0.115 (0.018)
1-2 months	-0.011 (0.003)	0.000 (0.000)	-0.253 (0.013)	-0.075 (0.020)	0.261 (0.023)
2-3 months	-0.028 (0.003)	0.000 (0.000)	-0.271 (0.016)	-0.129 (0.024)	0.260 (0.028)
3-4 months	-0.023 (0.004)	0.000 (0.000)	-0.197 (0.019)	-0.126 (0.028)	0.254 (0.033)
4-5 months	-0.014 (0.005)	0.000 (0.000)	-0.179 (0.022)	-0.104 (0.033)	0.216 (0.038)
5-6 months	-0.013 (0.005)	0.000 (0.000)	-0.180 (0.025)	-0.085 (0.037)	0.190 (0.043)

Standard error in brackets

Table 7.A: Logistic hazard regression model of re-employment probability by monthly unemployment duration: workers with short-term previous employment duration.

Unemployment duration	Age	Age^2	Sex	Married	Sex*Married
0-1 month	-0.014 (0.005)	0.000 (0.000)	-0.238 (0.023)	0.053 (0.037)	0.137 (0.041)
1-2 months	-0.027 (0.006)	0.000 (0.000)	-0.190 (0.029)	0.062 (0.047)	0.113 (0.053)
2-3 months	-0.022 (0.007)	0.000 (0.000)	-0.150 (0.035)	0.061 (0.058)	0.073 (0.064)
3-4 months	-0.026 (0.008)	0.000 (0.000)	-0.151 (0.040)	0.078 (0.066)	0.064 (0.074)
4-5 months	-0.041 (0.010)	0.000 (0.000)	-0.146 (0.046)	0.127 (0.077)	-0.014 (0.086)
5-6 months	-0.034 (0.011)	0.000 (0.000)	-0.169 (0.051)	0.143 (0.085)	-0.006 (0.095)

Standard error in brackets

**Table 8.A: Logistic hazard regression model of re-employment probability by monthly unemployment duration:
workers with long-term previous employment duration.**

Unemployment duration	Age	Age^2	Sex	Married	Sex*Married
0-1 month	-0.032 (0.003)	0.000 (0.000)	-0.212 (0.014)	0.044 (0.019)	0.137 (0.023)
1-2 months	0.009 (0.004)	0.000 (0.000)	-0.231 (0.018)	-0.124 (0.025)	0.295 (0.030)
2-3 months	-0.014 (0.005)	0.000 (0.000)	-0.258 (0.022)	-0.185 (0.031)	0.356 (0.037)
3-4 months	-0.008 (0.005)	0.000 (0.000)	-0.150 (0.026)	-0.200 (0.037)	0.318 (0.044)
4-5 months	0.007 (0.006)	0.000 (0.000)	-0.170 (0.031)	-0.217 (0.043)	0.341 (0.052)
5-6 months	0.006 (0.007)	0.000 (0.000)	-0.201 (0.035)	-0.159 (0.048)	0.327 (0.058)

Standard error in brackets