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# The Hiring Function Reconsidered: on Closing the Circle

by

Karen Mumford and Peter N Smith

**Department of Economics and Related Studies**
**University of York**
**Heslington**
**York, YO10 5DD**

# THE HIRING FUNCTION RECONSIDERED: ON CLOSING THE CIRCLE*

Karen Mumford[1,2] and Peter N. Smith[1]

[1]Department of Economics
University of York

[2] Centre for Economic Performance
London School of Economics

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**Abstract** JEL # J6

This paper investigates the matching of job searchers with vacant jobs: a key component of the dynamics of worker reallocation in the labour market. The job searchers may be unemployed, employed or not in the labour force and we estimate matching or hiring functions including all three groups. We show that previous studies, which ignore both employed job seekers and unemployed job seekers who are considered to be out of the labour force, produce biassed estimates of the coefficients of interest. By considering only unemployment outflows into jobs and ignoring interdependencies with other flows, these studies overlook an important aspect of job matching. Our estimates on Australian data support a more general approach and produce models that dominate those proposed previously. We find that concentrating on the aggregate matching function alone does not reveal the full extent of the interaction across job searchers. Indeed, we find that job searchers from the three groups do not receive a fair share of hires: there appears to be segmentation of hiring opportunities which may be explained by a form of ranking of applicants. Together these results demonstrate that the disaggregate worker flows and their interdependence are key features of the labour market and should be included in studies of the hiring process.

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## *I. Introduction*

There are three possible sources of gross worker flows into employment in the labour market: from unemployment to employment; from not in the labour force into employment; and from job to job. In this paper, we consider the hiring process through all three of these flows using data from the Australian labour market. The flow to employment from unemployment is the smallest of the three flows constituting, on average, 20% of the total flows. The corresponding outflow rate from unemployment into jobs is pro-cyclical (having a correlation coefficient of 0.76 with a measure of the business cycle).[1] Flows into jobs from outside of the labour force make up 37% of the total flows and the outflow rate is also procyclical (the correlation coefficient with the cycle is 0.44). Finally, the flow between jobs is the largest of the three flows (43% of the total) and the flow rate between jobs is similarly procyclical (with a correlation coefficient with the cycle of 0.50).

Much analysis of the flows from unemployment into employment has been carried out (eg., Blanchard and Diamond, 1989, Layard *et al*, 1991 and Burda and Wyplosz, 1994). There has been some work on the flow of those in jobs into new jobs and the possibility of the unemployed facing competition for this group (Burgess, 1993, and Van Ours, 1995). There has, however, been very little analysis of the flow of those people not in the labour force into employment. Indeed, a major simplifying assumption made in the literature is to concentrate exclusively on the flows of unemployed males. The justification usually offered for this assumption is insufficiency of data on those not in the labour force and the belief that this latter group is dominated by the behaviour of females who may face different constraints (eg., Pissarides, 1986, Layard *et al*, 1991, Burda and Wyplosz, 1994). By incorporating a range of complementary data sources we provide measures of all three of these stocks and flows. We address the possibility of interactions across the flows into employment and examine the idea of ranking of groups in terms of new employment. We believe that this is the first study which attempts a consistent, holistic, approach to investigating these three major gross worker flows and their interaction.

The commonly used mechanism to model the process by which the stock of vacant jobs

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[1]These figures are averages for the period 1980 to 1991. The correlation coefficients are for logarithms of outflow rates into jobs from each state with the log detrended GDP on quarterly data. A Hodrick Prescott filter (ë=1200) was used to estimate the trend in GDP.

and the stock of available job seekers are brought together to produce job offers and then job hires is the matching function. We can quickly see why it is important to include all the possible flows of job seekers by considering the complex nature of this function. Without describing in detail the strategies followed by firms and job seekers, we can assume that the individual job seekers and firms on either side of this market are behaving optimally to provide the combination of available jobs and job seekers to create matches. The matching function can then be written as:

$$M_t = f\,(S_t\,,\,V_t\,) \qquad (1)$$

where the flow of new job matches or hires ($M_t$) over period $t$ is produced from a function of the number of available job seekers ($S_t$) and number of vacancies ($V_t$) at the start of the period. This general relationship has been likened to a production function (Blanchard and Diamond, 1989) and in that spirit the notion of returns to scale introduced. Extensive empirical work in the United States (Blanchard and Diamond, 1990) and the UK and other European countries (Burda and Wyplosz, 1994, and Burgess, 1993, amongst others) has provided support for a constant returns-to-scale Cobb-Douglas functional form[2] such as:

$$M_t = \text{ã} S_t^{\text{á}} V_t^{1-\text{á}} \qquad (2)$$

where ã is a scale parameter capturing changes in the efficiency of the matching process (that would impact on all searchers equally).

We can address the general matching function (1) more fully by considering how each of its terms is constructed in more detail. The total number of matches $M_t$ is the sum of hires from unemployment $X_t$; from outside of the labour force $L_t$; and from employment (job to job flows) $J_t$ So:

$$M_t = X_t + L_t + J_t \qquad (3)$$

The sum of the stocks that produce these new job matches is the total number of job searchers $S_t$ which is the sum of unemployed job searchers $U_t$; not-in-the labour force (NLF) job searchers $N_t$; and employed job searchers. There is no direct measure of the number of on-the-job searchers (the OJS), we therefore approximate this stock with a function *ö* of the current stock of employed persons $E_t$; *ö*($E_t$). So:

[2]Whilst there is some evidence indicating mildly increasing returns to scale (Blanchard and Diamond, 1990), when incorporated into a general equilibrium model, the matching function is required to exhibit constant returns-to-scale for there to be a balanced growth path for the economy (Pissarides, (1990).

$$S_t = U_t + N_t + \ddot{o}(E_t) \qquad (4)$$

This implies that all searchers are perfect substitutes for each other in the hiring process regardless of their labour market status. This may not be true. It may be that the component groups of the total number of job searchers actually have differing search effectiveness for a given set of job vacancies. For example, the search effectiveness of each group may be a function of its reservation wage which may differ across labour market states (Mortensen, 1986, Layard *et al,* 1991;234). Also, we would expect that search effectiveness may be influenced by a range of personal characteristics such as the duration of unemployment for the unemployed job seeker (Budd *et al.*, 1988, and Blanchard and Diamond, 1994). Thus, the true measure of effective job searchers may be:

$$\tilde{S}_t = s_u U + s_n N + \ddot{o}(E_t) \qquad (4a)$$

where $s_u$ and $s_n$ measure the search effectiveness of the unemployed and NLF job searchers *relative* to the on-the-job-searchers (the OJS), and the search effectiveness of the latter group is normalised to unity.

The complete disaggregation laid out in equation (4a) above has, however, typically been ignored in the literature on matching functions in general and in the empirical literature, in particular. Traditionally (Pissarides, 1986, and Layard *et al*, 1991), it has been assumed that the constituent parts of total hires ($M_t$) are independent of each other thereby enabling the analyst to concentrate on the outflow from unemployment ($X_t$) determined by the unemployment stock ($U_t$) and vacancies ($V_t$). Adopting the constant returns-to-scale Cobb-Douglas functional form, the model is then:

$$X_t = \tilde{a} U_t^{\acute{a}} V_t^{(1-\acute{a})} \qquad (5)$$

This reduced model is unlikely to capture more than a part of the complete pattern of flows into jobs and its popularity would appear to be predominantly due to data limitations. In addition, Layard *et al* (1991) argue for independent treatment of these flows without acknowledging that the stocks *and* flows from initial states must be independent of one another. In a stochastic model this implies that they should be uncorrelated, an unlikely possibility given the cyclicality of all of the flows noted above. In some cases (Blanchard and Diamond, 1990), the number of matches has been more broadly measured whilst the stock of available job seekers is modelled by unemployment, resulting in potentially inconsistent flow and stock measures.

The coefficients estimated from such reduced models also may not necessarily measure what they purport to. The argument in Layard *et al* (1991) would suggest that the partial derivative $\ddot{a}X_t /\ddot{a}M_t$ will be equal to one. However, recent findings suggest two major implications for previous empirical work. A matching function relating $M_t$ to $U_t$ and $V_t$ alone will be misspecified and give a downward biassed estimate of the unemployment elasticity of matching (Broersma, 1996). Second, in the absence of a direct measure for the pool of searchers other than the unemployed, the resulting estimated equation will fail to reveal the complexity of the relationships between the various stocks and flows (Burgess, 1993). These two points will be considered in the estimation below. In this paper we use measures of all the flows underlying the matching function and address the possibility, and implications, of their interdependence. In particular, we assess the extent to which there is evidence of job competition between groups of job searchers and the implications of such competition for the aggregate matching function.

We present our estimating equation in Section 2, describe our data and the construction of the gross flows in Section 3, discuss our results in Section 4, and present conclusions and suggestions for future work in Section 5 of the paper.

### *II. Matching functions and flows into employment*

If all job vacancies are equally available to all seekers, we would expect that job seekers from any given group would receive a share of offers proportional to their share among the total number of job searchers. This fair share rule is:

$$\frac{M_t^{\,i}}{S_t^{\,i}} = \frac{M_t}{S_t} \tag{6}$$

where *i* represents the given group. Consider, for example, the determination of the hiring of the unemployed, $X_t$ (ie., $M_t^{\,i} = X_t$ and $S_t^{\,i} = U_t$ in equation (6)):

$$X_t/U_t = M_t/S_t \tag{7}$$

As discussed previously, it is important to use the right measures of job searchers in order to address the consistency problems raised by Broersma (1996) and the possibility of endogenous competition discussed in Burgess (1993). We therefore define the fair shares rule in terms of effective job searchers by substituting $s_u U_t$ for $U_t$ and $\tilde{S}_t$ for $S_t$ in equation (7)[3] to get:

$$X_t/(s_u U_t) = M_t/\tilde{S}_t \tag{7a}$$

Fair shares in hiring can be considered as *random hiring* or *no ranking*. In other words, when employers are faced with multiple applications for a vacancy, they do not exhibit any consistent preference for a candidate from one pool of job searchers than another (Blanchard and Diamond, 1995). At the other end of the spectrum, employers may exhibit full ranking whereby job seekers from one group will only have their application considered if no-one from the preferred group has applied for the vacancy. In between these two extremes lays a range of hiring outcomes that reflect the preferences of employers who are combining ranking and no-ranking elements when considering heterogenous applicants from recognisable groups (Blanchard and Diamond, 1994;433).

We are interested in testing the fair shares hypothesis. If there is no ranking in the hiring process, estimates of the shares of the component stocks of total searchers across the three share equations and the aggregate matching function will be the same (Blanchard and Diamond, 1989;34). We consider this possibility below[4]. To test equation (7a) in log-linear form we employ a Taylor series approximation for $\tilde{S}_t$:

$$ln(s_u U_t + s_n N_t + \ddot{o} E_t) \simeq constant + lnU_t + lns_u$$
$$+ \left(\frac{\overline{s_n N}}{\overline{s_u U} + \overline{s_n N} + \ddot{o}(\overline{E})}\right) ln\left(\frac{s_n N_t}{s_u U_t}\right) + \left(\frac{\ddot{o}(\overline{E})}{\overline{s_u U} + \overline{s_n N} + \ddot{o}(\overline{E})}\right) ln\left(\frac{\ddot{o}(E_t)}{s_u U_t}\right)$$

where, for example, $\overline{s_u U}$ is the steady-state value of $s_u U_t$. Consequently, we obtain an expression for the outflow rate from unemployment:

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[3]Whilst equation (7) is also at the heart of Burgess' (1993) model of job competition between unemployed and employed job seekers, he ignores those outside of the labour force. Van Ours (1995) also employs this apportioning of job offers but only between those in the labour force. Van Ours conditions this on the aggregate matching function (1) rather than on the total number of matches, $M_t$.

[4]Our premise here is that there is a general pool of vacancies, that there is a predetermined total number of matches whose determination (for the moment) we do not analyze, and that the matching process operates in such a way that the outcome may result in potentially unequal hiring rates across searchers from different labour market groups. Thus, we are conditioning on the total number of matches but allowing the data to identify the share of each group of job seekers in the total.

$$\ln(X_t/U_t) = á_0 + á_1 lnM_t + á_2 lnU_t + á_3 ln(N_t/U_t)$$

$$+ á_4 ln(ö(E_t)/U_t) + (1 + á_2 - á_3 - á_4) lns_u + á_3 lns_n$$

(8)

where $(1 + á_2 - á_3 - á_4) > 0$.

There are some additional measurement issues to solve before equation (8) can be estimated. For the number of job seekers outside of the labour force ($N_t$) we use a measure of those marginally attached to the labour force but not considered unemployed. We also need to model the stock of employed job searchers, *$ö(E_t)$*. We assume the number of employed job searchers, *$ö(E_t)$,* in period *t* is equal to $J_{t-1} / ã_{t-1}$ where $ã_{t-1}$ is the proportion of total employed job seekers who were successful in period *t-1*.[5] This proportion is unlikely to be constant, indeed it may be highly cyclical. We therefore model $ã_{t-1}$ as a function of the state of the business cycle directly, ie., $ã_{t-1} = \tilde{Y}_{t-1}^{â_1}$, where $\tilde{Y}_{t-1}$ is the detrended level of GDP. The empirical success of this particular choice of function will be our evidence for its suitability given the absence of any direct measure of the number of employed job seekers. We will also compare our formulation with that used by Burgess (1993). The *relative* search effectiveness of those not in the labour force ($s_n$) is assumed constant and that of the unemployed ($s_u$) is assumed to be a decreasing function ($s_u = (U_t^{LT}/U_t)^{-â_2}$) where $(U_t^{LT}/U_t)$ is the proportion of long-term unemployed in the total. We therefore estimate the determination of unemployment outflows into jobs as:

$$ln(X_t/U_t) = á_0 + á_1 lnM_t + á_2 lnU_t + á_3 ln(N_t/U_t)$$

$$+ á_4 ln(J_{t-1}/U_t) + á_5 ln(\tilde{Y}_{t-1}) + á_6 ln(U_t^{LT}/U_t) \qquad (9)$$

Analogous expressions can be derived for hires from outside the labour force:

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[5]In Burgess (1993) the number of employed job searchers is assumed to be an implicit function of the stock of those unemployed.

$$ln(L_t/N_t) = ä_0 + ä_1 lnM_t + ä_2 lnN_t + ä_3 ln(U_t/N_t)$$
$$+ ä_4 ln(J_{t-1}/N_t) + ä_5 ln(\tilde{Y}_{t-1}) + ä_6 ln(U_t^{LT}/U_t) \tag{10}$$

and from employment:

$$ln(J_t/J_{t-1}) = ç_0 + ç_1 lnM_t + ç_2 lnJ_{t-1} + ç_3 ln(U_t/J_{t-1})$$
$$+ ç_4 ln(N_t/J_{t-1}) + ç_5 ln(\tilde{Y}_{t-1}) + ç_6 ln(U_t^{LT}/U_t) \tag{11}$$

We would expect, given the discussion above, that $á_1 = ä_1 = ç_1 = 1$ implying all equations are for a share of total matches. The adding up restriction this implies dictates that we consider results from two out of the three flow-share equations at a time. We would also expect the shares of the total stock of job searchers to add up to one, this implies $á_2 = ä_2 = ç_2 = -1$. Of the remaining coefficients, some will reflect the importance of each of the relevant groups of searchers among the total pool of searchers. They will be the steady-state shares given the log-linearisation. In addition, the share of total effective searchers (implied by our estimates) of each group of job seekers should be identical across outflow rate equations. Evidence to the contrary would be indicative of unfair shares or ranking in the hiring process[6]. Other coefficients will reflect the determination of on-the-job-search and $s_u$ (the effectiveness of unemployed job searchers). Thus, under fair shares, we would expect that:

$$á_1 = ä_1 = ç_1 = 1; \qquad á_2 = ä_2 = ç_2 = -1; \qquad á_3 = ç_4 = -(\overline{s_n N})/\bar{\tilde{S}};$$
$$á_4 = ä_4 = -(\overline{ö(E)})/\bar{\tilde{S}}; \qquad á_5 = ä_5 = â_1(\overline{ö(E)})/\bar{\tilde{S}}; \qquad á_6 = -â_2(\overline{s_n N} + \overline{ö(E)})/\bar{\tilde{S}};$$
$$ä_3 = ç_3 = -(\overline{s_u U})/\bar{\tilde{S}}; \qquad ä_6 = ç_6 = -â_2(\overline{s_u U})/\bar{\tilde{S}}; \quad \text{and} \quad ç_5 = -â_1(\overline{s_u U} + \overline{s_n N})/\bar{\tilde{S}}.$$

Finally, we consider the consequences of our analysis and estimates for the aggregate matching function. This will take the form:

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[6]This is not to say that any one equation will capture the true relative differences in search effectiveness. It is not possible in practice to separate the demand and supply effects sufficiently to be able to distinguish between the impacts of search effort and the aggregate offer arrival rate for each group. However, differences across equations are indicative of hiring probabilities varying by job type and we interpret this as ranking in outcomes.

$$lnM_t = \tilde{è}_0 + \tilde{è}_1 lnV_t + \tilde{è}_2 ln(ö(E_t) + s_u U_t + s_n N_t) \qquad (12)$$

which log-linearised, as previously, becomes:

$$lnM_t = è_0 + è_1 lnV_t + è_2 lnU_t + è_3 ln(N_t/U_t)$$

$$+ è_4 ln(J_{t-1}/U_t) + è_5 ln(\tilde{Y}_{t-1}) + è_6 ln(U_t^{LT}/U_t) \qquad (13)$$

and in its restricted form, given fair shares, is:

$$lnM_t = è_0 + è_1 lnV_t + è_2 lnU_t + \frac{è_2\overline{s_n N}}{\bar{\tilde{S}}} ln(N_t/U_t) + \frac{è_2\overline{ö(E)}}{\bar{\tilde{S}}} ln(J_{t-1}/U_t)$$

$$- \frac{â_1 è_2\overline{ö(E)}}{\bar{\tilde{S}}} ln(\tilde{Y}_{t-1}) - â_2 è_2 (1 - \frac{(\overline{s_n N} + \overline{ö(E)})}{\bar{\tilde{S}}}) ln(U_t^{LT}/U_t) \qquad (14)$$

It is clear from equation (14) that the coefficients on the stocks of job searchers will be somewhat difficult to interpret. The aggregated coefficients measure the sum of ‘own stock’ effects and job competition effects. Consequently, the signs and sizes of the coefficients will depend on the relative importance of these effects. If equations (13 and 14) exhibit constant returns to scale then $è_1+è_2=1$. Given the fair shares rule, we would expect the following restrictions to apply to the aggregate matching function:

$$á_3 = ç_4 = è_3/è_2; \quad á_4 = ä_4 = è_4/è_2; \text{ and } á_5 = ä_5 = è_5/è_2.$$

Below, we estimate the aggregate matching function (14) along with two of the three share equations (9, 10, 11) and test these restrictions.

## *III. Establishing some stylised facts about gross worker flows*

### *a) Using the gross flows data*

It is possible to examine the issues raised above using data on gross worker flows which the Australian Bureau of Statistics (the ABS) has published on an almost continuous basis since late

1979.[7] The data are derived from the Labour Force Survey (LFS) of households and, in particular, the matched records of successive monthly surveys. The ABS surveys a sample of some 30,000 individual private and non-private dwellings each month. On the basis of this survey, each individual is assigned a labour market state for the week prior to the survey. The ABS then constructs estimates of the stocks of those employed, unemployed and not in the labour force. The construction of matched records between months is used to create flow data.[8] The quality of these data is affected by a number of factors. First, each month one eighth of the sample is replaced and no matching of records of those affected is possible. Second, it is not possible for the ABS to match the records of those surveyed in non-private dwellings. Third, there are the familiar problems of non-response and failure to match records of some who move location, etc. The net result is that only about 80% of survey responses are matched.

Whether, or not, the fact that 20 per cent of the survey sample are missing from the matched records is important for our analysis depends on whether the missing persons are randomly distributed across both states and flow groups. The ABS estimates that only half are randomly distributed. The remaining absences may exert some bias on the distribution of the data we have to analyse. There is also a second possible source of error in the data, caused by classification error, since some individuals fail to report their current labour market state accurately. An indication of the likely effects of both the missing data problem and the classification error problem can be judged from the results presented by Abowd and Zellner (1985) and Poterba and Summers (1986) on US data. (The Current Population Survey data are very similar in character to the ABS data used here.) The broad outcome of Abowd and Zellner's analysis of reinterview data is to make average adjustments to the gross flows of between -12 to 15 percent due to the missing data problem, and average adjustments of between 8 and 49 percent as a result of excluding spurious labour market transitions due to misclassifications. The size of

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[7]The core data used in this section are currently published by the Australian Bureau of Statistics as Table 33. Estimates of Labour Force Status and Gross Changes (Flows) Derived From Matched Records in The Labour Force Australia, 6203.0. Some additional unpublished data was provided by the ABS. Vacancy data is published by the ABS. Unemployment stock data come from The Labour Force Australia.

[8]For example, the level of unemployment in December 1986 stood at 655,000, over the six months prior to that date some 480,000 employees had become unemployed and 620,000 had left the state of unemployment for a job. Similarly, during those six months, there were 1.78 million occasions of people moving from unemployment or outside of the labour force into employment and 1.64 million flows in the opposite direction, whilst the level of employment stood at 7 million.

these adjustments suggests caution when interpreting results using the ABS data, since adjustments of the Abowd and Zellner type are not possible due to a lack of information about the missing data or classification error. The flows most subject to error, however, are mostly between unemployment and not in the labour force. Whilst we believe that those between non-employment and employment are not as badly affected, we recognise that our results may be affected by these errors. In what follows, therefore, we assume that any missing data are distributed randomly across flow types, in the absence of any additional information.

***b) Not in the labour force.***

Whilst the states of unemployment and employment are clearly established by official definition, there remains a major definitional issue concerning those defined to be not in the labour force. For example, this residual group contains those in full time education and those institutionalised as well as those who may want a job but do not satisfy the definition of unemployment. For the definition of $N_t$ above we want to specify the subset of those not in the labour force who are seeking work.

There are strict availability and job search requirements that must be fulfilled in order for an individual who is out of work to be classified as unemployed by the ABS. In particular, it is required that the person concerned should want to work, be currently actively looking for work and be available to start work within seven days of the interview. This constitutes availability for work and active job search. Satisfying these criteria is also required by the Commonwealth Employment Service (the CES) for those registering for unemployment benefits. However, the ABS/CES definition of the number of unemployed may well exclude a number of potential workers who happen not to exactly satisfy the criteria, but who we wish to treat as the stock of job seekers outside of the labour force.

In the group of non-workers which is classified by the ABS as not in the labour force, there is an identified group of people who want to work and are either actively looking for work but unavailable to start work immediately (within seven days) or not actively looking for work but able to start work within four weeks. This group is classified by the ABS as marginally attached to the labour force.[9] In the Supplementary Labour Force Survey, which has been held once or twice a year over recent years, the ABS attempts to distinguish four major reasons for inactive search: personal reasons; family reasons; discouraged job seekers[10]; and reasons of non-availability of jobs in suitable hours and other reasons (including misclassification). For both men and women, personal and family reasons make up about two thirds of the total. However, the majority of women cite family reasons and, in particular, the provision of child care. For men, personal reasons of which ill health and attendance at an educational institution are the most important.

Given the discussion above, we consider sub-dividing the marginally attached by extracting those with the closest attachment to the labour force. Whilst all of the categories of marginally attached individuals apply to those who want a job, we identify those who are actively looking for work but are unable to start work within seven days and those who want a job but are not actively looking *and* are classified as discouraged job seekers, as those groups with characteristics which make them job seekers. (In other words, we are not interested in those people who are not actively searching because they are physically unable to work.) The adequacy of our definition can be judged from its use in the econometric work below.

***c) Long-term unemployed.***

We also consider the possible role of the proportion of long-term unemployed as a potential determinant of the hiring rate. We define the long-term unemployed to be those unemployed for more than 12 months in their current spell. The arguments presented in Budd *et al* (1988) and rehearsed in more detail in chapter 7 of Layard *et al* (1991) suggest that the proportion of long-term unemployed would have a negative effect on the hiring rate. This is because this

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[9]The relative number of marginally attached women far exceeds that of men. In 1991 the number of marginally attached women was about double the number counted as unemployed, whereas the number of marginally attached men was half the number unemployed. The number marginally attached is closely related through time to the number unemployed.

[10]Those who are classified as discouraged job seekers make up a substantial group (between 10% and 19% of both male and female marginally attached). In answer to the question as to why no active job search is being undertaken despite the desire to have a job, the survey answers that classify an individual as discouraged include the following alternatives: the belief that the person was considered by employers to be: too young or too old; language difficulties or being from a different ethnic background; lack of sufficient skills, training, experience or schooling; the absence of job vacancies in a given locality or line of work; and a belief that no job vacancies exist at all.

proportion indicates the relative size of a group of unemployed persons whose outflow probability from unemployment is significantly lower than others, purely because of the length of time that they have been unemployed for.

***d) Job to job flows.***

The one important flow not covered by the gross flows data is that between jobs. As there is no change in labour market status in going from one job to another, the LFS fails to pick up movements across jobs between interviews. Evidence for a number of countries suggests that such flows are substantial (Davis et al, 1996). Here we estimate the size of these flows from the annual LFS survey question which covers current job duration for those currently employed excluding those who had no previous job in the year. Assuming that the duration of such jobs is replicated across the year we obtain a rate of job to job movements over a year. This annual rate is then interpolated into a quarterly rate and, with the use of the quarterly employment stock data, a quarterly flow is obtained. This is clearly an approximate method for calculating this important flow, however, we feel that it is superior to alternatives in the literature such as Blanchard and Diamond (1991) who apply a proportion of the quit rate in US manufacturing to the total employment stock to obtain a job to job flow for the whole economy. The success of our measure in the econometric analysis makes us more confident of its value.

***e) Vacancies.***

The final measurement issue is that of the number of available vacant jobs. In most countries the prime source of vacancy data is the government agency which runs employment offices (in Australia, this is the CES). We investigate the relationship between this data source and more general survey based data (produced by the ABS). The ABS series we use measures all the vacancies that firms claim to have available to be filled. Thus, it is a better measure than the CES series (which only covers those reported to their offices) or those based only on newspaper advertisements of vacant jobs. In brief, we find that the survey-based vacancy data produced by the ABS dominates CES vacancy series in the decisions of all job seekers suggesting that the latter is a subset of the former. We believe these data are superior to that used in studies of European labour market flows such as Burda and Wyplosz (1994) and Burgess (1993).

## *IV. Results.*

In this section we first present estimates of the individual share of total matches equations (9, 10 and 11) and the aggregate matching function (13). We then provide tests of the various restrictions generated by the discussion in Section II, above. In particular, we analyse joint estimation of two of the share equations and the aggregate matching function and test the fair shares hypothesis. Rejection of these restrictions leads us to analysis of the individual equation estimates and comparison of our specifications with those previously proposed for the outflow rate from unemployment.

### *a) Disaggregate matching.*

In Tables 1, 2 and 3 we present estimates for unemployment, not-in-the labour force and job-to-job flows respectively. We begin discussion with estimates of the unemployment outflows into jobs, equation (9), in Table 1. Column 1 gives unrestricted estimates. The estimated coefficients are of the anticipated sign if not all that well determined. The coefficients on the determinants of employed job search and unemployment search intensity are both significant and of size and sign consistent with the theory presented in Section III. There is no evidence of model misspecification at the 95% confidence level from misspecification tests $z_1$ to $z_4$ [11] and no evidence of instrument invalidity from the Sargan test ($z_5$). The additional instruments employed are two lags of the logarithms of total hires and total vacancies. The coefficient on the log of total hires is less than one but not significantly so. A Wald test ($z_6$) of this restriction is accepted at a low level of significance. Therefore, we impose this restriction in column 2 in line with the discussion above. All the right hand side variables are either flows lagged one period or stocks measured at the start of the period and thus predetermined so OLS is used to estimate the restricted equation. The estimate of the sum of shares of effective job searchers is the coefficient on $lnU_t$ equal to -0.84. Restricting this to minus unity is easily accepted as the $\div^2(1)$ statistic $z_6$ shows. Final restricted estimates are given in column 3. All coefficients are well determined. In particular, the coefficients on $ln(N_t/U_t)$ and $ln(J_{t-1}/U_t)$ are significant and suggest both NLF and employed job searchers have a significant share of $\tilde{S}_t$ when viewed from the perspective of hires from unemployment. According to the results, the steady-state shares of the NLF and OJS in the total stock of

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[11] $z_1$: Lagrange Multiplier test for up to 4th order autocorrelation distributed $\div^2(4)$; $z_2$: Reset test for incorrect functional form distributed $\div^2(1)$; $z_3$: Jarque-Bera test for non-normality distributed $\div^2(2)$; $z_4$: test for heteroscedasticity distributed $\div^2(1)$.

searchers are 51% and 28%, respectively. The implied share of the effective unemployed is 21%. A further important feature of our results is the significant negative coefficient on the long-term unemployment ratio. This demonstrates that the search effectiveness of those unemployed for more than 12 months is significantly lower than that of the short-term. This confirms the results for the UK in Budd *et al* (1988) and Burgess (1993). Finally, we find evidence for the idea of pro-cyclical success in on-the-job search from the significant positive coefficient on $ln(\tilde{Y}_{t-1})$. We analyse the nature of this relationship further below.

These results show that all three potential groups of searchers are important components of the stock of job searchers $\tilde{S}_t$ for outflows into jobs from unemployment. This finding supports and extends the results of Burgess (1993), amongst others. We have been able to make more precise the view that there is significant job competition between the unemployed and employed job seekers because we find a measure of the determinants of employed job search to be significant. Furthermore, we find that those job seekers who are NLF also provide effective competition for the unemployed for jobs. We consider formal comparisons of our model with others in (d), below.

The model for job inflows from outside of the labour force was estimated in a similar fashion to that for job inflows from unemployment. Estimates of equation (10) are given in Table 2 where the initial (unreported) finding of significant second-order serial correlation led to the inclusion[12] of the term $\text{Ä}^2(ln(N/L)_{t-2}-lnM_{t-2})$. The estimated coefficients are all of the anticipated sign although the cyclical indicator variable has an incorrectly signed and insignificant impact.[13] The estimated value of the coefficient on $lnM_t$ is again close to one in the unrestricted estimates in column 1. The test of the restriction ($z_6$) is again accepted at a low level of significance. These results suggest that, in the aggregate, the probability of a job seeker from outside of the labour force getting an acceptable job offer is affected by the number of all other classes of other job

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[12]In order to make comparison between this equation and those for hires from the other two sources comparable, we adopt the transformation originally proposed by Bewley (1979). The coefficients on the stocks of searchers are long-run coefficients whilst the short-run dynamics are captured by the coefficients on $\text{Ä}^2(ln(N/L)_{t-2}-lnM_{t-2})$. Consistent estimates of these equations is achieved by employing $(ln(N/L)_{t-2}-lnM_{t-2})$ as an additional instrument.

[13]Estimation of this equation using either the total number of those outside of the labour force or the wider measure of marginal attachment as $N_t$ is dominated by the results given in Table 2 using a non-nested test.

seekers. The impact of the cyclical variable and long-term unemployment proportion are not well defined in this set of results. The estimated shares of the unemployed and employed job seekers are 16% and 23%, respectively. The implied share of the NLF is consequently 61%.

Finally, we consider job-to-job flows in Table 3. The process of model restriction followed is identical to that for the first two flow equations. Again, the equations are well determined. The restriction that the job-to-job flow be modelled as a share of total matches is accepted easily Adding up, however, can only be accepted at the 2% level. For comparisons sake, we present the final restricted estimates in column 3. All coefficients are of the anticipated sign. Interestingly, the coefficients on the long-term unemployment ratio and the cyclical determinant of OJS are both significant and of the predicted sign. The implied steady-state shares are substantially different from those generated by the two share equations for the unemployed and NLF flows; the share of the unemployed and NLF job seekers is 22% and 9%, respectively and the implied share of the employed is 69%.

***b) Aggregate matching.***

Estimates of the aggregate matching function, equation (13), are given in Table 4. They support the modelling in Section 2 in that measures of the number of job searchers other than the unemployed have a significant impact on total matches. Constant returns to scale are imposed in column 2 whilst in column 1 the estimates are unrestricted. The $\div^2(1)$ test of this restriction is easily accepted. The aggregate searcher stock elasticity of matching is 0.94. Consequently, from the coefficients on $N_t$ and $J_{t-1}$, we can derive estimates if the steady-state shares of effective NLF searchers of 36% and of employed job seekers of 57%. Neither coefficients on the cyclical determinant of employed job search or the long-term unemployment ratio are significant. The searcher stock elasticity is very high and the consequent vacancy elasticity of 0.06 very low, implying a very inefficient processing of vacancies into hires. Also, the implied share of unemployed effective searchers in the total is only 6%, a very small value. Taken together, these results may suggest that the aggregate matching function is not a good vehicle for examining the matching process and that the simple aggregation of individual job searcher group matching function allowed by fair shares is not supported by the data, an issue to which we turn next.

***c) Fair shares.***

We test the fair shares hypothesis by estimating a system of two flow share equations and the aggregate matching function. Under fair shares, four structural parameters are derived from the parameter estimates which should be identical in each of the three equations. This provides for eight restrictions on twelve parameters. The restrictions on equations (9), (10) and (13) are given in Table 5.

Thus, Table 5 presents restricted estimates employing the unemployment and NLF outflow share equations, along with the aggregate matching function.[14] The restricted parameter estimates are well determined and consistent with our model. The restrictions are, however, resoundingly rejected. The Wald test of the eight restrictions has a value far in excess of conventional levels of significance. Thus, it appears that fair shares is rejected whilst the general specification is supported.

Consequently, we examine the full set of structural parameters for each of the inflow equations (9,10 and 11) and the aggregate equation (13). Whilst we have discussed these equations on a separate basis in (a) and (b) above, it is of interest to provide some comparison of the results here. We can quickly see, from Table 6, that our conclusions would differ depending on which equation we address. For example, if we consider the outflows from unemployment in equation (9) there is a substantial procyclical effect related to employed job searchers competing for jobs, there is also evidence of the long-term unemployed being much less effective job seekers. Neither of these findings are true when considering the outflows from not in the labour force (equation (10)). Considering the flows between jobs, equation (11), we once again find a significant procyclical effect on employed job seekers and a negative impact of long-term unemployment on the search effectiveness of the unemployed. However, there is now a much larger share going to employed job seekers than those NLF, implying that these employers are ranking the NLF third below the employed and the unemployed.

Our results clearly suggest that there are distinct groups amongst job searchers with

[14]Given the estimation method used (3SLS), the estimates are not invariant to the share equation excluded. There is, however, very little difference in the estimates of the restricted parameters between alternative share equation exclusion and no difference in inference.

differing degrees of search effectiveness and/or rankings across these groups in the hiring process. If this is indeed the case, then the simple functional form commonly assumed for aggregate matching functions is not valid and the latter 'should be taken only as data descriptions, or as log-linear approximations to yet underived matching functions' (Blanchard and Diamond, 1989;18). This may explain why our estimates of the aggregate matching function are not satisfactory and why there are large discrepancies amongst the results found by different authors when using these functions (Broersma, 1996). To reiterate, whilst fair shares would suggest that the simple aggregate matching function would take the same form as the individual matching functions, our rejection of the fair shares rule suggests that this simplification is not valid. Our results suggest a more complex functional form for the aggregate matching function is necessary.

***d) Comparative testing.***

An important aspect of our results is evidence of those groups competing with the unemployed for hires. Comparison with previous work on unemployment outflows is easily made. First, in line with Burgess' (1993) argument, we have found that the coefficient on total hires ($á_1$ in equation (9)) is equal to one once we allow for job competition from relevant other job seekers by including measures of employed and NLF job searchers. His equation excludes such measures. Estimates of Burgess' model for our data are given in column 1 of Table 7. Note that the coefficient on total hires is substantially less than one in line with his results. The Wald test ($z_6$) confirms that this difference is significant at the 99% level. Formally, the significance of $ln(N_t/U_t)$, $ln(J_{t-1}/U_t)$ and $ln(\tilde{Y}_{t-1})$ in the equation in column 3 of Table 1 means that our model encompasses that of Burgess. We find that competition from not-in-the-labour-force and employed job seekers is an identifiable improvement on previous models of unemployment outflows into jobs.

A second comparison can also be made with the traditional approach of estimating an individual matching function for the unemployed which only depends on vacancies and the stock of unemployed. Given the unlikely (implicit) assumption of independence highlighted above, we would expect that our model would dominate this approach. A representative model is a log-linear version of equation (5) above where we also allow the outflow rate from unemployment to be affected by the proportion of long-term unemployed. Estimates that confirm approximately constant returns to scale and some state dependence of unemployment outflows are given in column 2 of Table 7. The non-nested tests given show that the traditional model adds nothing significant to the explanation of the outflow rate from unemployment provided by the model in column 3 of Table 1. They also show that our model adds very significantly to the traditional model.

The job competition model presented here captures an empirically important feature of unemployment outflows into jobs; that interdependence of hiring from different labour market states matters. This result has implications for a large literature on the outflow rate and duration dependence of individual outflows from unemployment (eg., Narendranathan *et al*, 1985). The accurate modelling of the behaviour of competitors needs to be added to such analysis.

## *IV. Conclusions*

The literature on matching functions has, until recently, concentrated almost entirely on the outflow from unemployment into jobs. We show that this approach fails to capture important features of the process of vacant job matching with the available job seekers. We also show that the incorrect assumption of the independence of flows from unemployment into jobs leads to misspecified estimates of the parameter of interest, namely the unemployment elasticity of matching. This paper provides more evidence in favour of the case for a much more general approach to the analysis of worker flows. We show that substantial numbers of new worker hires come from all three possible alternative sources: unemployment, employment and outside of the labour force. We find evidence in favour of significant job competition between the three groups. This does not seem, however, to be consistent with the individual groups of searchers receiving fair shares of the available hires. The differences in behaviour and interdependencies of these flows that we find suggest that worker heterogeneity is an important feature of gross worker flows across labour markets. This may well be explained by employers ranking job searchers by group. Our results show that these features should be reflected in models of the dynamics of labour market adjustment and form the basis of ongoing research.

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**Table 1. Outflows from unemployment.**

| $\ln(X_t/U_t)$ | 1 | 2 | 3 |
|---|---|---|---|
| constant | -2.57<br>(1.22) | -2.88<br>(1.64) | -1.81<br>(41.6) |
| $\ln M_t$ | 0.84<br>(1.57) | 1.00<br>(-) | 1.00<br>(-) |
| $\ln U_t$ | -0.70<br>(1.28) | -0.84<br>(3.09) | -1.00<br>(-) |
| $\ln(N_t/U_t)$ | -0.28<br>(0.71) | -0.300<br>(0.82) | -0.51<br>(5.05) |
| $\ln(J_{t-1}/U_t)$ | -0.18<br>(0.51) | -0.28<br>(6.58) | -0.28<br>(6.66) |
| $\ln(\tilde{Y}_{t-1})$ | 1.79<br>(3.35) | 1.79<br>(3.55) | 1.90<br>(4.04) |
| $\ln(U_t^{LT}/U_t)$ | -0.21<br>(3.47) | -0.22<br>(4.70) | -0.24<br>(6.48) |
| $\bar{R}^2$ | 0.92 | 0.92 | 0.95 |
| se | 0.0351 | 0.0332 | 0.0329 |
| $z_1$ | 3.97 | 4.71 | 4.37 |
| $z_2$ | 4.34 | 0.34 | 3.26 |
| $z_3$ | 0.35 | 0.27 | 0.21 |
| $z_4$ | 1.39 | 3.21 | 2.35 |
| $z_5(÷^2(3))$ | 2.86 | - | - |
| $z_6(÷^2(1))$ | 0.09 | 0.37 | - |

Estimation period: 1980q4 - 1991q4. Equations also include seasonal dummy variables. Methods of estimation: column 1, IV; columns 2 and 3, OLS. Additional instruments for column 1: $lnM_{t-1}$, $lnV_t$, $lnM_{t-2}$, $lnV_{t-1}$ . t-statistics in parentheses.

**Table 2. Outflows from not-in-the labour force.**

| $\ln(L_t/N_t)$ | 1 | 2 | 3 |
|---|---|---|---|
| constant | -3.07 | -2.95 | -1.09 |
| | (2.21) | (2.55) | (33.3) |
| $Ä^2[\ln(L_t/N_t)\text{-log } M_t]$ | 0.23 | 0.23 | 0.26 |
| | (2.41) | (2.64) | (3.24) |
| $\ln M_t$ | 1.08 | 1.00 | 1.00 |
| | (2.98) | (-) | (-) |
| $\ln N_t$ | -0.78 | -0.71 | -1.00 |
| | (2.34) | (4.00) | (-) |
| $\ln(U_t/N_t)$ | -0.26 | -0.25 | -0.16 |
| | (3.27) | (3.71) | (4.44) |
| $\ln(J_{t-1}/N_t)$ | -0.28 | -0.23 | -0.23 |
| | (1.22) | (8.31) | (8.57) |
| $\ln(\tilde{Y}_{t-1})$ | -0.22 | -0.23 | -0.004 |
| | (0.65) | (0.66) | (0.01) |
| $\ln(U_t^{LT}/U_t)$ | 0.02 | 0.02 | -0.01 |
| | (0.49) | (0.71) | (0.46) |
| $\bar{R}^2$ | 0.98 | 0.95 | 0.94 |
| se | 0.0205 | 0.0211 | 0.0206 |
| $z_1$ | 3.99 | 6.59 | 5.33 |
| $z_2$ | 0.05 | 3.69 | 4.38* |
| $z_3$ | 1.28 | 1.12 | 1.39 |
| $z_4$ | 0.84 | 2.85 | 2.44 |
| $z_5(÷^2(3))$ | 1.73 | - | - |
| $z_6(÷^2(1))$ | 0.05 | 2.58 | - |

Estimation period: 1980q4 - 1991q4. Equations include seasonal dummy variables. Method of estimation: IV; column 2 and 3 $\ln(L_{t-2}/N_{t-2})-\ln M_{t-2}$, in place of $Ä^2[\ln(L_t/N_t)-\ln M_t]$. Additional instruments for column 1: $\ln M_{t-1}$, $\ln V_t$, $\ln M_{t-2}$, $\ln V_{t-1}$, $[\ln(L_{t-2}/N_{t-2})-\ln M_{t-2}]$, t-statistics in parentheses.

**Table 3. Job to job flows.**

| $\ln (J_t/J_{t-1})$ | 1 | 2 | 3 |
|---|---|---|---|
| constant | 2.45<br>(1.89) | 2.26<br>(1.82) | -0.71<br>(21.7) |
| $\ln M_t$ | 0.92<br>(3.42) | 1.00<br>(-) | 1.00<br>(-) |
| $\ln(J_{t-1})$ | -1.39<br>(4.69) | -1.46<br>(7.67) | -1.00<br>(-) |
| $\ln(U_t/J_{t-1})$ | -0.07<br>(0.96) | -0.08<br>(1.20) | -0.22<br>(5.41) |
| $\ln(N_t/J_{t-1})$ | -0.68<br>(2.73) | -0.68<br>(2.70) | -0.09<br>(1.62) |
| $\ln(\tilde{Y}_{t-1})$ | -0.31<br>(0.88) | -0.32<br>(0.89) | -0.61<br>(1.73) |
| $\ln(U_t^{LT}/U_t)$ | 0.07<br>(1.86) | 0.06<br>(1.93) | 0.11<br>(4.07) |
| $\bar{R}^2$ | 0.56 | 0.96 | 0.91 |
| se | 0.0227 | 0.0233 | 0.0248 |
| $z_1$ | 3.13 | 4.46 | 4.57 |
| $z_2$ | 0.46 | 0.01 | 1.65 |
| $z_3$ | 1.25 | 2.27 | 1.25 |
| $z_4$ | 0.16 | 1.03 | 0.01 |
| $z_5$(÷$^2$(3)) | 4.46 | - | - |
| $z_6$(÷$^2$(1)) | 0.10 | 5.75* | - |

Estimation period: 1980q4 - 1991q4. Equations also include seasonal dummy variables. Methods of estimation: column 1, IV; columns 2 and 3, OLS. Additional instruments for column 1: $lnM_{t-1}$, $lnV_t$, $lnM_{t-2}$, $lnV_{t-1}$. t-statistics in parentheses.

**Table 4. The aggregate matching function.**

| $\ln M_t$ | 1 | 2 |
|---|---|---|
| constant | 1.28 | 0.99 |
| | (0.98) | (23.5) |
| $\ln V_t$ | 0.06 | 0.06 |
| | (2.10) | (2.17) |
| $\ln U_t$ | 0.89 | 0.94 |
| | (4.44) | (-) |
| $\ln(N_t/U_t)$ | 0.28 | 0.34 |
| | (1.07) | (6.27) |
| $\ln(J_{t-1}/U_t)$ | 0.54 | 0.54 |
| | (10.7) | (10.9) |
| $\ln(\tilde{Y}_{t-1})$ | -0.27 | -0.30 |
| | (0.69) | (0.84) |
| $\ln(U_t^{LT}/U_t)$ | -0.20 | -0.20 |
| | (0.37) | (0.32) |
| $\bar{R}^2$ | 0.95 | 0.99 |
| se | 0.0247 | 0.0243 |
| $z_1$ | 4.71 | 4.66 |
| $z_2$ | 1.06 | 2.17 |
| $z_3$ | 0.86 | 1.16 |
| $z_4$ | 0.04 | 0.17 |
| $z_5(÷^2(1))$ | 0.05 | - |

Estimation period: 1980q4 - 1991q4. Equations also include seasonal dummy variables. Methods of estimation: OLS. t-statistics in parentheses.

**Table 5. The restricted model.**

System of unemployment and not-in-the-labour-force outflow equations and aggregate matching functions; equations (9), (10) and (14).

Eight cross-equation restrictions:

| eqn (9) | eqn (10) | eqn (14) | |
|---|---|---|---|
| $-á_4$ | $= -ä_4$ | $= è_4/è_2$ | $= (\overline{ö(E)})/\bar{\tilde{S}}$ |
| $-á_3$ | $= (1 + ä_3 + ä_4)$ | $= è_3/è_2$ | $= (\overline{s_n N})/\bar{\tilde{S}}$ |
| $á_5/á_4$ | $= ä_5/ä_4$ | $= -è_5/è_4$ | $= â_1$ |
| $á_6/(á_3 + á_4)$ | $= ä_6/ä_3$ | $= -è_6/(è_2 - è_3 - è_4)$ | $= â_2$ |

Estimates:

| | |
|---|---|
| $(\overline{ö(E)})/\bar{\tilde{S}}$:0.27(0.02) | $â_1$:2.76(0.62) |
| $(\overline{s_n N})/\bar{\tilde{S}}$:0.59(0.025) | $â_2$:0.27(0.04) |
| $è_2$:0.84(0.02) | |

Minimum Distance Function: Q = 61.90

| | s.e. |
|---|---|
| eqn (9) | 0.0421 |
| eqn (10) | 0.0198 |
| eqn (13) | 0.0423 |

Wald test of restrictions: $÷^2(8) = 203.3$

Estimation period: 1980q4 - 1991q4. Equations include seasonal dummy variables. Method of estimation: 3SLS. Instruments: $lnU_t$, $lnN_t$, $lnJ_{t-1}$, $ln\,\tilde{Y}_{t-1}$, $ln(U_t^{LT}/U_t)$, $lnV_t$, $[ln(L_{t-2}/N_{t-2})-lnM_{t-2}]$, constant and seasonal dummy variables. Standard errors in parentheses

**Table 6. Equation by equation estimates of the structural parameters.**

| Outflows | Shares | | | Cycle | Implied search effectiveness |
|---|---|---|---|---|---|
| | employed | NLF | unemployed | $\hat{a}_1$ | $\hat{a}_2$ |
| unemployment | 0.28** | 0.51** | 0.21** | 6.86** | 0.30** |
| eqn (9) | (0.04) | (0.10) | (0.06) | (1.55) | (0.04) |
| NLF | 0.23** | 0.61** | 0.16** | -0.02 | 0.07 |
| eqn (10) | (0.03) | (0.05) | (0.04) | (1.31) | (0.16) |
| employed | 0.69** | 0.09* | 0.22** | 2.0* | 0.51** |
| eqn (11) | (0.03) | (0.06) | (0.04) | (1.08) | (0.10) |
| aggregate | 0.57** | 0.36** | 0.06 | 0.56 | 0.29 |
| eqn (14) | (0.04) | (0.06) | (0.05) | (0.66) | (0.74) |

Standard errors in parentheses. **significantly different to zero at the 95% confidence level, **significantly different to zero at the 88% confidence level.

**Table 7. Unemployment to job flows - a comparison.**

| Log ($X_t/U_t$) | 1 | 2 |
|---|---|---|
| constant | -3.47<br>(5.53) | -0.496<br>(1.03) |
| $lnM_t$ | 0.698<br>(10.14) | |
| $lnV_t$ | | 0.202<br>(7.73) |
| $lnU_t$ | -0.397<br>(10.93) | -0.206<br>(3.76) |
| $ln(LTU_t/U_t)$ | -0.156<br>(3.89) | -0.317<br>(5.01) |
| $\bar{R}^2$ | 0.898 | 0.837 |
| se | 0.0401 | 0.0503 |
| $z_1$ | 4.27 | 2.77 |
| $z_2$ | 0.38 | $6.24^{**}$ |
| $z_3$ | 0.19 | 2.40 |
| $z_4$ | 2.02 | 1.87 |
| $z_5(\chi^2(4))$ | 5.85 | - |
| $z_6(\chi^2(1))$ | $17.4^{*}$ | - |

Non-nested tests

| | | |
|---|---|---|
| a) | SC_c test of Pesaran and Pesaran (1995) | |
| | M1 against M2 | $-10.31^{**}$ |
| | M2 against M1 | 1.65 |
| b) | PE test of MacKinnon, White and Davidson (1983) | |
| | M1 against M2 | $7.37^{**}$ |
| | M2 against M1 | 1.01 |

where M1: traditional model in column 2 above, M2: model in column 3 of Table 1.

Estimation period: 1980q4 - 1991q4.
Methods of estimation: column 1, IV; column 2, OLS. Additional instruments for column 1: $lnM_{t-1}$, $lnV_t$, $lnM_{t-2}$, $lnV_{t-1}$ . t-values in parentheses.