



# Stock-flow matching and the performance of the labor market

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## Abstract

We estimate outflow equations for vacancies and unemployed workers in Britain, departing from the stock-based analysis of matching in two ways. First, we deal with the temporal aggregation problem that arises when discrete time data are used to describe continuous time processes. Second, we allow for a stock-flow matching mechanism in which the stock of traders on one side of the market matches with the flow of traders on the other side. Our estimates are in line with the predictions of stock-flow matching in terms of higher exit rates of flows and of matching combinations between labor market stocks and flows. Furthermore, employer search effectiveness did not seem to decline between the 1960s and the 1990s. Nevertheless, some deterioration in worker search effectiveness is detected, however less severe than that implied by previous, stock-based work.

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## 1. Introduction

Modern labor markets are characterized by large flows of jobs and workers between the states of activity and inactivity.<sup>1</sup> A key building block in the modelling of labor market flows is the aggregate matching function, which represents a trading technology between workers looking for jobs and firms looking for workers, eventually brought together into productive matches. The key idea is that a complicated exchange process can be summarized by a well-behaved matching function that gives the number of jobs formed at any moment in time in terms of the inputs of firms and workers into search. Variations in job matches at given inputs reflect changes in the intensity of frictions that characterize labor market trade. With stronger frictions, the labor market becomes less effective in matching unemployed workers to available vacancies and the resulting matching rate is reduced (see Pissarides, 2000, Chapter 1; Blanchard and Diamond, 1989). In this perspective, the instability detected in estimated matching functions for several OECD countries (see Petrongolo and Pissarides, 2001) seems to reflect a deterioration in the matching effectiveness of respective labor markets.<sup>2</sup>

In this paper, we argue that part of the instability of estimated matching functions derives from problems of misspecification. We study misspecification arising from two sources. First, when discrete-time data are used to estimate a continuous-time matching process, a temporal aggregation problem arises. As shown by Burdett et al. (1994), this generates a bias in the resulting estimates, whose magnitude depends on the time-series properties of the conditioning variables, and is inversely related to the frequency of the data. We deal with the temporal aggregation problem by conditioning matching rates on the whole number of agents that can trade within some time interval, i.e. the beginning-of-period stock plus the new inflow.

Second, most of the empirical matching literature rests on the assumption of random search, a process in which unemployed workers take a vacant job at random and apply for it.<sup>3</sup> This implies that agents that are matched at any moment in time are randomly selected from the pool of existing unemployed workers and job vacancies, independently of the duration of search on either side of the match. We contrast this assumption by emphasizing a systematic element in search. We consider a model of non-random matching, in which the role of information channels in a labor market with search is explicitly recognized. Thanks to information channels, job seekers have complete information about the location of available vacancies and

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<sup>1</sup>See Davis et al. (1996), Blanchard and Diamond (1990) and Burda and Wyplosz (1994).

<sup>2</sup>Comparable information can be gathered from the performance of the Beveridge curve, which represents the equilibrium outcome of the matching process in terms of the resulting level of unemployment and vacancies. Existing estimates reveal an outward shift in the Beveridge curve in a number of OECD countries (see Jackman et al., 1990), in which a roughly untrended vacancy rate became consistent with a progressively higher unemployment rate across decades.

<sup>3</sup>The typical representation of this matching process is the urn-ball problem (see Butters, 1977; Hall, 1979; Pissarides, 1979, among others).

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. Those who remain unmatched and keep searching do so because there are no trading partners that are suitable for them among the existing pool. It follows that no job vacancy or unemployed worker who has been through one round of sampling will attempt to match later with a pre-existing job seeker or vacancy. Previous contributions in this literature include Coles (1994) and Coles and Smith (1998). Their original framework has been extended in order to analyze price determination in a market equilibrium with non-random search (Coles and Muthoo, 1998; Coles, 1999).

Although the assumption of full sampling within a matching period is a simplifying one, this modeling captures a realistic feature of search markets, that a job seeker scans the bulk of advertisements before deciding where to apply and once an advertisement has been scanned and rejected, return to it is less likely than application to a new one. The stock of unmatched traders on one side of the market is thus trying to match with the flow of new traders on the other side, and labor market search is characterized by *stock-flow* matching. Under stock-flow matching agents have a relatively high probability to trade during the first period they are on the market, being able to sample all existing offers. Matching rates decline after this initial round of sampling, when agents have to wait for new entries in order to trade.

We construct time-aggregated matching functions which encompass stock-flow matching and show that both innovations to previous matching function modelling imply that labor market flows should play a crucial role on the right-hand side of estimated matching equations. We estimate the resulting unemployment and vacancy outflow equations on aggregate British data for the period 1967–1996. We find that, first, our estimates are in line with the predictions of stock-flow matching, both in terms of higher exit probabilities of newcomers in the labor market, and in terms of trading combinations between the stocks and flows of unemployed workers and job vacancies. Second, the stability analysis performed on our outflow equations reveals that the matching effectiveness of job vacancies did not decline in Britain between the 1960s and the 1990s. Nevertheless, there remains some deterioration in the matching effectiveness of the unemployed since the early 1970s, which is however less severe than that implied by previous stock-based results. This view suggests that ignoring flows in matching is not an appropriate simplifying assumption and may produce a misleading view of matching effectiveness over time.

The organization of the paper is as follows. Section 2 outlines the main predictions of a stock-flow matching model and compares them with those deriving from the assumption of random matching. The data used to test these predictions are described in Section 3. Estimation results presented in Section 4 support a stock-flow matching technology, and suggest a revision of some widespread conclusions on labor market matching effectiveness. Section 5 considers an additional source of non-randomness in matching, namely the presence of vertical heterogeneity among traders. Section 6 concludes.

## 2. The matching process

This section provides a framework that encompasses the two important properties of the matching process. First, matching is treated in continuous time. This requires dealing with the temporal aggregation problem that arises when discrete time data are used to describe a continuous-time matching process. A time-aggregated matching function is constructed, that still does not negate the standard assumption of random matching. Second, the time-aggregated function is modified, in order to embody a non-random matching mechanism, in which the stock of traders on one side of the market can only match with the flow of new traders on the other side.

### 2.1. Random matching

When labor market trade is decentralized and uncoordinated, firms and workers need to invest time and resources in a search process, before job creation and production can take place. Search frictions derive from information imperfections about trading partners, heterogeneities, and possibly a number of other factors, and are conveniently captured by an aggregate matching function, which gives the number of new matches formed in terms of the inputs of firms and workers into search. The simplest form of the matching function is

$$M_t = m(U_t, V_t), \quad (1)$$

where  $M_t$  is the number of jobs formed at time  $t$ ,  $U_t$  is the number of unemployed workers looking for work and  $V_t$  is the number of vacant jobs. The function  $m(\cdot)$  is increasing and concave in both arguments, with  $m(U_t, 0) = m(0, V_t) = 0$ . Unemployed workers and job vacancies that are matched at each point in time are randomly selected from the sets  $U_t$  and  $V_t$ , respectively. Hence, unemployed workers move into jobs at a Poisson rate  $\lambda_{U_t} = M_t/U_t$ , and vacancies are filled at a Poisson rate  $\lambda_{V_t} = M_t/V_t$ .

While  $M_t$  is the number of matches formed at each point in time, in the data we observe time aggregated matches over consecutive periods, quarters in our case. Normalizing the length of quarters to 1, time aggregated matches over a quarter are given by

$$\begin{aligned} M &= \int_0^1 m(U_t, V_t) dt \\ &= \int_0^1 U_t \lambda_{U_t} dt. \end{aligned} \quad (2)$$

Note that  $U_t$  is the unemployment stock at each point in time during the quarter, which can be computed by noticing that all unemployed workers who ever enter the labor market exit at rate  $\lambda_{U_t}$ :

$$U_t = U_0 \exp\left(-\int_0^t \lambda_{U_s} ds\right) + \int_0^t u_t' \exp\left(-\int_t' \lambda_{U_s} ds\right) dt', \quad (3)$$

where  $U_0$  is the unemployment stock at the beginning of the quarter and  $u_t$  is the unemployment inflow during the quarter. The first term in (3) represents the fraction of the beginning-of-quarter stock that does not match between time 0 and time  $t$ , while the second term represents the fraction of the unmatched unemployment inflow, also between 0 and  $t$ .

In order to estimate (2), one needs to make assumptions on the within-quarter evolution of  $u_t$  and  $\lambda_{U_t}$ . As there is no information available in the data about intra-quarter movements in variables of interest, these assumptions are indeed identifying assumptions and cannot be tested. We assume that the unemployment inflow is uniform within the quarter:  $u_t = u$ , and that the unemployment exit rate is constant during the quarter:  $\lambda_{U_t} = \lambda_U$ . In principle, this is not a worse assumption than any other, and it delivers the most tractable empirical specification. In practice it means that the quarter-to-quarter variation in our regressors is large relatively to the within-quarter variation.

Substituting  $u_t = u$  and  $\lambda_{U_t} = \lambda_U$  in (3) gives the number of time aggregated job matches during the quarter. In our empirical analysis we will use the unemployment outflow during each quarter as a measure of job matches. As the two concepts may differ,<sup>4</sup> we will use notation  $M_U$  for the unemployment outflow:

$$M_U = (1 - e^{-\lambda_U})U_0 + \left(1 - \frac{1 - e^{-\lambda_U}}{\lambda_U}\right)u. \quad (4)$$

The term  $1 - (1 - e^{-\lambda_U})/\lambda_U$  is bounded between 0 and 1, and therefore describes a plausible outflow rate from the inflow. Also note that the outflow rate from the inflow is lower than the one from the stock,  $1 - e^{-\lambda_U}$ , for the reason that the inflow has, on average, less time available for making successful match during the measuring interval. For small enough  $\lambda_U$ , the outflow rate from the inflow could be approximated as half the outflow rate from the stock, using a second order Taylor expansion of  $e^{-\lambda_U}$  around  $\lambda_U = 0$ .

A symmetric expression to (4) gives  $M_V$ , the number of vacancies that are matched during a unit interval:

$$M_V = (1 - e^{-\lambda_V})V_0 + \left(1 - \frac{1 - e^{-\lambda_V}}{\lambda_V}\right)v, \quad (5)$$

where  $V_0$  and  $v$  are the beginning-of-quarter stock and new inflow of vacancies, respectively, and  $\lambda_V$  is the Poisson rate at which vacancies are filled.

## 2.2. Stock-flow matching

In this section, we illustrate how labor market trade is affected when there exists some established information channel that coordinates search.

<sup>4</sup>The unemployment outflow may not coincide with the number of job matches as the destination of some unemployment spells is out of the labor force, rather than employment, and some job matches may involve categories of job-seekers other than the claimant unemployed, like the non-claimant or employed job-seekers.

Consider a market in which a centralized agency provides information on the location of buyers and sellers of a differentiated commodity. Given centralized information, upon entry new buyers can locate and contact the current stock of sellers. A new buyer who does not find a variety he or she likes among the initial stock of sellers subsequently contacts the flow of later new sellers. Otherwise, if a gain to trade is possible between the new buyer and at least an old seller, the new buyer will immediately trade, and similarly for new sellers. [Coles and Muthoo \(1998\)](#) show that, in this environment, the equilibrium is characterized by immediate trade: if a buyer and a seller can profitably trade, deferring trade simply discounts the available benefits, while not giving them a chance of a better match in the future. Whether there exist profitable trading opportunities between buyers and sellers depends on the buyers' evaluation of the variety being considered. Coles and Muthoo assume that buyers' evaluation of a given variety is a draw from a Bernoulli distribution, being one with some positive probability, and zero otherwise. But the immediate trade results is easily extended to more general distributions for the buyers' evaluation of sellers' varieties.

These ideas have interesting and testable implications for labor market search in an environment with differentiated jobs and workers. If the information provided by information channels (such as newspapers, job centres, unions etc.) is accessible to all labor market traders, they do not need to spend time and resources in order to locate one another. In the limit we can think of a centralized marketplace, in which every worker can sample the whole pool of job vacancies in each period. Unlike in the random matching model, there are no search frictions due to information imperfections. But because of job and worker differentiation, not all job matches turn out to be acceptable. All acceptable matches are sorted out so that no firm and worker who could form an acceptable match remain unmatched. Those who remain unmatched do so because there are no trading partners that are suitable for them among the existing pool. It follows that no job vacancy or unemployed worker who has been through one round of matching will attempt to match again with a pre-existing job seeker or vacancy.

While random matching assumes that it is time consuming to sample vacancies, and thus a worker only samples a negligible fraction of the existing stock, under stock-flow matching it takes no time to sample vacancies, so that the whole stock is sampled at once. Although the reality probably lies somewhere between these two extremes, the attractiveness of stock-flow matching is that it captures a realistic feature of search markets, that a worker scans a lot of advertisements before deciding where to apply, and once a job opening has been scanned and rejected, return to it is less likely than application to a new opening.

Under these assumptions there is a sharp distinction between the stocks of unemployed workers and vacant jobs and the new inflows. The stock of unemployed workers at the beginning of each period will not match with the stock of vacant jobs also at the beginning of the period, because they were both participants in the matching round in the previous period. Instead, it has to wait for the flow of newly-advertised vacancies in order to match. The resulting matching process is therefore

one in which the unmatched stock of traders on one side of the market is trying to match with the flow of traders on the other side.

Stock-flow matching implies a step-wise relationship between matching rates and duration of search. Exit rates are higher upon entry, and drop once the existing pool of potential traders has been sampled. In other words, inflows have higher trading probabilities than stocks, represented by the possibility of finding a partner in the existing stock when they first enter the market, with no need to wait for the inflow of new trading candidates.

The implied drop in exit rates is very much in line with evidence on vacancy durations. Coles and Smith (1998) compute that one quarter of all vacancies in Britain are filled on the first day they are opened and, after that, their matching rates decline sharply. The jump in exit rates is however less pronounced for unemployed workers. This may be due to the fact that the search process is highly asymmetric, with vacancies being posted at job centres and unemployed workers sampling them at their preferred pace. Moreover, as we note below, vacancy inflows relative to vacancy stocks are fairly large, at least compared to the corresponding ratio for unemployment. This implies that, even under stock-flow matching, unemployment exit rates need not fall as sharply as vacancy exit rates when an agent switches from the unemployment inflow to the stock.

We now need to model the transition of entrants from the “flow” to the “stock” status, and the consequent fall in their matching rates, in the time-aggregated matching function derived in Section 2.1. Higher matching probabilities of the unemployment inflow are represented by a positive instantaneous probability  $p_u$  that workers are re-employed as soon as they enter the matching market. With probability  $1 - p_u$ , unemployed workers need to wait for new vacancies in order to trade, at hazard rate  $\lambda_U$ . Note therefore that  $p_u$  represents the probability of an immediate match upon entry, while  $\lambda_U$  represents the hazard rate for those surviving after entry.

Allowing for the initial matching probability  $p_u$  gives the following unemployment outflow equation:<sup>5</sup>

$$M_U = (1 - e^{-\lambda_U})U_0 + \left[1 - \frac{1 - p_u}{\lambda_U} (1 - e^{-\lambda_U})\right]u. \tag{6}$$

Note that with  $p_u > 0$  the exit rate from the inflow may now exceed the exit rate from the stock. Moreover  $\lambda_U$  now depends on the flow of new job vacancies being posted period after period, while  $p_u$  is affected by the existing supply of job vacancies.

A symmetric expression can be derived for the vacancy outflow, where  $\lambda_V$  depends on the flow of new unemployed workers entering the market, while  $p_v$  depends on the stock of unemployed job-seekers:

$$M_V = (1 - e^{-\lambda_V})V_0 + \left[1 - \frac{1 - p_v}{\lambda_V} (1 - e^{-\lambda_V})\right]v. \tag{7}$$

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<sup>5</sup>This is derived, as for Eq. (4), under the assumption of constant  $u$  and  $\lambda_U$  within each quarter.

### 2.3. *The expected duration of search*

It is also useful to compare the predictions of alternative matching models for completed and incompleting durations of search spells.

Under random matching, labor market transitions follow a memoryless Poisson process and the duration distribution is exponential. It follows that the completed search duration of all entrants and the incompleting (elapsed) duration of the current stock have the same expected value in steady state, equal to the inverse of the hazard rate:  $1/\lambda_i$ ,  $i = U, V$  (see Lancaster, 1990, pp. 91–93).

Under stock-flow matching, the duration distribution is a mixture of a distribution degenerate at zero (with mass  $p_i$ ,  $i = u, v$ ) and an exponential distribution with hazard rate  $\lambda_i$  (with mass  $1 - p_i$ ). The expected incompleting duration of search remains  $1/\lambda_i$ , and the expected completed duration falls at  $(1 - p_i)/\lambda_i$ .

A positive instantaneous matching probability drives therefore a wedge between completed and incompleting durations of spells. In what follows we move on to testing the significance of the key parameter  $p_i$  by estimating matching functions such as Eqs. (6) and (7) and comparing completed and incompleting durations of search spells.

## 3. The data

We use British data on unemployment and vacancies. They are aggregate, quarterly time series of stocks, inflows and outflows, for the period 1967:1–1996:3.

Unemployment data until October 1982 consisted of all workers who registered as unemployed at the Ministry of Labour's Employment Exchanges (later Jobcentres), at Branch Employment Offices, or at Youth Employment Bureaux (later Youth Employment Service Career Offices). Registration at Jobcentres became voluntary in October 1982, and the administrative measure of unemployment was changed to the count of workers claiming unemployment-related benefits at Unemployment Benefit Offices.<sup>6</sup> Vacancy data are collected at Employment Exchanges/Jobcentres, and include job opportunities for self-employed workers as well as part-time jobs, on top of standard full-time vacancies.<sup>7</sup>

The data used come from two sources. All series until 1985:3 come from the Department of Employment Gazette, while those for the later period are extracted from the NOMIS database of official labour market statistics (<http://www.nomis-web.co.uk>). Given that the data for the earlier period are only available as seasonally adjusted, we seasonally adjust all series for the later period.<sup>8</sup>

<sup>6</sup>A comprehensive description of British unemployment data can be found in *Labour Market Trends*, January 1996.

<sup>7</sup>Gregg and Wadsworth (1996) report that Jobcentres are used by roughly 80% of the claimant unemployed, 30% of employed job seekers and 50% of employers. The vacancy data used here and their limitations are fully described in *Labour Market Trends*, November 1995.

<sup>8</sup>Flow figures are collected for 4 or 5 week periods between unemployment or vacancy count dates. Raw series are converted to a standard  $4\frac{1}{3}$  week month and then seasonally adjusted. Seasonal adjustment is performed using the Census X-11 program, keeping the yearly sum of quarterly series constant after seasonal adjustment.



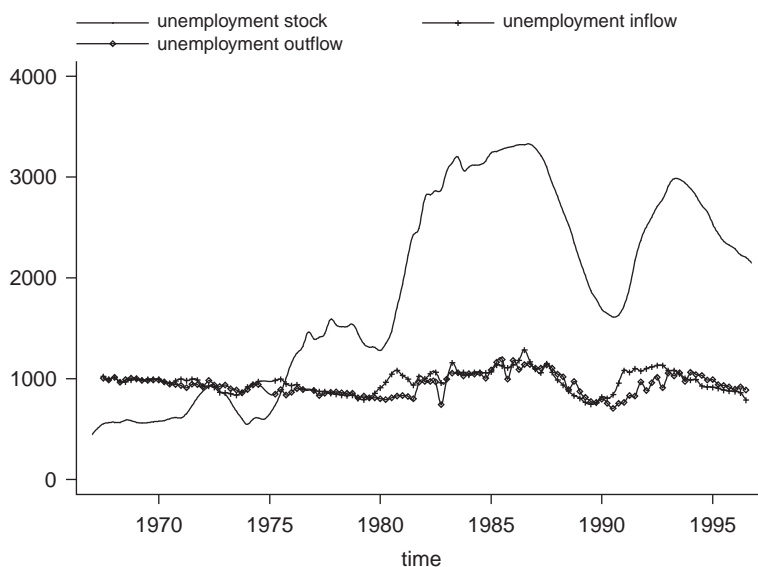


Fig. 1. Unemployment stock, inflow and outflow in Britain (thousands): 1967:1–1996:3. Data seasonally adjusted. *Source:* Employment Gazette (various issues) and NOMIS.

Figs. 1 and 2 plot time series of these variables. For the unemployed, the ratio between the flows and the stock is 0.7 on average, starting off at nearly 2 in the late 1960s and falling at 0.3 in the early 1990s. For vacancies, turnover is much higher, flows being, on average, 3.7 times larger than the stock. This ratio is strongly countercyclical but does not display a definite trend over the whole sample period.

Quarterly inflows and outflows of unemployed workers track each other closely. Interestingly, the correlation between the unemployment outflow and the stock is 0.46, while the correlation between the unemployment inflow and outflow is 0.65. Vacancy correlations are even more striking: 0.76 and 0.97 respectively. The number of matches therefore spectacularly mirrors the flow of new job openings. From either figure, it can be seen that the number of matches (measured as the unemployment outflow or the vacancy outflow in turn) is much more volatile than the change in the respective stock. This implies that an increase in the number of matches is mainly driven by an increase in the inflow of new vacancies and unemployed, thereby leaving the underlying stocks largely unchanged. A very similar picture is provided by Blanchard and Diamond (1989) on US data.

Data on unemployment and vacancy durations are only available since 1985:2 and 1986:2, respectively. They come in the following form: (i) workers leaving unemployment each quarter by duration classes; (ii) stock of unemployed at the end of each quarter by duration classes; (iii) average completed duration of vacancies being filled during each quarter; (iv) average incompleting duration of the stock of unfilled vacancies at the end of each quarter. From this information we derive

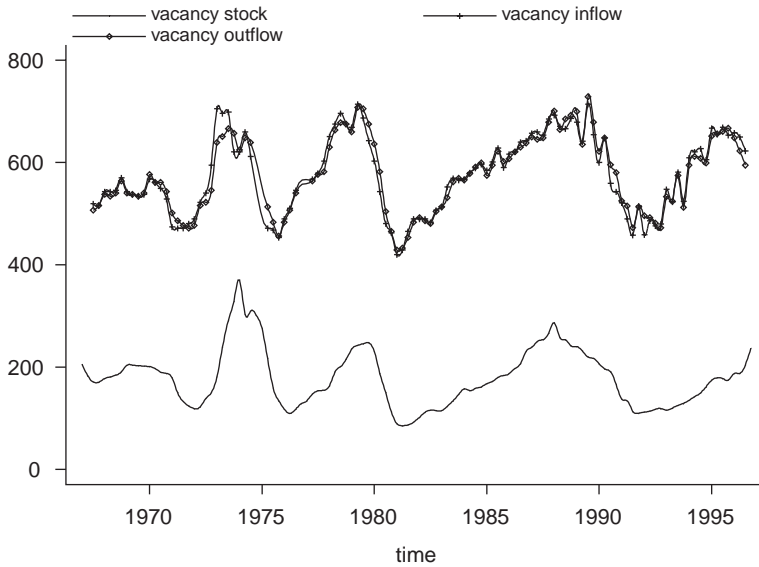


Fig. 2. Vacancy stock, inflow and outflow in Britain (thousands): 1967:1–1996:3. Data seasonally adjusted. *Source:* Employment Gazette (various issues) and NOMIS.

completed and incompleted durations of all spells. In particular, unemployment duration is computed by assigning to each duration class its mid-value (having closed the last open class with duration  $> 260$  weeks at 312 weeks).

These series are plotted in Fig. 3. The average completed duration of unemployment is around 30 weeks and the incompleted one is between 50 and 80 weeks. Fig. 4 plots the average duration of filled and unfilled vacancies. Observed durations are one order of magnitude smaller than the corresponding ones for unemployment, but, similarly as for unemployment, the ratio between incompleted and completed durations is in the range 2–2.5. These ratios are very much at odds with the predictions of the random matching model, that deliver equal completed and incompleted durations of search in steady state. A positive initial matching probability  $p_i$  may reconcile the predictions of a stock-flow matching model with the observed duration series, by reducing the predicted duration of completed spells below that of incompleted ones.<sup>9</sup>

In the next section we estimate outflow equations such as (6) and (7), precisely to test the hypothesis  $p_i > 0$ . Also, by allowing outflow equations to shift over time, we explore the evolution of matching effectiveness under the assumption of stock-flow matching.

<sup>9</sup>The wedge between completed and incompleted search durations might alternatively be generated by forms of duration dependence other than stock-flow matching or unobserved heterogeneity, which will be discussed in more detail in Section 5.

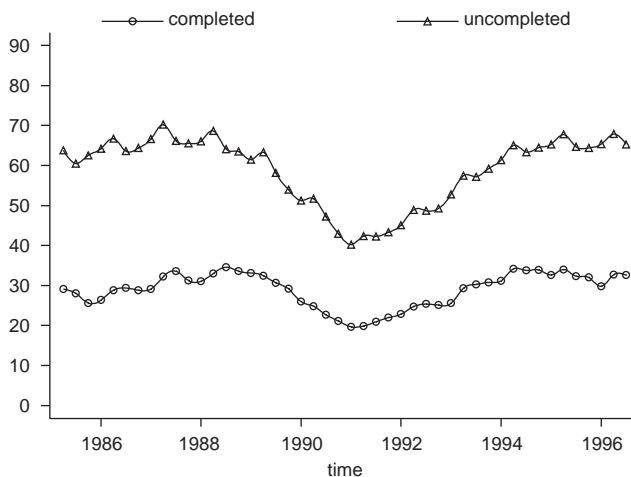


Fig. 3. Average completed and incomplete unemployment duration in Britain (weeks): 1985:2–1996:3. Data not seasonally adjusted. *Source*: NOMIS.

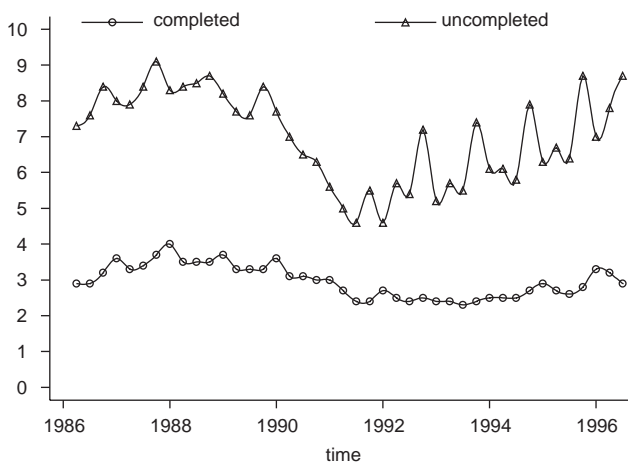


Fig. 4. Average completed and incomplete vacancy duration in Britain (weeks), 1986:2–1996:3. Data not seasonally adjusted. *Source*: NOMIS.

## 4. Estimation

### 4.1. Econometric specification

In this section we explore the performance of the matching function in Britain, moving away from the traditional stock-based analysis of matching. This involves two steps. The first deals with temporal aggregation issues but does not negate the

assumption of random matching, as represented in Eqs. (4) and (5). The second allows for stock-flow matching, as represented in Eqs. (6) and (7). We therefore proceed by estimating alternative specifications of these equations for both the unemployed and job vacancies. In each estimated outflow equation, we include a first-order serially correlated disturbance. More detail on the implications of serially correlated disturbances is given in Appendix A.

We estimate three basic models, which we describe below: a random matching model; a model nesting both random and stock-flow matching with fixed  $p_i$ ; and finally a stock-flow matching model in which  $p_i$  is allowed to vary with relevant labor market regressors.

A generic unemployment outflow equation can be written in the following way:

$$M_{Uq} = a_q U_{q-1} + b_q u_q + \varepsilon_{Uq}, \tag{8}$$

where  $M_{Uq}$  is the unemployment outflow during quarter  $q$ ,  $u_q$  is the corresponding inflow,  $U_{q-1}$  is the beginning-of-quarter stock,  $a_q$  and  $b_q$  are the quarterly outflow rates of stocks and inflows respectively (to be estimated), and  $\varepsilon_{Uq}$  is a disturbance term. Under random matching, which we label as Model 1,  $a_q = 1 - e^{-\lambda_{Uq}}$  and  $b_q = 1 - (1 - e^{-\lambda_{Uq}})/\lambda_{Uq}$ , according to Eq. (4). In choosing a functional form for  $\lambda_{Uq}$ , we assume that the function  $m(\cdot)$  in Eq. (1) is Cobb–Douglas with constant returns to scale, i.e.:

$$\lambda_{Uq} = \exp \left[ \alpha_0 + \alpha_1 \ln \left( \frac{V_{q-1}}{U_{q-1}} \right) \right], \tag{9}$$

where  $\alpha_0$  and  $\alpha_1$  are parameters to be estimated. The complete regression equation is reported in Appendix B.<sup>10</sup>

Model 2 allows for stock-flow matching.  $\lambda_{Uq}$  now denotes the hazard rate of the unemployment stock and  $p_u$  denotes the instantaneous matching probability of the unemployment inflow. In order to nest random and stock-flow matching,  $\lambda_{Uq}$  is now expressed as

$$\lambda_{Uq} = \exp \left[ \alpha_0 + \alpha_1 \ln \left( \frac{V_{q-1}}{U_{q-1}} \right) + \alpha_2 \ln \left( \frac{v_q}{U_{q-1}} \right) \right] \tag{10}$$

and  $p_u$  is estimated as a constant parameter. Random matching would predict  $\alpha_1 > 0$  and  $p_u = 0$ , while stock-flow matching would predict  $\alpha_1 = 0$  and  $p_u > 0$ .

In Model 3, we let  $p_u$  vary with labor market conditions in a similar way as for  $\lambda_{Uq}$ . Given that  $p_u$  measures the instantaneous matching probability of the

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<sup>10</sup>Note incidentally that estimating (8) with  $\lambda_{Uq}$  given by (9) provides an approximate solution to the time aggregation problem, obtained as a first-order Taylor expansion of  $e^{-\lambda_{Uq}}$  around  $\lambda_{Uq} = 0$ . The second-order expansion would deliver instead

$$\lambda_{Uq} = \exp \left[ \alpha_0 + \alpha_1 \ln \left( \frac{V_{q-1} + 0.5v_q}{U_{q-1} + 0.5u_q} \right) \right],$$

i.e. time aggregated stocks are now approximated by beginning-of-quarter stocks, plus half the corresponding inflows. This latter specification was also estimated on our data and results obtained did not alter in any significant way the conclusions of the Sections 4.2 and 4.3.

newly-unemployed, we specify it as

$$p_{uq} = \exp \left[ \gamma_0 + \gamma_1 \ln \left( \frac{V_{q-1}}{u_q} \right) \right]. \quad (11)$$

The last step allows outflow equations to shift over time, so as to explore the evolution of matching effectiveness over the period 1967–1996. The shift is assessed by including a quadratic trend in the expression for both  $\lambda_{Uq}$  and  $p_{uq}$  in all specifications above. The quadratic trend seems an appropriate and parsimonious way to capture a possibly non-monotonic pattern in matching effectiveness. But clearly one should abstain from using this parametric representation of matching patterns for extrapolation.

The same modelling steps are followed to build vacancy outflow equations. All the specifications estimated are reported in Appendix B.

#### 4.2. Unemployment outflow equations

Table 1 reports estimates of non-linear outflow equations for the unemployed. Values reported in square brackets for  $\lambda_U$  and  $p_u$  are (the sample average of) those predicted by the underlying models (see Eqs. (9)–(11)), using the estimated parameter vectors  $\alpha$  and  $\gamma$ , respectively.

In column 1 we estimate Model 1, which represents the unemployment outflow under random matching and controls for temporal aggregation. The stock of vacancies seems to contribute significantly to the unemployment outflow, as shown by the coefficient  $\alpha_1$ , but the overall econometric specification does not perform satisfactorily, given the near unit value of the  $AR(1)$  coefficient in the error term. Column 2 estimates Model 2, allowing for stock-flow matching. We find a positive effect coming through the inflow of new vacancies, represented by  $\alpha_2 > 0$ , and a non-significant effect coming through the stock of old vacancies ( $\alpha_1$  is not significantly different from zero).  $p_u$  is positive and highly significant, suggesting that a half of the newly-unemployed find a suitable job at their first round of sampling. The estimates of column 2 thus provide evidence that the vacancy stock does not significantly affect the matching rate of the unemployed, in line with stock-flow matching. Matching elasticities, computed at sample averages of relevant regressors, clearly confirm the picture that flows play a much more important role in matching than stocks. In column 3 a further specification of Model 2 is estimated, in which  $\alpha_1$  is restricted to zero. The results are virtually unchanged from column 2.

Column 4 estimates Model 3, and delivers an estimate for  $\gamma_1$  which is not significantly different from zero, although the average value of  $p_u$  (reported in squared brackets) stays fairly close to the estimates of columns 2 and 3. An estimated value of  $\gamma_1$  close to zero seems to suggest that the newly-unemployed are not matching with the vacancy stock, although the unemployment flow still has a higher matching rate than the corresponding stock. This may reflect pure vertical heterogeneity among job vacancies, in the sense that the stock of left-over vacancies may be of very low quality and therefore is not useful to any job-seeker. Section 5 explores this issue further but does not find evidence in this direction.

Table 1

Estimates of outflow equations for unemployed workers in Britain, 1967:1–1996:3

	1 Model 1	2 Model 2	3 Model 2 $\alpha_1 = 0$	4 Model 3	5 Model 1 quadratic trend	6 Model 2 quadratic trend	7 Model 2 quadratic trend $\alpha_1 = 0$	8 Model 3 quadratic trend
$\lambda_U$	[0.408]	[0.321]	[0.324]	[0.381]	[0.715]	[0.427]	[0.427]	[0.368]
$\alpha_0$	-0.494 (0.338)	-0.547 (0.234)	-0.370 (0.165)	-0.191 (0.213)	1.154 (0.057)	0.118 (0.143)	-0.021 (0.148)	-0.184 (0.179)
$\alpha_1$	0.186 (0.084)	-0.162 (0.129)	—	—	0.290 (0.028)	0.083 (0.057)	—	—
$\alpha_2$	—	1.077 (0.168)	0.886 (0.073)	0.913 (0.070)	—	0.416 (0.087)	0.555 (0.047)	0.445 (0.058)
$p_u$	—	0.502 (0.077)	0.499 (0.078)	[0.421]	—	[0.339]	[0.406]	[0.410]
$\gamma_0$	—	—	—	-1.117 (0.533)	—	-0.617 (0.133)	-0.534 (0.122)	-0.175 (0.190)
$\gamma_1$	—	—	—	-0.143 (0.173)	—	—	—	0.155 (0.065)
$t$	—	—	—	—	-0.033 (0.002)	-0.015 (0.002)	-0.012 (0.002)	-0.015 (0.002)
$t^2/1000$	—	—	—	—	0.195 (0.016)	0.091 (0.012)	0.069 (0.013)	0.086 (0.011)
$\rho_U$	0.965 (0.021)	0.703 (0.072)	0.705 (0.070)	0.711 (0.072)	0.466 (0.088)	0.247 (0.098)	0.400 (0.090)	0.230 (0.097)
Mean dur.:	32.6	26.8	26.9	26.7	26.0	26.5	23.5	26.6
Elasticities:								
$\partial \ln M / \partial \ln U$	0.504	0.031	0.043	0.035	0.517	0.267	0.245	0.270
$\partial \ln M / \partial \ln V$	0.126	-0.068	—	-0.053	0.214	0.045	—	0.055
$\partial \ln M / \partial \ln u$	0.194	0.593	0.591	0.588	0.268	0.467	0.526	0.460
$\partial \ln M / \partial \ln v$	—	0.451	0.373	0.436	—	0.226	0.299	0.220
$R^2$	0.699	0.782	0.782	0.790	0.765	0.836	0.834	0.848
No. obs.	111	110	110	110	111	110	110	110

Data seasonally adjusted. Dependent variable: quarterly unemployment outflow. Estimation method: non-linear least squares. Asymptotic standard errors are reported in brackets.  $\rho_U$  represents the  $AR(1)$  coefficient in the error term. Expected duration is measured in weeks, and computed as  $13(1 - p_u)/\lambda_U$ . Matching elasticities are sample averages. *Source*: Employment Gazette (various issues) and NOMIS.

Columns 5–8 replicate regressions 1–4, allowing for some shift in the matching rates of both stocks and flows. According to the coefficients on our trends, the random matching model of column 5 reveals a deterioration in the matching effectiveness of the unemployed until 1988:4, and a slight recovery thereafter. This finding is consistent with the outward shift in the Beveridge curve in Britain, that seems to have come to a halt in the late 1980s (see Jackman et al., 1989; Gregg and Petrongolo, 1997). Column 6 introduces stock-flow matching, and broadly confirms the results of column 2, with  $p_u > 0$  and  $\alpha_1$  non-significantly different from zero. Interestingly, when stock-flow matching is introduced in regressions 6 and 7, the deterioration of the matching effectiveness of the unemployed is reduced, as shown by the coefficients on the trend variables. Column 8 endogenizes  $p_u$ , and shows a

positive and significant impact of the supply of old vacancies on the matching probabilities of the newly-unemployed. Therefore part of the reason why  $\gamma_1$  was not significantly different from zero in column 4 is the correlation between  $\ln(V_{q-1}/u_q)$  and the quadratic trend.

The estimates in Table 1 predict an expected completed duration of unemployment around 26 weeks, obtained as the sample average of  $13(1 - p_u)/\lambda_U$ , so as to convert quarterly durations into weeks. According to stock-flow matching, this is an average of search spells of zero length by those (roughly 40%) who find a job just after entry, and search spells of length  $13/\lambda_U$  (roughly 40 weeks) by those that end up waiting for new vacancies being posted period after period.

Unemployment durations can also provide evidence on the quantitative importance of the deterioration in matching rates. We therefore compute the predicted change in unemployment duration that is *solely* explained by the quadratic trend, by keeping fixed all labor market variables at their 1967:1 values. The random matching model of column 5 predicts that unemployment duration starts off at 6 weeks in the late 1960s, increases by a factor of 4 until the 1988 peak, and then decreases to 20 weeks at the end of the sample. A fall in  $\ln(V_{q-1}/U_{q-1})$  is clearly the source of the further rise in unemployment duration up to the current value of 30 weeks (see Fig. 3). Under the stock-flow matching model of column 7, the decline in the matching effectiveness of the unemployed is less pronounced. Predicted duration goes from 6 weeks in the late 1960s to 15 weeks in 1988, and subsequently falls to 13 weeks. The bulk of the increase in unemployment duration seems now explained by a fall in  $\ln(v_q/U_{q-1})$ .

It is important to notice why stock-flow matching—while implying that unemployment exit rates should be more correlated to  $v_q/U_{q-1}$  than to  $V_{q-1}/U_{q-1}$ —may also explain a large part of the deterioration in worker matching effectiveness between the late 1960s and the late 1980s. During this period, the  $v_q/U_{q-1}$  ratio experiences a much more pronounced fall than the  $V_{q-1}/U_{q-1}$  ratio. Therefore the  $v_q/U_{q-1}$  ratio does quite a good job at explaining movements in unemployment exit rates during the first two decades of our sample period, with little explanatory power left to the quadratic trend.

#### 4.3. Vacancy outflow equations

We next turn to vacancy outflow equations in Table 2. In the first half of the table we obtain qualitatively similar results to those found for the unemployed. When accounting for stock-flow matching in regression 2, the unemployment stock does not raise significantly the probability of filling an old vacancy, and three quarters of newly-posted vacancies are filled very quickly, as implied by the estimated value of  $p_v$ . It is worthwhile to note the substantial drop in  $\lambda_V$  when moving from regression 1 to regressions 2 and 3: the interpretation is that while all vacancies that are ever advertised match at an average hazard of 3.6, the sub-set of vacancies that survive after their first round of sampling have a hazard around 0.5–0.7. The determinants of  $p_v$  are considered in regression 4. The estimated value of  $\delta_1$ , measuring the effect of the unemployment stock on the matching rate of new vacancies, is positive, although

Table 2  
Estimates of outflow equations for vacancies in Britain, 1967:1–1996:3

	1 Model 1	2 Model 2	3 Model 2 $\beta_1 = 0$	4 Model 3	5 Model 1 quadratic trend	6 Model 2 quadratic trend	7 Model 2 quadratic trend $\beta_1 = 0$	8 Model 3 quadratic trend
$\lambda_V$	[3.633]	[0.515]	[0.731]	[0.710]	[3.428]	[0.515]	[0.775]	[0.837]
$\beta_0$	0.369 (0.096)	-0.941 (0.266)	-1.081 (0.263)	-0.987 (0.252)	0.676 (0.134)	-1.548 (0.370)	-1.072 (0.247)	-1.235 (0.275)
$\beta_1$	0.393 (0.053)	0.085 (0.054)	—	—	0.389 (0.048)	-0.326 (0.233)	—	—
$\beta_2$	—	0.334 (0.111)	0.433 (0.095)	0.364 (0.111)	—	0.851 (0.295)	0.436 (0.083)	0.541 (0.117)
$p_v$	—	0.744 (0.068)	0.78 (0.057)	[0.786]	—	[0.844]	[0.768]	[0.753]
$\delta_0$	—	—	—	-0.269 (0.077)	—	-0.282 (0.065)	-0.308 (0.086)	-0.327 (0.091)
$\delta_1$	—	—	—	0.028 (0.018)	—	—	—	-0.047 (0.047)
$t$	—	—	—	—	-0.009 (0.005)	0.004 (0.001)	0.001 (0.001)	0.003 (0.002)
$t^2/1000$	—	—	—	—	0.043 (0.042)	-0.002 (0.001)	-0.008 (0.007)	-0.016 (0.010)
$\rho_V$	0.940 (0.038)	0.637 (0.083)	0.648 (0.081)	0.633 (0.083)	0.825 (0.061)	0.481 (0.094)	0.595 (0.086)	0.537 (0.092)
exp. dur.:	3.9	4.0	4.0	4.0	4.0	4.0	4.0	4.0
Elasticities:								
$\partial \ln M / \partial \ln U$	0.110	0.014	0	0.016	0.112	-0.039	0	-0.024
$\partial \ln M / \partial \ln V$	0.178	0.098	0.086	0.095	0.177	0.056	0.089	0.075
$\partial \ln M / \partial \ln u$	0	0.057	0.067	0.055	0	0.102	0.070	0.090
$\partial \ln M / \partial \ln v$	0.718	0.828	0.845	0.831	0.712	0.879	0.839	0.857
$R^2$	0.966	0.971	0.971	0.972	0.966	0.973	0.973	0.973
No. obs.	110	110	110	110	110	110	110	110

Data seasonally adjusted. Dependent variable: quarterly vacancy outflow. Estimation method: non-linear least squares. Asymptotic standard errors are reported in brackets.  $\rho_V$  represents the  $AR(1)$  coefficient in the error term. Expected duration is measured in weeks and computed as  $13(1 - p_v)/\lambda_V$ . Matching elasticities are sample averages. *Source*: Employment Gazette (various issues) and NOMIS.

it hardly reaches the standard significance levels. As we noted above for unemployment outflow equations, this result may suggest the presence of vertical heterogeneity among the unemployed. Finally, the information conveyed by the computed matching elasticities is quite extreme, showing that the bulk of matches are explained by movements in the vacancy inflow.

Including a quadratic trend in regression 5 reveals some deterioration in the matching effectiveness of vacancies until 1993:4. Due to this tendency in matching effectiveness, vacancy duration would have increased from 4.2 weeks in the late 1960s to 6.8 weeks in the early 1990s. Column 6 introduces stock-flow matching, and two important changes can be detected. First, there is a slight improvement in



vacancy matching rates until 1990:2. Second, the unemployed stock seems to have a negative effect on the matching rate of old vacancies. Unemployed stocks entering vacancy outflow equations with a negative sign are also found by [Burgess and Profit \(2001\)](#). Their and our specifications have in common some control for the shift of the outflow function, that clearly interacts with the unemployment stock, this being itself quite similar to a time trend. The negative  $\beta_1$  coefficient in column 6 proxies a deterioration in vacancy matching rates, which is then offset by the positive time trend. The vacancy equation becomes in fact perfectly stable when the unemployment stock is removed in column 7, given the non-significant coefficient on the trend variables, and shows once more a favorable shift when the unemployment stock is introduced in column 8 as a determinant of the matching probabilities of newly-posted vacancies. We should therefore conclude that the characterization of the matching process in terms of stock-flow matching removes the instability from vacancy outflow equations.

Turning to vacancy durations, the estimates of [Table 2](#) predict an average vacancy duration of around 4 weeks, which is also confirmed by raw data for the later period in [Fig. 4](#). However, a failure to match initially implies a much longer duration around 16 weeks, obtained as  $13/\lambda_V$  (estimates from regression 8).

It can thus be concluded that three quarters of vacancies and 40% of the unemployed match almost immediately, but those that are not successful at this juncture face low matching rates and a fairly long expected remaining duration. In particular, our estimates imply that long-term unemployment in the UK is a significant problem for as much as 60% of those who ever become unemployed.

Two important results emerge from the estimates of these last two sub-sections. First, matching appears to be non-random, in the sense that stocks do not match with stocks, but with the corresponding flows, as clearly shown by the non-significant estimates of  $\alpha_1$  and  $\beta_1$ . This in turn implies that labor market flows have a higher matching rate than the corresponding stocks, represented in our estimates by the positive values of  $p_u$  and  $p_v$ . Second, allowing for stock-flow matching implies near complete stability in the matching effectiveness of vacancies, and reduces the deterioration in the matching effectiveness of the unemployed. We speculate further on this result in the concluding section of the paper.

Before moving to our conclusions however, we attempt to isolate the effect of stock-flow matching on labor market dynamics from that of an extra source of non-randomness.

## 5. Stock-flow matching and heterogeneity

The results of the previous section imply that agents with relatively short elapsed search duration have higher matching rates. Lower exit rates for the long-term unemployed have long been recognized (for an overview, see e.g. [Devine and Kiefer, 1991](#); [Layard et al., 1991](#), Chapter 5) and they are typically attributed to two main sources. First, skill obsolescence, discouragement and/or the stigma attached to the long-term unemployed may reduce the probability of finding a job at long

unemployment durations, therefore introducing negative duration dependence in unemployment exit rates. Second, the presence of heterogeneity—both observed and unobserved—among the unemployed, implies that workers with higher hazard rates exit unemployment first, so that the average exit rate among the stock of unemployed falls over time. Similarly as for the unemployed, vacancy heterogeneity would deliver an inverse relationship between duration and average matching rates. Much less is known, however, on the time pattern of vacancy matching rates, with few notable exceptions (Van Ours and Ridder, 1993; Abbring and Van Ours, 1994; Burdett and Cunningham, 1998), partly because of lack of data and partly because a long-term vacancy is rarely observed.

Stock-flow matching suggests a further rationale for the presence of negative duration dependence in matching rates of unemployed workers and vacancies, which is related to the wider range of matching partners that can be sampled upon labor market entry. In this section we aim at separately identifying the effect of worker and vacancy heterogeneity on the one hand and stock flow-matching on the other hand in determining the time pattern of unemployment exit rates.

We look at vacancy heterogeneity first. In a pool of heterogeneous job vacancies, some job vacancies are more attractive to the unemployed, and therefore are easier to fill than others. As good vacancies get filled, the existing stock is increasingly made of hard-to-fill vacancies, and the average matching rate declines. Using the notation of the previous sections, this would deliver a positive  $p_v$ , as stock-flow matching would also predict. But unlike stock-flow matching, heterogeneity predicts that all the unemployed prefer new vacancies to old ones. Average quality is in fact higher among new vacancies than in the stock left over, and therefore the former are preferred to the latter by unemployed workers at all durations. NOMIS data contain information on how many workers find jobs and how many remain unemployed, disaggregated by duration classes, for the period 1985:2 onwards, which allow us to distinguish the effect of vacancy heterogeneity and stock-flow matching in unemployment exit rates. Our test consists in estimating separate log-linear outflow equations for the unemployment stock and the unemployment inflow. This allows us to test the responsiveness of each outflow rate to stocks and flows of job vacancies.

We denote by  $\theta_q^0$  and  $\theta_q^{1+}$  the unemployment exit rates during quarter  $q$  for those unemployed for 1 quarter or less, and for more than one quarter, respectively. These exit rates can be computed on our data using information on unemployment outflows for different duration classes. In our time framework,  $\theta_q^0$  and  $\theta_q^{1+}$  represent the exit rates for the unemployment inflow and the unemployment stock, respectively. The following outflow equations are estimated:

$$\ln \theta_q^0 = a_0 + a_1 \ln v_q + a_2 \ln V_{q-1} + \varepsilon_{Uq}, \quad (12)$$

$$\ln \theta_q^{1+} = b_0 + b_1 \ln v_t + b_2 \ln V_{q-1} + \varepsilon_{Vq}. \quad (13)$$

Under stock-flow matching we expect  $a_1, a_2, b_1 > 0$ , and  $b_2 = 0$ , because the unemployment stock does not match with the vacancy stock. Vacancy heterogeneity should in turn deliver  $a_1 > a_2$  and  $b_1 > b_2$ , as the vacancy stock would not be too

Table 3  
The determinants of unemployment outflow rates in Britain for two duration classes, 1986:2–1996:3

Dependent variable:	U-inflow $\ln \theta_q^0$	U-stock $\ln \theta_q^{1+}$
$\ln v_q$	0.138 (0.126)	0.364 (0.172)
$\ln V_{q-1}$	0.247 (0.060)	0.133 (0.087)
$\rho$	0.494 (0.120)	0.765 (0.072)
const.	-6.048 (1.277)	-7.995 (1.787)
quarterly dummies	yes	yes
$R^2$	0.750	0.753
No. obs.	42	42

Notes: The dependent variables is (log of) the exit rate for the unemployment inflow (with duration shorter or equal to 1 quarter) and the unemployment stock (with duration longer than 1 quarter). Sample period: 1985:4–1996:3. Data not seasonally adjusted.  $\rho$  represents the *AR*(1) coefficient in the error term. Standard errors in brackets.

Source: NOMIS.

useful to all the unemployed, being already depleted of the best job opportunities. Note therefore that while difference  $a_1 - a_2$  is only explained by vacancy heterogeneity (as there would be no reason, under pure stock-flow matching, why the unemployment inflow should prefer the vacancy inflow to the vacancy stock), the difference  $b_1 - b_2$  stems instead from both effects (unobserved heterogeneity and stock-flow matching). The difference between  $a_1 - a_2$  and  $b_1 - b_2$  should therefore provide a measure of the importance of stock-flow matching alone. The results are reported in Table 3. While the vacancy stock has a positive and significant impact on the exit rate of the unemployment inflow, it has no significant impact on the exit rate of the unemployment stock. The exit rate for the unemployment inflow is actually less sensitive to the vacancy inflow than the vacancy stock: any positive difference between the two effects would suggest the presence of vertical heterogeneity among vacancies, but we do not find evidence in this direction.

We should however note that the small sample size may have lowered the precision of our estimates, and therefore understated the importance of vacancy heterogeneity in matching. But, as a final check, the positive and significant value of  $b_2$  suggests that vacancy heterogeneity—if any—does not prevent the unemployment inflow from matching with old vacancies.

Unfortunately, as vacancy data in the NOMIS are not disaggregated by duration classes, we cannot run the symmetric estimation to the one reported in Table 3, to test for the importance of worker heterogeneity in the matching rates of new and old vacancies. However, Van Den Berg and Van Ours (1996) show that time series data on unemployment outflow rates from different duration classes can be used to

distinguish duration dependence in the unemployment exit rate from worker heterogeneity.<sup>11</sup> In particular, they compute the ratio between unemployment exit rates from two subsequent duration classes as a function of parameters of both the heterogeneity and the duration dependence distributions. Below, we briefly describe their method, and then apply it to our analysis.

Let us denote by  $\theta_q^d(v)$  the probability that an individual leaves unemployment right after  $d$  periods of unemployment, given calendar time  $q$ , and conditional on his or her unobserved characteristics,  $v$ . Assuming a mixed proportional hazard specification, this it can be written as  $\theta_q^d(v) = \phi(d)\psi(q) \cdot v$ , where the functions  $\phi(\cdot)$  and  $\psi(\cdot)$  represent duration dependence and calendar time dependence, respectively, and  $v$  has distribution  $G(v)$ , independent of  $d$  and  $q$ . Let us denote by  $\theta_q^d$  the corresponding unconditional exit rate:  $\theta_q^d = E_v \theta_q^d(v)$ . It can be shown that  $\theta_q^d / \theta_q^{d-1}$  is a (highly non-linear) function of (i) the unemployment exit rates for all duration classes shorter than  $d$ ; (ii) the first  $d + 1$  moments of the  $G(v)$  distribution,  $\mu_1, \dots, \mu_{d+1}$ ; and (iii) a parameter capturing duration dependence. More specifically, estimating  $\theta_q^d / \theta_q^{d-1}$  functions require identifying  $d + 1$  parameters with non-linear least squares.

Given our small sample size, we save on the number of parameters to be identified and pick  $d = 1$ . We therefore estimate an equation for  $\theta_q^1 / \theta_q^0$ , where  $\theta_q^0$  denotes the exit rate during quarter  $q$  for those unemployed for up to one quarter, and  $\theta_q^1$  denotes the corresponding exit rate for those unemployed for more than one quarter and up to two quarters. For this case, it can be shown that (see Van Den Berg and Van Ours, 1996, for derivation):

$$\frac{\theta_q^1}{\theta_q^0} = \eta \frac{1 - \gamma \theta_{q-1}^0}{1 - \theta_{q-1}^0}, \tag{14}$$

where  $\eta \equiv \phi(1)/\phi(0)$  captures duration dependence (with  $\eta < 1$  implying negative duration dependence between duration class 0 and duration class 1) and  $\gamma = 1 + \text{var}(v)/\mu_1^2$  captures unobserved heterogeneity (with  $\gamma > 1$  implying  $\text{var}(v) > 0$ , and therefore revealing the presence of unobserved heterogeneity).

We estimate (14) in log form, having added quarterly dummies and a first order serially correlated error term, for the period 1985:2–1996:3. The results for the parameters of interest are  $\hat{\eta} = 0.834$  (s.e. 0.056) and  $\hat{\gamma} = 1.021$  (s.e. 0.086). While  $\hat{\eta}$  is significantly lower than 1, revealing significance duration dependence in unemployment exit rates,  $\hat{\gamma}$  is not significantly different from 1, detecting therefore no significant unobserved heterogeneity. As this result hints at significant duration dependence just after one quarter of unemployment, stock-flow matching may provide a more plausible explanation for such a fall in exit rates rather than traditional concepts of duration dependence based on loss of skills or discouragement, which should mostly be at work at longer durations.

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<sup>11</sup>See also Van Den Berg and Van Ours (1998) and Abbring et al. (2002) for applications.

The picture that emerges from this section is one in which unobserved heterogeneity in either the vacancy or the unemployment stocks does not seem to play a dominant role in shaping unemployment exit rates. As the estimates of this section are obtained on small samples, they should be treated with some care, and a more conservative view should not rule out altogether the presence of unobserved heterogeneity. But it can be safely concluded that unobserved heterogeneity, if any, cannot explain alone the higher initial matching rates of unemployed workers and job vacancies.

## **6. Summary and discussion**

The aggregate matching function is a simple and powerful tool for analyzing labor market effectiveness in matching job vacancies and unemployed job-seekers. The standard stock-based matching function analysis has been interpreted as providing evidence of deteriorating labor market effectiveness in Britain until the late 1980s, which has been halted or slightly reversed since. But appearances can be deceptive.

In this paper, we dealt with two major issues in the specification of empirical matching functions. One is the temporal aggregation problem that arises when discrete time data are used to describe a continuous time process. We dealt with it by taking into account the whole pool of traders during the interval between two subsequent observations and constructing the corresponding time-aggregated matching function. The second issue derives from the view of labor market trade implied by random matching of unemployed and vacancies. Stock-flow matching is supported instead by empirical evidence on the duration of search spells and by estimates of outflow equations which allow for higher matching rates for inflows than for stocks.

We explained higher initial matching probabilities using a stock-flow model, in which the stock of traders on one side of the market is matching with the inflow of traders on the other side. In this set-up, inflows have higher trading probabilities than stocks, represented by the possibility of finding a partner in the existing stock when they first enter the market, with no need to wait for the inflow of new trading candidates. This interpretation is reinforced by the fact that unobserved heterogeneity does not seem to play too strong a role in raising initial matching rates.

Our evidence suggests that most new vacancies are filled very quickly. However, a minority do not match with the unemployment stock and have to rely on the next round of newly-unemployed in order to match. These vacancies have low matching rates and form the bulk of the stock of unfilled vacancies at any point in time. Symmetric considerations hold for the pool of unemployed workers. When combined with a proper treatment of temporal aggregation in the matching function, the stock-flow matching framework suggests that there has been no deterioration in the matching effectiveness of vacancies, but the conventional deterioration results still apply (although with reduced magnitude) to the matching effectiveness of the unemployed.

Mixed results on the two sides of the matching market may be reconciled by noting that not all vacancy outflows involve a match with a claimant unemployed—including flows of the non-claimant into jobs and job-to-job moves—and not all unemployment outflows represent moves into jobs. Interestingly, Gregg and Wadsworth (2000) show that the job entry probabilities of out-of-work individuals with a working partner have been rising in Britain over the past two decades, while those for individuals with no partner or a non-working one were falling. Those with a working partner are systematically under-represented in the claimant count. As this group increases their share of job matches, outflows of claimants would fall with no change in the matching effectiveness of vacancies. Concerning job switches, Fuentes (1998) documents an increase in on-the-job search since the mid-1970s. The implication is that overall matching effectiveness in the labor market may have not deteriorated since the late 1960s, but claimants of unemployment-related benefits are facing stronger competition from other labor market segments and therefore are taking a lower proportion of available jobs.

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### Appendix A. Serially correlated disturbances

The generic unemployment outflow equation of Section 4.1:

$$M_{Uq} = a_q U_{q-1} + b_q u_q + \varepsilon_{Uq} \quad (15)$$

describes a matching technology, and the disturbance  $\varepsilon_{Uq}$  can be interpreted as a technological shock affecting matching rates. The presence of the disturbance term may derive from the omission from (15) of variables that may affect the matching technology. Insofar any of the omitted variables are autocorrelated, our disturbances are also autocorrelated, delivering inefficient least squares estimates of the coefficients of interest. In our specific case, however, autocorrelated disturbances may also lead to inconsistent estimates. To see this, note that inflows and outflows are linked by the following identity, on top of the matching technology (15):

$$U_q = U_{q-1} + u_q - M_{Uq}. \quad (16)$$

Rewriting (16) one period back, and substituting  $M_{U_{q-1}}$  using (15) gives

$$\begin{aligned} U_{q-1} &= U_{q-2} + u_{q-1} - M_{U_{q-1}} \\ &= (1 - a_{q-1})U_{q-2} + (1 - b_{q-1})u_{q-1} - \varepsilon_{U_{q-1}}. \end{aligned} \quad (17)$$

Suppose now that the error term follows a stationary  $AR(1)$  process

$$\varepsilon_{Uq} = \rho_U \varepsilon_{Uq-1} + \eta_{Uq} \tag{18}$$

with  $|\rho_U| < 1$  and  $\eta_{Uq} \sim \text{i.i.d.} N(0, \sigma_{\eta_U}^2)$ . Eq. (17) implies that  $U_{q-1}$  is correlated with  $\varepsilon_{Uq-1}$ , which, given (18), also implies that  $U_{q-1}$  is correlated with the error term in (15). In order to obtain consistent estimates of the parameters of interest, we allow for  $AR(1)$  disturbances in all outflow equations:

$$M_{Uq} = \rho_U M_{Uq-1} + a_q U_{q-1} - \rho_U a_{q-1} U_{q-2} + b_q u_q - \rho_U b_{q-1} u_{q-1} + \eta_{Uq}, \tag{19}$$

where  $\eta_{Uq}$  is uncorrelated with all regressors.

### Appendix B. Regression equations

*Unemployment outflow equations:*

Model 1:

$$\begin{aligned} M_{Uq} &= \{1 - \exp[-\exp(\alpha_0 + \alpha_1 \ln(V_{q-1}/U_{q-1}))]\} U_{q-1} \\ &+ \left\{ 1 - \frac{1 - \exp[-\exp(\alpha_0 + \alpha_1 \ln(V_{q-1}/U_{q-1}))]}{\exp(\alpha_0 + \alpha_1 \ln(V_{q-1}/U_{q-1}))} \right\} u_q \\ &+ \rho_U \varepsilon_{Uq-1} + \eta_{Uq}. \end{aligned}$$

Model 2:

$$\begin{aligned} M_{Uq} &= \{1 - \exp[-\exp(\alpha_0 + \alpha_1 \ln(V_{q-1}/U_{q-1}) + \alpha_2 \ln(v_q/U_{q-1}))]\} U_{q-1} \\ &+ \left\{ 1 - \frac{(1 - p_u)\{1 - \exp[-\exp(\alpha_0 + \alpha_1 \ln(V_{q-1}/U_{q-1}) + \alpha_2 \ln(v_q/U_{q-1}))]\}}{\exp(\alpha_0 + \alpha_1 \ln(V_{q-1}/U_{q-1}) + \alpha_2 \ln(v_q/U_{q-1}))} \right\} u_q \\ &+ \rho_U \varepsilon_{Uq-1} + \eta_{Uq}. \end{aligned}$$

Model 3:

$$\begin{aligned} M_{Uq} &= \{1 - \exp[-\exp(\alpha_0 + \alpha_2 \ln(v_q/U_{q-1}))]\} U_{q-1} \\ &+ \left\{ 1 - \frac{[1 - \exp(\gamma_0 + \gamma_1 \ln(V_{q-1}/u_q))]\{1 - \exp[-\exp(\alpha_0 + \alpha_2 \ln(v_q/U_{q-1}))]\}}{\exp(\alpha_0 + \alpha_2 \ln(v_q/U_{q-1}))} \right\} u_q \\ &+ \rho_U \varepsilon_{Uq-1} + \eta_{Uq}. \end{aligned}$$

*Vacancy outflow equations:*

Model 1:

$$\begin{aligned} M_{Vq} &= \{1 - \exp[-\exp(\beta_0 + \beta_1 \ln(U_{q-1}/V_{q-1}))]\} V_{q-1} \\ &+ \left\{ 1 - \frac{1 - \exp[-\exp(\beta_0 + \beta_1 \ln(U_{q-1}/V_{q-1}))]}{\exp(\beta_0 + \beta_1 \ln(U_{q-1}/V_{q-1}))} \right\} v_q \\ &+ \rho_V \varepsilon_{Vq-1} + \eta_{Vq}. \end{aligned}$$

Model 2:

$$M_{Vq} = \{1 - \exp[-\exp(\beta_0 + \beta_1 \ln(U_{q-1}/V_{q-1}) + \beta_2 \ln(u_q/V_{q-1}))]\} V_{q-1} + \left\{1 - \frac{(1 - p_v)\{1 - \exp[-\exp(\beta_0 + \beta_1 \ln(U_{q-1}/V_{q-1}) + \beta_2 \ln(u_q/V_{q-1}))]\}}{\exp(\beta_0 + \beta_1 \ln(U_{q-1}/V_{q-1}) + \beta_2 \ln(u_q/V_{q-1}))}\right\} v_q + \rho_V \varepsilon_{Vq-1} + \eta_{Vq}.$$

Model 3:

$$M_{Vq} = \{1 - \exp[-\exp(\beta_0 + \beta_2 \ln(u_q/V_{q-1}))]\} V_{q-1} + \left\{1 - \frac{[1 - \exp(\delta_0 + \delta_1 \ln(U_{q-1}/v_q))]\{1 - \exp[-\exp(\beta_0 + \beta_2 \ln(u_q/V_{q-1}))]\}}{\exp(\beta_0 + \beta_2 \ln(u_q/V_{q-1}))}\right\} v_q + \rho_V \varepsilon_{Vq-1} + \eta_{Vq}.$$

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