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Random and stock-flow models of labour market matching—Swedish evidence*

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Abstract

In this paper we estimate aggregate matching functions taking advantage of a rich data base that enables us to compute observations on the variables in the matching function at (virtually) any frequency to assess the importance of the time aggregation problem. We also generate stocks, outflows and inflows of vacancies and job seekers to shed light on the importance of stock-flow matching. Finally, we assess the contribution of labour market programme participants to matching.

Our evidence rejects random matching. More precisely, we find that a non-trivial fraction of new job seekers match instantly (within the first week), that stocks of "old" vacancies and job seekers do not contribute significantly to matching and that the inflow of vacancies matches with the lagged stock of job seekers. Our results also suggest that labour market programme participants contribute to matching to a lesser extent than openly unemployed job seekers.

We also find that the use of lagged stocks as right-hand side variables in matching functions (i.e., ignoring the within-period inflow of job seekers and vacancies) gives lower estimates of matching elasticities and that this is more pronounced the lower the measurement frequency.

Keywords: Stock-Flow Matching, Time Aggregation
JEL codes: J6, J64

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Contents

1 Introduction

Labour markets are characterised by frictions, implying that the reallocation of jobs and workers normally involves the coexistence of unemployment and vacancies as well as large flows of jobs and workers. An efficient matching process in the labour market contributes to both lower unemployment and higher employment rates. Hence, it is a prominent policy target to promote an efficient matching between vacancies and job seekers in the labour market. For this to be effective, we need good indicators of labour market matching efficiency. Shifts in Beveridge curves (the relation between unemployment and vacancies) have often been used as evidence of changes in matching efficiency. However, Beveridge curves may shift for a number of reasons, not all connected to the efficiency of the matching process.[1] A more direct way to look at matching is by means of aggregate matching functions. Estimated matching functions, typically giving the number of matches as a function of the numbers of vacancies and job seekers, provide information on how matching efficiency, reflecting labour market frictions has evolved. Over time, an increasing number of empirical studies using a matching function framework has accumulated.

Empirical results, presented in a recent survey of the matching function literature (Petrongolo & Pissarides 2001), indicate that matching functions have been unstable in a way consistent with deteriorating matching efficiency in several OECD countries. However, the analysis in Gregg & Petrongolo (2005) suggests that the instability in estimated matching functions partly reflects mis-specification problems. More specifically, the authors point to problems of time aggregation when using discrete-time data (Burdett et al. 1994, Berman 1997) and the existence of non-random matching, leading to so called stock-flow matching models (Coles 1994, Coles & Smith 1998, Coles & Petrongolo 2003).

There are only two previous studies (Edin & Holmlund 1991, Hallgren 1996) of matching functions on Swedish data. Neither of them explicitly considers the stability of the matching function. Instead the focus is on the contribution of active labour market programmes to matching. Their main result in this respect is that programme participants contribute less to matching than openly unemployed job seekers.

In the present paper we estimate aggregate matching functions, paying

[1] It is, for example, well known that changes in the inflow rate to unemployment, *ceteris paribus*, give rise to shifts in the Beveridge curve.

special attention to time aggregation and stock-flow matching. In doing this, we take advantage of a rich data base, that enables us to compute observations on the variables entering the matching function at (virtually) any frequency. This means that we can assess the importance of the time aggregation problem. We can also generate stocks, outflows and inflows of vacancies and job seekers at any chosen frequency. Hence, we can also shed light on the importance of stock-flow matching. Because we observe the durations of unemployment spells, we can investigate whether the negative relationship between programme participants and matching may be more than just a correlation induced by long unemployment durations among programme participants.

2 The matching function

The *matching function* is a way to summarise the results of the efforts of workers looking for jobs and firms looking for workers to fill vacancies. This is a complicated process involving a large variety of activities. The usefulness of the matching function as an analytical device hinges critically on the assumption that the complicated matching process can be summarised by a (reasonably) stable function that relates the number of matches at any point in time to the number of job-seekers, the number of vacancies and (possibly) a small number of other variables.

The simplest matching function can be written

$$M_t = m(U_t, V_t);\ m_1 > 0,\, m_2 > 0 \tag{1}$$

where M_t is the number of matches (jobs formed) in a given point in time, U_t is the number of unemployed job seekers[2] and V_t is the number of vacant jobs.[3]

Random matching Under random matching[4] unemployed workers and vacancies are randomly selected from U_t and V_t and job seekers find jobs

[2]More generally, we could include all job seekers, for example participants in labour market programmes and "on-the-job" seekers, not only the unemployed.

[3]A number of additional assumptions are often imposed and sometimes tested (for example concavity, homogeneity of degree 1, $m(0, V) = m(U, 0) = 0$).

[4]This is the "standard" model; for references, see the survey in Petrongolo & Pissarides (2001).

and vacancies are filled at the Poisson rates $\lambda_{U_t} = M_t/U_t$ and $\lambda_{V_t} = M_t/V_t$, respectively.

The number of matches over any time period (the length of which we normalise to 1) is then given by[5]

$$M = \int_0^1 m(U_t, V_t)\mathrm{d}t = \int_0^1 U_t \lambda_{U_t} \mathrm{d}t \tag{2}$$

U_t is, in turn, given by

$$U_t = U_0 \exp\left(-\int_0^t \lambda_{U_s} \mathrm{d}s\right) + \int_0^t u_{t'} \exp\left(-\int_{t'}^t \lambda_{U_s} \mathrm{d}s\right) \mathrm{d}t' \tag{3}$$

where U_0 is the beginning of period unemployment stock and u_t is the inflow into employment during the period. The outflow rate will under random matching be the sum of "old" and "new" job seekers.

To estimate (2), one must assume something about the within-period development of the inflow of new unemployed, u_t and the outflow rate λ_{U_t}. The assumptions here will be $u_t = u$ and $\lambda_{U_t} = \lambda_U$. Substituting these into (3) and then into (2), we get unemployment outflow (matches) as

$$M = \left(1 - e^{-\lambda_U}\right) U_0 + \left(1 - \frac{1 - e^{-\lambda_U}}{\lambda_U}\right) u \tag{4}$$

The message of *Equation* (4) is that the number of matches depends on the outflow rate λ, the beginning-of-period stock of job seekers and the within-period inflow of job seekers.

The time aggregation problem when estimating (4) on discrete-time data arises because the second term on the right-hand side involves the inflow of job seekers, which is typically not observed. If the inflow of new job seekers is non-trivial compared to the stock, the measurement error will also be non-trivial and result in potentially seriously biased estimates.

Stock-flow matching Under stock-flow matching,[6] workers flowing into unemployment first sample the stock of vacancies and some of the workers immediately match. The remaining, unmatched workers (the stock) will sample the inflow of vacancies and leave unemployment at some rate.

[5] We present the matching model only in terms of the job-finding rate.

[6] See Coles (1994), Coles & Smith (1998), Coles & Petrongolo (2003) and Gregg & Petrongolo (2005).

We represent this by letting the probability of direct matching be p_u. With probability $1 - p_u$ unemployed workers must wait for new vacancies to match at the rate λ_U. Under the same assumptions as under random matching, we get the following unemployment outflow equation under stock-flow matching:

$$M = \left(1 - e^{-\lambda_U}\right) U_0 + \left[1 - \frac{1 - p_u}{\lambda_U}(1 - e^{-\lambda_U})\right] u \tag{5}$$

The main difference between the expression (5) under stock-flow matching and its counterpart (4) under random matching is that a proportion p_u of the within-period inflow of job seekers will match immediately.

3 The data

3.1 Data sources and definitions

The data used in the empirical analysis derive from the Swedish *HÄNDEL* data base collected by the National Labour Market Board (LMB) since August, 1991. This data base includes records of all contacts between job seekers and the employment offices of the Public Employment Service (PES). Search through the PES is a necessary condition for UI benefit eligibility, so unemployed job seekers have strong incentives to register at the PES. The contacts between job seekers and the PES result in a categorisation of job seekers into openly unemployed and participants in different labour market programmes.[7] When a job seeker leaves the register, a destination is specified. From this register we have constructed series of stocks of openly unemployed and programme participants as well as inflows, all at the municipality level. As the records are daily, we could in principle compute daily figures for our variables. We have, however, chosen to compute data weekly, monthly and quarterly.[8] These series form the basis of our measures of job seekers. The outflow of job seekers to work, taken from the same source, is one of the two measures of the number of matches we use. Although there are problems in the registers (Bennmarker et al. 2000), we believe that we measure our variables of interest with reasonable accuracy

[7] Technically, a job seeker is put into one of a large number of different categories in the register. Some of these categories correspond to "open unemployment" and some categories contain programme participants.

[8] We believe that daily series would be plagued by too much measurement error.

in most cases.[9] The possible exception is the measure of outflow to jobs. A substantial fraction of the job seekers leave the register for unknown reasons. Studies by Bring & Carling (2000), Sahin (2003), and Forslund et al. (2004) indicate that roughly 50 % of these actually leave the register for a job. Hence, as a baseline we add 50 % of those leaving the register for unknown reasons when we compute the number of matches. We have checked the importance of this and the results with and without this addition were very similar.

The registers from the LMB also include information of vacancies. We have used these raw data to compute vacancy stocks and inflows as well as outflows of vacancies[10] as an alternative measure of the number of matches. Reporting of vacancies to the public employment service (PES) is mandatory in Sweden. However, it is well known that far from all vacancies are reported to the PES.[11] It may also very well be the case that coverage varies over time. Statistics Sweden has recently started collecting vacancy data by survey methods, but these time series are as yet too short to be useful in our analysis. Hence, there is reason to believe that we have measurement errors in our vacancy data.

The exact data definitions are presented in *Appendix A*.

3.2 A brief description of the aggregate data

The data (seasonally adjusted) are plotted in *Figures 1* and *2*. A number of points are worth noting. *First*, the correlation between the outflow and inflow of job seekers is higher than the correlation between the outflow and the stock of job seekers, although the difference is not staggering (0.53 as compared to 0.45). Looking instead at vacancies, the correlation between the inflow and the outflow is 0.16, whereas the stock and the outflow are negatively correlated; the correlation is -0.17.

To some extent these patterns in the data indicate that increases in matching to a non-trivial extent are driven by increased inflows of vacancies and unemployed with stocks much less volatile. Similar patterns are also

[9] Indeed, given the way we have been able to construct our data, we believe that the quality of our data is better than in most other studies.

[10] The part of the outflow that represents filled vacancies rather than "withdrawn" vacancies.

[11] See, for example, Ekström (2001), where the results of a survey to firms concerning their modes of recruiting personnel are reported. Almost 40 % of the firms in that survey reported that they used the PES.

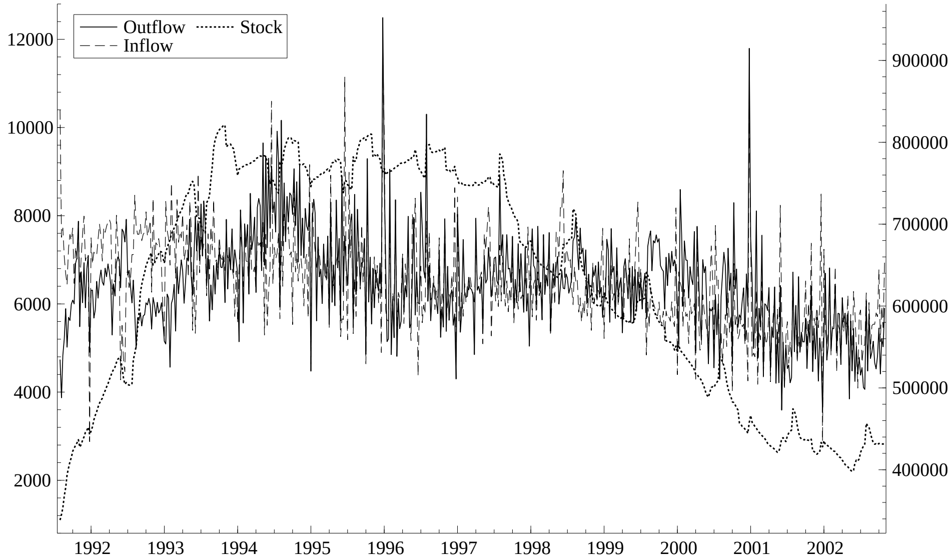

Figure 1: Weekly inflow, outflow (left-hand side axis), and stock of job seekers (right-hand side axis).
Note: Data seasonally adjusted using centered dummies.

found in the UK (Gregg & Petrongolo 2005) and the US (Blanchard & Diamond 1989).

Looking at the time series properties of the variables, ADF tests forcefully reject non-stationarity in all flows, whereas the results for the stocks are somewhat ambiguous.[12]

Further inspection of *Figure 2* reveals that even the weekly inflow of vacancies is of a non-trivial size compared to the stock. This should serve as yet a warning against the use of the beginning of period stock as a measure of available vacant jobs over a week, and of course even more so if the time period under consideration is longer. This time-aggregation problem is less serious for the unemployed job seekers, where the inflow is much smaller relative to the stock. This difference between vacancies and unemployment is a mirror image of the durations of the spells, which are

[12]The test results depend on the presence of a deterministic trend.

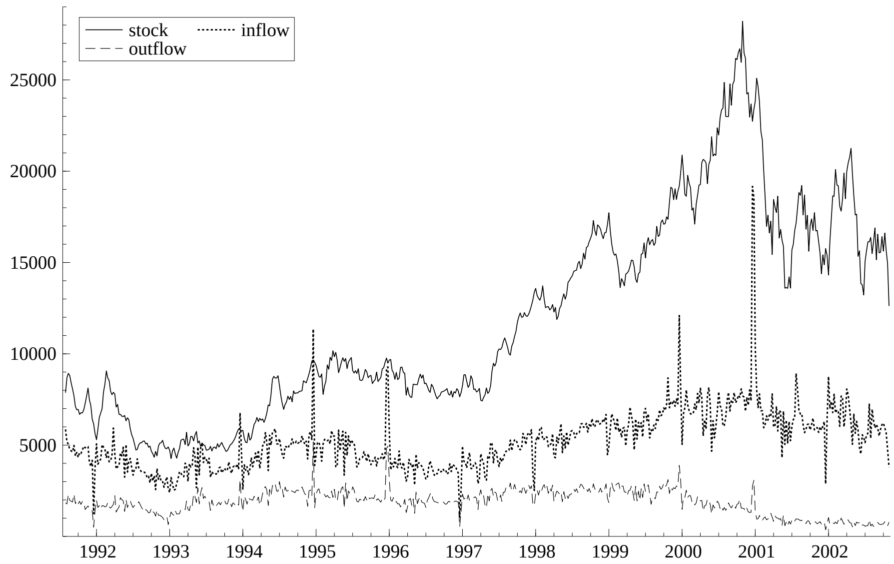

Figure 2: Inflow, outflow, and stock of vacancies (weekly).
Note: Data seasonally adjusted using centered dummies.

plotted in *figures 3* and *4*.

Figure 3 shows the development of the duration of ongoing and completed spells of unemployment from late 1991 to late 2002.[13] The development in the first half of the 1990s is partly an artifact reflecting that the register begins in August, 1991. Some spells starting earlier have a recorded starting date, but some do not. This means that the rise in duration is overestimated.[14] However, we see that the average spell typically lasts between some 30–40 weeks (completed spells) and 60–80 weeks (ongoing spells).

Figure 4 shows the development of the duration of vacancy spells (filled and unfilled). These durations are much shorter than the unemployment

[13] What we actually measure is the duration of spells in the registers of the National Labour Market Board, where cycling between open unemployment and participation in ALMPs is counted as a continuous spell.

[14] The problem is probably not so big; the time pattern of median of the spell lengths is very similar to the time pattern of the mean.

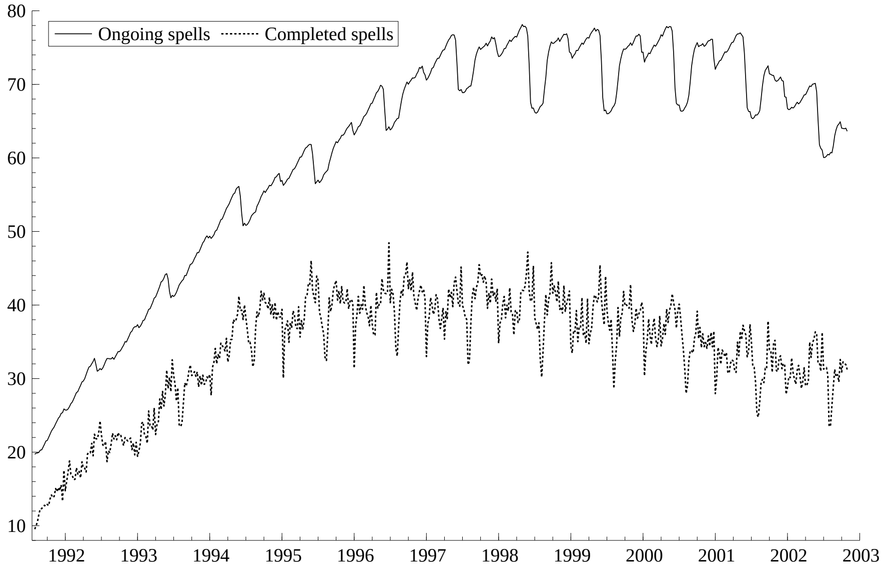

Figure 3: Average duration (weeks) of ongoing and completed unemployment spells.
Note: Data not seasonally adjusted.

durations shown in *Figure 3* (between 1 and 2 weeks for filled vacancies). However, also for vacancies it is true that the average duration of spells in the vacancy stock is significantly longer than the average duration of the filled vacancies.

The observation that the durations for ongoing spells of unemployment and vacancies are significantly longer than for the completed spells is clearly at odds with the predictions of random matching models, where we would expect ongoing and completed spells to be of equal length in a steady state. The observed pattern could reflect duration dependence, but it is also consistent with predictions of the stock-flow matching framework presented in *Section 2*.

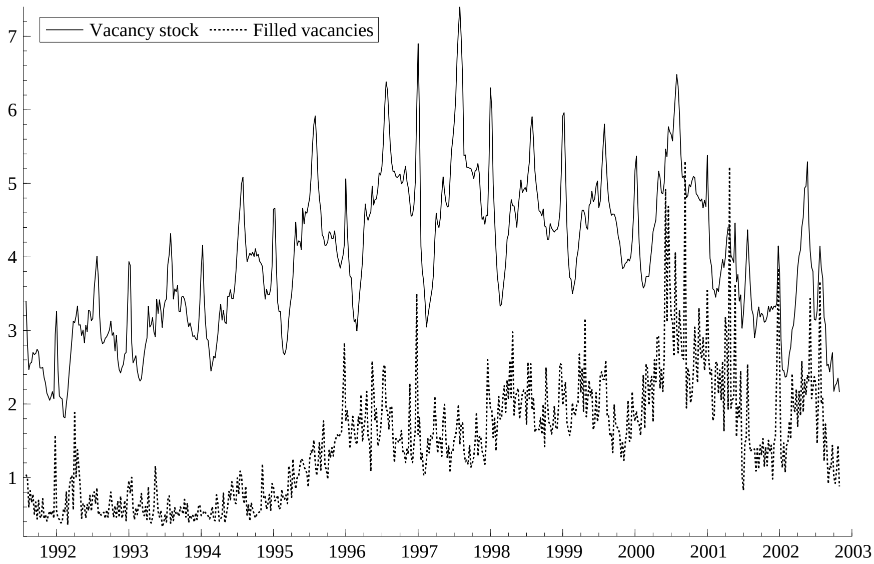

Figure 4: Average completed and uncompleted vacancy duration (weeks). Note: Data not seasonally adjusted.

3.3 The job seekers

Our data base contains information that enables us to describe the job seekers in some detail. In *Table 1* we show the numbers of persons in different categories of job seekers as well as the outflow rates to jobs[15] from each of these categories. We show the job seekers by the duration of the spells in the registers of the PES as well as by "type" of job seeker (i.e., openly unemployed, programme participants, employed job seekers and those part-time unemployed, employed by the hour or temporary employed; all according to the PES registers).

Looking first at the number of persons in different categories of job seekers, we see that openly unemployed and programme participants vastly outnumber the different types of employed (or semi-employed) job seekers in our data base. In terms of outflow rates to jobs, the unemployed and the category including temporary employed and other "semi employed" persons

[15] The weekly outflow in relation to the stock.

Table 1: Some characteristics of different categories of job seekers

Category	**Average number of persons**	**Average weekly outflow rate**
By type of job seeker:		
Openly unemployed	317 106	.021
Programme participants	146 712	.004
Employed job seekers	29 477	.009
Temporary employed, employed by the hour, part-time employed	59 500	.020
By duration of spell:		
0–30 days	43 043	.032
31–60 days	39 436	.020
61–90 days	36 341	.032
91–120 days	26 509	.026
121–240 days	84 229	.021
241–360 days	54 852	.016
361–480 days	38 735	.012
481–600 days	28 645	.010
>600 days	112 027	.007

Note: Data for August 1991–October 2002.

exit to jobs much more rapidly than employed job seekers and, especially, programme participants. This feature would suggest that one could gain by disaggregating across different types of job applicants in the estimation of the matching functions.

Looking next at job seekers with different spell lengths, the exit rates to employment decrease by spell lengths almost monotonically, the main exceptions being exit rates from spells lasting between 60 and 90 days. As programme participants, almost by construction, have longer spells than the openly unemployed on average, there is a problem in the separate identification of the contributions of openly unemployed job seekers and programme participants on the one hand, and job seekers with different durations of spells on the other hand. Earlier findings (Edin & Holmlund 1991, Hallgren 1996) that programme participants contribute to matching to a lesser extent than the openly unemployed hence may reflect duration dependence or selection as well as programme effects per se. In *Section 5.2* we deal with this issue briefly.

4 Econometric specification

Let M_t denote the expected flow matching rate at time t. Then

$$M_t = p_t u_t + \lambda_t U_t \tag{6}$$

where u_t denotes the inflow of job seekers, p_t the proportion of these that match immediately, U_t the stock of job seekers and λ_t the rate at which the stock matches.[16] We have experimented with estimating models for both the outflow to work of job seekers and the outflow of vacancies. The latter models did not, however, give any sensible results, so we restrict our discussion to the outflow of job seekers.[17]

In discrete time, equation (6) can be written

$$M_t = a_t U_{t-1} + b_t u_t + \varepsilon_t \tag{7}$$

where ε_t is an added disturbance term (unrelated to any time aggregation problem).

We now use the expressions derived in *Section 2* to specify a_t and b_t for both random matching and stock-flow matching.

Random matching Under random matching we have (see Equation (4))

$$\begin{aligned} a_t =& \quad 1 - e^{-\lambda_U} \\ b_t =& \quad 1 - \tfrac{1-e^{-\lambda_U}}{\lambda_U} \end{aligned}$$

To complete the specification of the random matching model, a functional form for the matching equation (1) must be chosen. If it is assumed to be a constant-returns Cobb-Douglas function, we get

$$\lambda_{U_t} = \exp\left[\alpha_0 + \alpha_1 \ln\left(\frac{V_{t-1}}{U_{t-1}}\right)\right] \tag{8}$$

[16] The exposition follows the presentation in Gregg & Petrongolo (2005), where more details are found.

[17] We suspect that this may reflect the measurement problems discussed in Section 3.1.

Stock-flow matching Under stock-flow matching we get

$$\begin{aligned} a_t &= 1 - e^{-\lambda_U} \\ b_t &= \left[1 - \tfrac{1-p_u}{\lambda_U}(1 - e^{-\lambda_U})\right] \end{aligned}$$

and

$$\lambda_{U_t} = \exp\left[\alpha_0 + \alpha_1 \ln\left(\frac{V_{t-1}}{U_{t-1}}\right) + \alpha_2 \ln\left(\frac{v_t}{U_{t-1}}\right)\right] \tag{9}$$

Next, we also allow the instantaneous matching probability (p_u) of the unemployment inflow to dependent on labour market conditions:

$$p_{u_t} = \exp\left[\gamma_0 + \gamma_1 \ln\left(\frac{V_{t-1}}{u_t}\right)\right] \tag{10}$$

Finally, we include a quadratic trend in the expressions for λ_{U_t} and p_{u_t}, either imposing the same trend for both or estimating separate trends for λ_{U_t} and p_{u_t}[18]

Comparing the models for random matching and stock-flow matching, we see that the latter models reduce to the former if $\alpha_2 = 0$ and $p_u = 0$, whereas stock-flow matching implies $\alpha_1 = 0$. These restrictions are easily tested.

5 Results

Our data enable us to look closer into some issues discussed in the introduction. First, to discuss problems of time aggregation, we will show estimates of aggregate log-linear matching functions using weekly, monthly and quarterly data. In doing this, we both use beginning-of-period stocks of vacancies and job seekers and input measures that include half of the inflows during the period in question. Burdett et al. (1994) showed that if stocks are mean reverting, then the use of beginning-of-period stocks gives rise to a downward bias in matching elasticities with respect to vacancies and job seekers and that this bias is an increasing function of the length of the time interval. The use of the beginning-of-period stocks plus half the inflow is a solution to this problem that has been suggested by Gregg &

[18] Estimates of models with separate trends did not converge unless other restrictions were imposed and are not reported.

Petrongolo (1997) and follows from a Taylor expansion of $\exp(-\lambda)$ around $\lambda = 0$ in *equation* (4).

The main part of our results, however, pertain to whether random matching or stock-flow matching seems to be a better description of the matching process in the Swedish labour market.

We have experimented (quite a lot) with different regional matching models, e.g. allowing (parametrically) for spatial correlations or taking averages over separate time-series models for each municipality. However, all results of those experiments led to the conclusion that nothing was gained by disaggregating across regions.

Employed job seekers In Petrongolo & Pissarides (2001) it is shown that, under reasonable assumptions, neglecting employed job seekers when measuring the total number of job seekers will produce biased estimates of the parameters in the matching function.[19] In our data, we have information on employed job seekers who are registered at the PES. Although the registered employed job seekers are a selected subset of all employed job seekers, they are likely to be reasonably representative for the employed job seekers who apply for the registered vacancies.

The estimated models all use measures of the number of job seekers including the number of employed job seekers as well as the number of part-time unemployed, temporarily employed and those employed by the hour. Our measures of the outflow to employment, consequently, includes not only the unemployed and the programme participants, but also employed job seekers and part-time unemployed, temporarily employed and those employed by the hour changing employment status to "more" employment.[20]

The number of job seekers To sum up our discussion of measurement issues, we end up using a measure (used in all estimated models) of the number of matches containing the following components:

1. openly unemployed job seekers leaving the register for work

[19] Job search among the employed is most likely rather responsive to labour market tightness. If this is the case, the effect of vacancies on the number of matches will be under-estimated and the effect of unemployed job seekers over-estimated.

[20] See *Appendix A* for a precise definition of what this means. One example of "more employment" would be that a part-time unemployed becomes full-time employed.

2. programme participants leaving the register for work

3. employed job seekers and part-time unemployed, temporarily employed and those employed by the hour changing employment status to "more" employment

4. half the number of persons leaving the register for unknown reasons.

Although not flawless, this measure should be considered accurate in comparison with most alternatives previously used to estimate Swedish matching functions.[21]

5.1 Random matching: log-linear matching functions

To check how sensitive the estimates are to the sampling frequency in the data, we have estimated standard log-linear matching functions on weekly, monthly and quarterly data. We have also used lagged stocks plus half of the inflow of vacancies and unemployment (at the same frequencies) as suggested by Gregg & Petrongolo (1997) as regressors. The results are displayed in the first six columns of *Table 2*.[22]

By and large, the results are consistent with the theoretical predictions. Hence, the estimated scale elasticity is decreasing with decreasing measurement frequency in the data. Furthermore, for each frequency, the estimated scale elasticity is higher when the measures of job seekers and vacancies include half the inflow during the period than when the beginning-of-period stocks are used. In fact, all point estimates of the scale elasticity are well below unity and only non-significantly different from unity in the model estimated on weekly data including the half of the inflows during the week of vacancies and job seekers.

The estimated elasticities are generally much higher for job seekers than for vacancies. This may, of course, partly reflect measurement error in the vacancy series. However, the finding seems to be fairly consistent with the results reported in Petrongolo & Pissarides (2001), although the results reported there vary a lot.[23]

[21]Previous Swedish studies have mainly used knowledge of the inflow of vacancies and vacancy stocks to construct a measure of the outflow of vacancies.

[22]The same models have been estimated using an outflow measure excluding those leaving the register for unknown reasons. The results were qualitatively similar.

[23]Estimating models including quadratic time trends generally give somewhat higher point estimates for vacancies and somewhat lower point estimates for the number of

5.2 Labour market programmes, unemployment duration and matching

Edin & Holmlund (1991) and Hallgren (1996) found that programme participants contribute to matching to a lesser extent than openly unemployed job seekers. However, because programme participants on average also have longer spells of non-employment, it is not clear whether the earlier results reflect that programme participation causes smaller hazards to jobs or that the lower job-finding rates of programme participants simply reflects that they on average have longer non-employment durations.[24]

In columns 7 and 8 in Table 2 we present the results of adding the share of programme participants of the total number of job seekers as well as the fraction of long-term unemployed ($>$ 12 months; column 7) and short-term unemployed ($\leq$ 12 months; column 8) to the log-linear matching model. The effects are fairly precisely estimated and clearly indicate that programme participants contribute to matching to a lesser extent than openly unemployed job seekers, also when controlling for the shares of long-term or short-term unemployed job seekers.[25] Hence, the estimated negative effect of programme participants on matching seems not only to reflect that programme participants on average have longer unemployment durations.

job seekers. The estimated scale elasticities are fairly similar in those models, except for the models estimated on quarterly data, where the estimated scale elasticities are much higher, especially in the model including half of the within-period inflows, where the estimated elasticity is significantly greater than unity (point estimate 1.64).

[24]Neither Edin & Holmlund (1991) nor Hallgren (1996) had information on both durations and programme participation.

[25]The shares of long-term and short-term unemployed enter the estimated model with the expected signs, negative and positive, respectively.

Table 2: Estimated log-linear matching functions

	1	2	3	4	5	6	7	8
Frequency	weekly	weekly	monthly	monthly	quarterly	quarterly	weekly	weekly
Variable								
const	2.03	-1.73	4.82	3.66	7.68	5.61	-5.26	-4.94
	(1.24)	(1.59)	(1.48)	(1.45)	(1.18)	(1.76)	(1.47)	(1.60)
V_{t-1}	0.06		0.15		0.08			
	(0.03)		(0.04)		(0.03)			
U_{t-1}	0.47		0.32		0.24			
	(0.08)		(0.09)		(0.07)			
$V_{t-1} + .5v_t$		0.24		0.22		0.15	0.26	0.26
		(0.05)		(0.05)		(0.06)	(0.04)	(0.04)
$U_{t-1} + .5u_t$		0.63		0.35		0.32	0.84	0.85
		(0.10)		(0.12)		(0.09)	(0.08)	(0.10)
R_{t-1}/U_{t-1}							-0.21	-0.21
							(0.09)	(0.09)
$\frac{U_{t-1}(>12m)}{U_{t-1}}$							-0.18	
							(0.04)	
$\frac{U_{t-1}(\leq 12m)}{U_{t-1}}$								0.49
								(0.14)
Scale elast. μ	0.53	0.87	0.47	0.57	0.32	0.47	1.10	1.11
P($\mu = 1$)	0.00	0.30	0.00	0.00	0.00	0.00	0.39	0.42
# Obs.	580	580	129	129	38	38	580	580
$\bar{R}^2$	0.47	0.49	0.46	0.45	0.69	0.69	0.51	0.50

Note: Weekly, monthly, and quarterly data 1991-2002. The outflow includes half of those leaving the register for unknown reasons. Newey-West standard errors in brackets. Data seasonally adjusted using centered dummies. Error term assumed to follow AR(5) process and parameters for this process have been estimated (but not reported in the table) using Eviews.