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SCALE EFFECTS IN MARKETS WITH SEARCH*

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Estimates of aggregate matching functions may miss important scale effects in frictional labour markets because of the reactions of job seekers to scale. We estimate a semi-structural model of search and matching on a British sample of unemployed people, testing for scale effects on the probability of receiving an offer and on the distribution of wage offers. We find them only in wage offers but we also find that reservation wages rise to deliver higher post-unemployment wages but not faster matches. So aggregate matching functions should be unaffected by scale but wage equations should be showing them.

Are unemployed workers better off when searching in a larger market? Intuitively the answer seems obvious – yes, because in a larger market there are more firms and more choice. This intuition led some authors to work with search models characterised by increasing returns to scale. For example, Diamond (1982) has shown that increasing returns can support high-activity and low-activity equilibria. In the low-activity equilibrium buyers do not come into the market because there are not enough sellers, and sellers do not come in because there are no buyers. Other authors have shown that if there are increasing returns in search, the externalities due to thin or congested markets cannot be internalised by wages (Pissarides, 1984; Howitt and McAfee, 1987). With constant returns the externalities can be internalised. In a different context, it has been shown that when the matching process is characterised by increasing returns, industry is more likely to agglomerate, to take advantage of the increasing returns by creating a larger local labour market (Helsley and Strange, 1990; Amiti and Pissarides, 2005).

The realisation that scale effects can have such implications gave rise to a large amount of empirical work; see Petrongolo and Pissarides (2001) for a survey. The most common test for increasing returns is to estimate matching functions for the economy as a whole, or for regions, or for individual workers. A matching function is a relation between the inputs into search, usually the number of workers looking for a job and the number of available vacant jobs, and the output, the number of successful matches. For individual workers the relevant function is the hazard rate, or the probability of leaving unemployment. Increasing returns in aggregate matching functions cannot be rejected if a proportional increase in the numbers of job seekers and job vacancies increases the matching rate by a bigger proportion. In regional matching functions or in hazard-function estimation scale effects can also be tested by estimating the impact of the size of the local labour market on the number of matches or on the typical individual's hazard rate.

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But despite the intuition behind increasing returns, empirical work has largely supported constant returns to scale. Of course, there are exceptions but the exceptions are not ones that consistently apply to some cases or some periods. Rather, a few diverse estimates support increasing or decreasing returns, with the majority supporting constant returns.[1] The estimates used to test for scale effects, however, are usually based on reduced forms. Our main claim in this paper is that it is feasible for constant returns in matching functions and hazard rates to coexist with increasing returns at one of the structural levels of the search process.

For a match to occur two things need to be satisfied. First, a firm with a vacancy has to meet with a worker who qualifies for the job. These meetings are the outcome of a 'meetings technology' and they depend on the channels that bring firms and workers together in labour markets, such as word of mouth, newspaper advertising or the internet. Second, the match needs to be productive enough in relation to the available alternatives to make it acceptable to both the firm and the worker. We will argue that it is possible to have increasing (or decreasing) returns either in the meetings technology or in the productivity of the match, and yet observe constant returns in the overall matching process, because the responses of firms and workers to the increasing returns can cancel out their effects on the probability of making the match.

It is useful to think in terms of a market that is organised as follows. A meetings technology brings together firms with job vacancies and workers looking for a job. When a meeting takes place, the firm observes the productivity of the match and makes a wage offer. Workers accept or reject this wage offer on the basis of a reservation wage rule. If matches are on average more productive in larger markets because of scale effects, the mean wage offer in a larger market will be higher. Workers observe the higher mean wage offer and in general choose a higher reservation wage. It is possible – in fact we argue that it is likely – that reservation wages are raised sufficiently to offset any impact that the higher wage offers may have on the overall matching probability. In such cases the estimated matching function should be independent of scale. The increasing returns are associated with higher post-unemployment wages but not with shorter durations of unemployment. They should show up in estimated wage equations but not in estimated matching functions.

We outline a standard model of search and make the theoretical case for the coexistence of increasing returns at the structural level and constant returns at the aggregate matching level. We show that at the structural level scale effects could be observed at two levels: at the level of the arrival of job offers and at the level of the distribution of wage offers. In both cases optimal reservation wages could adjust to

[1] Some may claim that the statement in the text is unduly strong. For example, estimates using translog matching functions, like the ones by Warren (1996) and Yashiv (2000), are more supportive of increasing returns than estimates using loglinear functions. Also, estimates restricted to manufacturing are more supportive of increasing returns than estimates that use whole-economy data; see Blanchard and Diamond (1990) and again, Warren (1996). But it would be premature to generalise from this small number of examples and claim that increasing returns are a feature of all such cases. Some other authors even find decreasing returns, e.g., Burda and Wyplosz (1994) for France and Fahr and Sunde (2004) for Germany, and at least one author identifies a change in the returns to scale in Germany, from increasing returns to constant or decreasing (Gross, 1997).

offset, partially and sometimes even completely, their effects on the individual's hazard rate, and by extension on the aggregate matching rate. The extent to which they do depends on the properties of the distribution of wage offers and on the relation between reservation wages and unemployment income.[2] We should emphasise that the distinction that we are drawing is not necessarily between the 'micro' level and the 'macro' level. It is between the distribution of wage offers and the arrival of job offers on the one hand and their joint outcome, the matching rate, on the other hand.

We estimate our model and look for scale effects at both the structural and aggregate levels by making use of a British sample of 3,000 unemployed individuals. We can do this because in addition to the usual variables (personal and local labour-market characteristics, censored and uncensored durations of unemployment and post-unemployment wages) it also contains information on reservation wages. We decompose hazard functions into the probability of receiving an offer and the probability of accepting it, and estimate the influence of personal and local labour-market characteristics on each.

We find scale effects in the productivity of the job match (proxied by the mean of the wage offer distribution) but not in the arrival of job offers. But we also find that reservation wages increase to nearly offset the impact of increasing returns on the unemployment hazard rate. Because in larger markets workers search with higher reservation wages, the effect of scale shows up as a higher post-unemployment wage and not as a shorter duration of unemployment. Matching functions derived from our sample satisfy constant returns.

Theory suggests that reservation wages should offset the effects of scale on hazard rates only if unemployment income (net of search costs) is small. We show that our estimates imply that even conventionally 'high' average replacement ratios, 40% of the mean wage rate net of search costs, imply that the scale effects in the productivity of job matches should be reflected primarily on post-unemployment wages. A small effect on hazard rates remains but we show that it is sufficiently small that reduced-form estimation is not likely to pick it up, even in the absence of other offsetting mechanisms. Our theoretical analysis goes further to suggest that in general if the impact of the mean wage offer on the unemployment hazard is small, the impact of the offer arrival rate on the hazard will be large.

This last finding and our estimates of the structural equations contain an unexpected result. The aggregate matching function is a black box, in the sense that not much is known about its internal structure and microfoundations. Our objective here was not to probe into the microfoundations of matching functions, but our analysis implies a restriction that should prove useful in future work; namely, shifts in variables that influence the search process through the mean of the distribution of wage offers shift mainly the post-unemployment wage distribution, with virtually no influence on matching rates. And shifts in variables that work through the mechanics of the meetings technology shift the matching function, with virtually no influence on the post-unemployment wage distribution.

[2] Teulings and Gautier (2002) argue that scale effects at the structural level could also be offset by other agent reactions related to the equilibrium process, e.g., labour or job mobility.

In our empirical tests we adopt two alternative measures of local markets. One is the county. There are 66 counties in Great Britain, with mean employment level 322,285 people and range 6,000 to 3,515,400. The other is the Travel-To-Work-Area, which is more disaggregate and should roughly coincide with commuting districts. There are 310 TTWAs in Britain, with mean employment level 68,618, and range 1,500–3,131,600. We find qualitatively very similar results for the two alternative measures.

The article is organised as follows. In Section 1 we outline an infinite-horizon search model and show the effect of changes in both the arrival rate of job offers and the mean wage offer on the job-finding rate. Section 2 describes our data set and presents some preliminary evidence. In Section 3 we specify the likelihood function and estimate the model, letting both the arrival rate of job offers and the mean wage offer depend on individual and local labour market characteristics. The results are discussed in Section 4. Section 5 draws out more general implications of our estimates for aggregate matching functions. General conclusions are brought together in Section 6.

1. The Model

An unemployed individual searches for a job in a local labour market. Offers arrive randomly according to a Poisson distribution with parameter $p(\mathbf{x})$, where $\mathbf{x}$ is a vector of personal and local labour-market characteristics. When an offer arrives, the individual has the option of accepting a wage which is randomly drawn from the known and fixed distribution $F(w)$. We assume that $F(w)$ is lognormal with mean $\mu(\mathbf{z})$, where $\mathbf{z}$ is another vector of personal and local labour-market characteristics, and standard deviation σ_w, which is a fixed parameter.[3] If the worker accepts the offer she leaves unemployment and earns w for the duration of the job. If she rejects the offer she waits for a new offer to arrive, and on average one does after $1/p(\mathbf{x})$ periods. The stopping rule is governed by the reservation wage w^*, which is a choice variable. The unemployment hazard rate is h, defined by:

$$h = h(\mathbf{x}, \mathbf{z}) = p(\mathbf{x})\{1 - F[w^*; \mu(\mathbf{z}), \sigma_w]\}. \tag{1}$$

Our data contain information on w^* and unemployment durations for each individual (from which we can make inferences about h), and on a variety of personal and local labour-market characteristics, which are candidates for the vectors $\mathbf{x}$ and $\mathbf{z}$. This allows us to estimate $p(\mathbf{x})$, $\mu(\mathbf{z})$ and σ_w for each individual, conditional on the distribution F and on an optimising search model. Our primary interest is two fold. First, to identify separately whether scale affects the offer arrival rate or the mean of the offer distribution; formally, whether the vectors $\mathbf{x}$ and $\mathbf{z}$ contain variables for the size of the local labour market. Second, to compute the reaction of reservation wages to the vectors $\mathbf{x}$ and $\mathbf{z}$, and from these to obtain the reduced form hazard function. The key question is whether there are size variables

[3] If E() is the expectations operator, $\mu = \mathrm{E}(\ln w)$. Let $\bar{w}$ be the mean wage offer, then $\mu = \ln \bar{w} - \frac{1}{2}\sigma_w^2$, so for any variable z, $\mu'(z) = \bar{w}'(z)/\bar{w}$. We refer to μ as the mean of the wage offer distribution and to $\bar{w}$ as the mean wage offer.

that influence either p or μ, where intuition about scale effects normally applies, but which do not influence the hazard rate, because of the dependence of the latter on reservation wages.

The search model is a conventional continuous-time model for an unemployed individual with infinite horizon looking for a permanent job. The labour market environment is stationary and the unemployment hazard independent of duration. The model is partial, in the sense that both p and $F(w)$ are exogenous. During search, unemployed individuals enjoy some flow real return b (typically including the imputed value of leisure and unemployment insurance benefits, net of the cost of search) and discount future incomes at the instantaneous discount rate r. Under these assumptions we can use Bellman equations to derive stationary values for unemployment and employment, respectively denoted by V_n and $V_e(w)$. The Bellman equation satisfied by the value of unemployment is

$$rV_n = b + p\left\{\int \max[V_n, V_e(w)]dF(w) - V_n\right\}. \tag{2}$$

Employment is an absorbing state; its value is given by

$$rV_e(w) = w. \tag{3}$$

Trivially, the choice between V_n and $V_e(w)$ inside the integral of (2) can be described by a reservation rule. There is a unique reservation wage w^* such that $V_n = V_e(w^*) = w^*/r$. The reservation wage satisfies an equation derived from (2),

$$\begin{aligned} w^* = rV_n &= b + p\int_{w^*}[V_e(w) - V_n]\mathrm{d}F(w) \\ &= b + \frac{p}{r}\int_{w^*}(w - w^*)\mathrm{d}F(w). \end{aligned} \tag{4}$$

Let x now be an element of the vector $\mathbf{x}$, a parameter that influences p but not F, and without loss of generality let $p'(x) > 0$. Differentiation of (1) with respect to x yields, in elasticity form,

$$\frac{\partial h}{\partial x}\frac{x}{h} = \frac{xp'(x)}{p(x)} - \frac{w^* F'(w^*)}{1 - F(w^*)}\frac{\partial w^*}{\partial x}\frac{x}{w^*}. \tag{5}$$

and from (4),

$$\frac{\partial w^*}{\partial x}\frac{x}{w^*} = \frac{xp'(x)}{p(x)}\frac{w^* - b}{w^*}\frac{r}{r + h} \geq 0. \tag{6}$$

Substitution from (6) into (5) yields

$$\frac{\partial h}{\partial x}\frac{x}{h} = \frac{xp'(x)}{p(x)}\left[1 - \varepsilon(w^*)\frac{w^* - b}{w^*}\frac{r}{r + h}\right], \tag{7}$$

where we have introduced the symbol $\varepsilon(w^*)$ for the absolute value of the elasticity of the acceptance probability $1 - F(w^*)$ with respect to the reservation wage.

In general, the sign of $\partial h/\partial x$ is ambiguous, because the sign of the term in the brackets of (7) is ambiguous. The direct effect of x on the hazard is positive. The indirect effect via the reservation wage is negative. Reservation wages increase when the arrival of offers increases and this can offset the direct impact on the hazard rate.

For a given value of the elasticity of the reservation wage with respect to x, the negative impact on the hazard is proportional to the elasticity $\varepsilon(w^*)$, which depends on the wage-offer distribution. For example, for a uniform distribution the elasticity is $w^*/(\hat{w} - w^*)$, where $\hat{w}$ is the highest wage offer, and for the Pareto distribution it is a constant. For the lognormal the expression is more complicated. In general, Burdett (1981) and Van den Berg (1994) have shown that it is possible to find distributions that imply $\partial h/\partial x < 0$, because of the value taken by that elasticity, although empirically reasonable distributions normally imply $\partial h/\partial x \geq 0$. Past empirical work also confirmed a positive impact of the offer arrival rate on hazard rates.[4] The lognormal distribution that we use in our empirical model certainly satisfies Van den Berg's restrictions for a positive impact of the offer arrival rate on the hazard, so the focus of our research is not whether the impact is positive or negative but how large it is and how much of the direct effect is offset by adjustments in the reservation wage.

Consider next a parameter z that improves the wage offer distribution, i.e., let F depend on z such that $F(w; z)$ stochastically dominates $F(w; z')$ if $z > z'$. The effect of a small displacement in z on the hazard rate is

$$\frac{\partial h}{\partial z} = -p\left[\frac{\partial F(w^*)}{\partial z} + F'(w^*)\frac{\partial w^*}{\partial z}\right]. \tag{8}$$

By the stochastic dominance assumption made, $\partial F(w^*)/\partial z < 0$, and from (4) it immediately follows that $\partial w^*/\partial z > 0$, so once again there is an ambiguity in the effects of an improvement in the offer distribution. In our empirical work we restrict the estimation to shifts in the mean of the lognormal wage-offer distribution, holding variance constant. The effect is still ambiguous but it can now be calculated and estimated.

The density and cumulative density of the lognormal and normal distributions are related by

$$F'(w) = \frac{1}{w\sigma_w}\Phi'\left(\frac{\ln w - \mu}{\sigma_w}\right) \tag{9}$$

and

$$F(w) = \Phi\left(\frac{\ln w - \mu}{\sigma_w}\right), \tag{10}$$

where $\Phi(\cdot)$ is the cumulative normal density. For any parameter z that influences the mean of the lognormal, (10) yields

[4] The empirical ambiguity has been noted in the literature for some time. See Barron (1975) for an early contribution. Of course, if reservation wages reversed the effect of contact rates on the hazard rate Beveridge curves would slope upwards. There is overwhelming evidence that they slope downwards. See Pissarides (2000) for more discussion of these points, especially chapter 6.

$$\frac{\partial F(w^*)}{\partial z} = -\frac{1}{\sigma_w}\Phi'\left(\frac{\ln w - \mu}{\sigma_w}\right)\mu'(z) \\ = -w^* F'(w^*)\mu'(z). \tag{11}$$

Given results for the lognormal we can write, see, e.g., Eckstein and Wolpin (1995, p. 275):

$$\int_{w^*} w \mathrm{d}F(w) = \exp\left(\frac{1}{2}\sigma_w^2 + \mu\right)\left[1 - \Phi\left(\frac{\ln w^* - \mu}{\sigma_w} - \sigma_w\right)\right], \tag{12}$$

so the reservation wage in (4) becomes

$$w^* = \frac{rb + p\exp\left(\frac{1}{2}\sigma_w^2 + \mu\right)\left[1 - \Phi\left(\frac{\ln w^* - \mu}{\sigma_w} - \sigma_w\right)\right]}{r + p\left[1 - \Phi\left(\frac{\ln w^* - \mu}{\sigma_w}\right)\right]}. \tag{13}$$

As for (4), this equation satisfies the envelope property by the optimality of the reservation wage, so by differentiation we obtain

$$\frac{\partial w^*}{\partial z} = \frac{p\exp\left(\frac{1}{2}\sigma_w^2 + \mu\right)\left[1 - \Phi\left(\frac{\ln w^* - \mu}{\sigma_w} - \sigma_w\right)\right]}{r + p\left[1 - \Phi\left(\frac{\ln w^* - \mu}{\sigma_w}\right)\right]}\mu'(z). \tag{14}$$

Making use of (13) and the definition of the hazard function in (1), we obtain,

$$\frac{1}{w^*\mu'(z)}\frac{\partial w^*}{\partial z} = \frac{w^*(r+h) - rb}{w^*(r+h)}. \tag{15}$$

Substitution of $\partial F(w^*)/\partial z$ from (11) and $\partial w^*/\partial z$ from (15) into (8) yields

$$\frac{\partial h}{\partial z}\frac{1}{h} = \frac{rb}{(r+h)w^*}\varepsilon(w^*)\mu'(z), \tag{16}$$

which, given the argument in footnote 3, is equivalent to

$$\frac{\partial h}{\partial z}\frac{z}{h} = \frac{z\bar{w}'(z)}{\bar{w}(z)}\frac{rb}{(r+h)w^*}\varepsilon(w^*), \tag{17}$$

where $\bar{w}$ is the mean wage offer.

Thus, for any proportional change in the mean wage offer, the impact on the hazard is bigger when the elasticity of the acceptance probability with respect to the reservation wage is bigger and when the gap between the discount rate and the hazard rate is smaller. Note that these conditions were the ones that gave a smaller impact on the hazard from changes in the job arrival rate. But a higher ratio of unemployment income to the reservation wage implies higher impact from both x and z on the hazard. To show these connections more formally, and provided $b > 0$, we substitute $\varepsilon(w^*)$ from (17) into (7) to obtain,

$$\frac{\partial h}{\partial x}\frac{x}{h}\bigg/\frac{xp'(x)}{p(x)} = 1 - \left[\frac{\partial h}{\partial z}\frac{z}{h}\bigg/\frac{z\bar{w}'(z)}{\bar{w}(z)}\right]\frac{w^* - b}{b}. \tag{18}$$

The significance of this equation becomes more transparent if we treat the offer arrival probability and the mean wage offer as the primitive parameters and rewrite it as

$$\frac{\partial h}{\partial p}\frac{p}{h} = 1 - \frac{\partial h}{\partial \bar{w}}\frac{\bar{w}}{h}\left(\frac{w^*}{b} - 1\right). \tag{19}$$

Thus, for given ratio of unemployment income to the reservation wage, there is an inverse linear relation between the impact of the mean wage offer on the hazard and the impact of the offer arrival rate. If the reservation wage is twice as big as unemployment income, which is plausible, the two elasticities sum to 1. Without wanting to anticipate too much the empirical results, one of our main conclusions is that empirically the impact of the mean wage offer on the hazard turns out to be small and consequently the impact of the offer arrival rate is large.

Our empirical strategy is to use information on reservation wages and unemployment durations to uncover the dependence of the offer arrival rate and the mean of the wage offer distribution on the size of the local market and other parameters. We explain how (1) and (4) can be used to construct a likelihood function after a description of the data.

2. Data

The data used for this study come from the UK Survey of Incomes In and Out of Work (SIIOW). This was a one-off survey that collected individual information on a representative sample of men and women who started a spell of unemployment, and registered at any of the 88 Unemployment Benefit Offices (UBO) selected, in the four weeks starting March 16, 1987. Information on survey participants was collected from two separate personal interviews. The first interviews were carried out shortly after unemployment began, between April and July 1987, and a total of 3,003 interviews were completed. The second interviews were held about nine months later, in January 1988, on respondents who had been interviewed in 1987 and had consented to a second interview. A total of 2,146 interviews were completed at this second stage. We use available information on all respondents interviewed once or twice, by assuming that attrition between the first and second interview is random.

The first interview focused on individuals' personal characteristics and their employment history during the 12 months prior to the interview, including employment and unemployment income, type of job held and job search activities while unemployed. The follow-up interview covered individuals' employment history since their first interview.

The data contain three types of unemployment spells. *Completed spells*, by respondents who had found jobs by the time of the first or second interview. Completed spells are measured by the number of weeks between the date the worker signed at the UBO and the date he or she re-entered employment. The longest completed spells in the sample are between nine and ten months. *Censored spells*, by respondents still unemployed at the time of the second interview (or the first interview for those who only had one interview), measured by the number of weeks between the date the respondent registered at the UBO and the date of the interview. Finally, *censored spells* by respondents who left the register without finding a job. This type of censored spell is measured by the number of weeks that the respondent was on the unemployment register. We call the third type of spell a censored spell following the logic of a competing risk duration model. Exits into jobs compete with exits into other states but given that our focus is on the determinants of the exit into jobs, all unemployment durations finishing with destinations other than jobs are treated as censored, under the assumption that distinct destinations depend upon disjoint subset of parameters (Narendranathan and Stewart, 1993).

In addition to data on unemployment spells, we use information on worker reservation wages and on their post-unemployment wages. The information on reservation wages comes from the question 'what is the lowest weekly take-home pay you might consider accepting', which is asked of all unemployed workers, or the question 'what is the lowest weekly take-home pay you might have considered accepting', which is asked of those already employed at the time of the first interview. We then obtain hourly reservation wages by using information on the expected number of hours to be worked each week. Post-unemployment hourly wages are constructed from a question on the usual weekly take-home pay in the first job after the unemployment spell and a question on the usual hours worked. Although for our purposes it would be more appropriate to estimate the parameters of the pre-tax wage distribution, better representing the productivity distribution across firms, we have no choice but to estimate the distribution of take-home pay, as information on the (subjective) pre-tax reservation wage is not available (and constructing a tax schedule for each individual is also not feasible).

Using self-reported information on reservation wages involves a problem, namely that it is not guaranteed that the reservation wage falls always between net unemployment income and the post-unemployment wage, as required by our model.[5] We find that self-reported reservation wages are higher than post-unemployment wages for 16% of observations in our sample. We explain in the next Section how we deal with this apparent discrepancy between theory and observation. It is a lot more difficult to compare reported wages with income during unemployment. In the absence of information on the cost of search, we cannot directly compare reservation wages with *net* unemployment income. A comparison of reservation wages with reported unemployment income shows that unemployment benefits exceed reported reservation wages in only 5% of our sample.[6]

[5] In some cases, e.g. when having a job increases the entitlement to unemployment compensation, it may be optimal to set the reservation wage below actual unemployment income. See Mortensen (1977).

[6] Further tests on the reliability of the reservation wage information in the SIIOW were carried out by Manning and Thomas (1997), who estimated both wage regressions and unemployment duration models on these data. They showed that, consistent with our search model, both post unemployment wages and unemployment duration depend positively on self-reported reservation wages. For more general discussion of the problems and benefits involved in the use of self-reported reservation wage data see Lancaster and Chesher (1983), who make use of two British surveys of unemployed workers (the P.E.P. survey of 1973 and the Oxford survey of 1971). More recently a number of authors have used Dutch data on self-reported reservation wages, where econometric procedures are also discussed, e.g., Van den Berg and Gorter (1997), Van den Berg (1990) and Bloemen and Stancanelli (2001).

The information on hourly reservation wages is missing for 773 workers. 1,445 workers in the sample found a job within the survey period, while 1,558 were still jobless at the time of the second interview or had left the unemployment register. Among those who found jobs, the information on the hourly take-home pay is missing in 330 cases. These 330 cases are included in the sample and we make use of the information that they still convey; that they have had an offer exceeding their reservation wage. The final sample consists of 2,229 respondents, the missing ones being the 773 with no reservation wage information and 1 observation with no age information.

Given a roughly 25% non-response rate on the reservation wage question, one may worry whether non-response is random. The best we can do in this case is to check whether individuals with missing information on reservation wages differ systematically from those included in our sample in terms of observed characteristics. We thus run a regression of (log) wages on the set of variables used for our main estimates, plus a dummy for the missing reservation wage. The coefficient on the dummy variable was insignificant both when no other variables were included in the regression and when all the other controls were included (p–values being 0.76 and 0.55 respectively). We conclude that there are no systematic relationships between individual characteristics and failure to report reservation wages, so we treat non-reporting as random. Some summary statistics of the sample used are presented in Table 1.

We use two alternative characterisations of local labour markets. The first is represented by counties: there are 66 counties in Britain, with an average population slightly above 800,000, and respondents in the SIIOW reside in 43 of them. We have an average of 52 individuals per county, ranging from 14 in Wiltshire and the Lothian Region to 267 in Greater London. The second is more disaggregate and is represented by Travel-To-Work-Areas, roughly coinciding with commuting districts: in 1987 there were 310 TTWAs in Britain, with an average population slightly above 170,000, and respondents resided in 63 of them. We have an average of 35 individuals per TTWA, from 8 in Tunbridge Wells to 183 in London (the

Table 1

Sample Characteristics of the Unemployment Inflow

Variables	Mean	St.dev.	No.obs.
Uncensored	52.7		2,229
Uncensored duration	12.3	11.1	1,174
Censored duration	23.9	17.4	1,055
Females	37.7		2,229
Age	36.9	11.5	2,229
Skilled	43.4		2,229
Hourly res. wage	2.38	0.98	2,229
Hourly take-home pay	2.57	1.30	927

Notes. *Uncensored*: includes all those who found jobs by the second interview date. *Skilled*: includes all those who attended school or vocational training courses until the age of 18, plus those with higher education. *Hourly res. wage*: denotes the lowest weekly take-home pay that the worker considers accepting, divided by the expected number of hours worked. *Source*. SIIOW.

Greater London county and the London TTWA do not coincide as the first roughly corresponds to the London and Heathrow TTWAs).

We then merge individual records from the SIIOW with official labour market statistics at both the county and the TTWA level, extracted from the NOMIS database (http://www.nomisweb.co.uk/). For confidentiality reasons the SIIOW does not attach explicit geographic identifiers to interviewees. The only geographical information that is provided is the code of the UBO at which the worker is registered. Using NOMIS information, we achieved mappings between UBOs and counties, and between UBOs and TTWAs. The information on local labour markets that we use in our estimates is reported in Table 2 for both counties and TTWAs. The only variable that is not available at the TTWA level but is instead available at the county level is the number of registered businesses.

A preliminary picture of the relationship between market size and different aspects of the job search process can be gathered by simply regressing local mean wages, mean reservation wages and mean unemployment duration, respectively, on market size. In particular, we compute mean wages, mean reservation wages and mean unemployment duration by 2 educational groups and 43 counties (or 64 TTWAs). These are regressed on an education dummy, the local labour market tightness (denoted by θ), the number of vacancies in one's skill segment (V_s), representing the effect of size, and their fraction in total vacancies (V_s/V), representing tightness by skill, in the absence of data on unemployment by skill at the local level. The estimated coefficients on market size are reported in Table 3. The figures reported in the first row show that local wages are positively correlated with the number of job openings, although the size effect becomes insignificantly

Table 2

Local Labour Markets in Britain

	Counties		TTWAs	
Variables	Mean	St.dev.	Mean	St.dev.
Unemployed	59,986	68,698	27,057	48,484
Vacancies	4,140	5,639	1,772	3,773
Tightness	0.08	0.03	0.05	0.05
Skilled vacancies	1,072	1,614	230	487
Unskilled vacancies	2,710	3,397	825	1,784
Firms	26,118	30,463	-	-
Average firm size	15.8	4.3	-	-
Area size (acres)	347,258	431,079	66,301	54,193
No. of observations	43		64	

Notes. *Unemployed*: number of claimant unemployed, April 1987. *Vacancies*: vacancies advertised at Job Centres, April 1987. *Tightness*: vacancies/unemployed. *Skilled vacancies*: vacancies advertised at Job Centres, March 1987, in the following KOS occupations: managerial; professional: supporting; professional (education, welfare); literary, artistics, sports; professional (science, engineering); managerial (excluding general); clerical and related. *Unskilled vacancies*: vacancies advertised at Job Centres, March 1987, in the following KOS occupations: selling; security and protective; catering, cleaning etc.; farming, fishing and related; processing (excl. metal); making/repairing; processing (metal./elect.); repetitive assembling etc.; construction, mining; transport operating; miscellaneous. *Firms*: stock of VAT registered businesses at the end of 1986 (information not available at the TTWA level). *Average firm size*: employment/firms. *Area size*: area of county/TTWA, in acres. *Source*: NOMIS.

Table 3

Mean Wages, Reservation Wages, Unemployment Duration and Labour Market Size

	Counties		TTWAs	
Dependent variable	Whole sample	Excl. London	Whole sample	Excl. London
Wages	0.038**	0.005	0.033***	0.023*
	(0.016)	(0.024)	(0.011)	(0.013)
Reservation wages	0.045***	−0.005	0.037***	0.019*
	(0.011)	(0.017)	(0.007)	(0.010)
Unemployment duration	0.007	−0.001	0.023	0.024
	(0.023)	(0.038)	(0.016)	(0.021)

Notes. The dependent variable in row 1 is the (log) mean wage across 2 educational groups and 43 counties/64 TTWAs. In row 2 it is the (log) mean reservation wage and in row 3 it is the (log) mean unemployment duration. Figures reported are coefficients on the (log) market size, proxied by the number of vacancies by skill. Each regression also includes a skill dummy, the (log) local labour market tightness and the (log) fraction of vacancies in each skill segment. Estimation method: weighted least squares, with weights given by the number of observations in each skill/local labour market cell. Significance at 10%, 5% and 1% levels is denoted by *, **, and *** respectively. *Source*: SIIOW and NOMIS.

different from zero when we exclude Greater London. When using data at the TTWA-level, we detect a (marginally) significant size effect on wages whether or not we include London in our sample. While the results on reservation wages closely follow those found for post-unemployment wages (second row), in no specification can any scale effect be detected on mean unemployment duration (third row).

3. Estimation Specification

Having modelled unemployment duration in continuous time, the likelihood contribution of an individual with an unemployment spell length of d_i, and, in the case the spell is completed, a wage w_i is

$$\begin{aligned} L_i &= \exp[-p\Pr(w \geq w^*)d_i][p\Pr(w \geq w^*|w_i)\Pr(w_i)]^{c_i} \\ &= \exp[-p\Pr(w \geq w^*)d_i][pf(w_i)]^{c_i}, \end{aligned} \tag{20}$$

where c_i is a censoring indicator that takes value 1 if the unemployment spell is completed and 0 otherwise (we ignore for the moment workers with completed spells but missing post-unemployment wage). Under the log-normality assumptions, (23) becomes

$$L_i = \exp\left\{-p\left[1 - \Phi\left(\frac{\ln w^* - \mu}{\sigma_w}\right)\right]d_i\right\}\left[p\frac{1}{w_i\sigma_w}\phi\left(\frac{\ln w_i - \mu}{\sigma_w}\right)\right]^{c_i}. \tag{21}$$

The parameters of the model can be estimated by maximising the log likelihood of a sample of n observations, $\log L = \sum_{i=1}^{n} \log L_i$, with L_i given by (21), with respect to p, w^*, μ and σ_w, under the restriction imposed by (13) and $w^* > 0$. The availability of data on reservation wages in our data set avoids a problem often encountered by studies that have to estimate the reservation wage. Flinn and Heckman (1982) show that if observed wages are measured without error, the maximum likelihood estimator for w^* is the minimum accepted wage $\underline{w}$. But this method implies that the reservation wage cannot be greater than any observed wage in the sample, so the presence of outliers in the observed wage distribution disproportionately affects the results, by attributing the distance between the observed wage and the reservation wage to unobservable or chance events.

When we use reported reservation wage data for w^*, it is no longer guaranteed that realised wages always exceed reservation wages. In the context of the empirical model an observation with $w < w^*$ has a zero likelihood, as the distribution of realised wages should be truncated from below at the reservation wage. But the inconsistency between theory and observation arises only if both reservation wages and post-unemployment wages are measured without error. We generalise the empirical model by assuming that post-unemployment wages are measured with error, i.e., we let $\ln w^0 = \ln w + u$, where w denotes the wage offer received by the worker and w^0 our observation of the wage. The measurement error u is assumed to be normally distributed with 0 mean and variance σ_u^2, and independent of w. Therefore observed wages w^0 are log-normally distributed, with mean μ and variance $\sigma^2 = \sigma_w^2 + \sigma_u^2$. Under these assumptions, the probability of receiving an acceptable offer remains $1 - \Phi[(\ln w^* - \mu)/\sigma_w]$. The joint probability that the true wage exceeds the reservation wage and that w^0 is observed can be computed using the moments of the distribution of w, conditional on w^0. In particular:

$$\Pr(w \geq w^*|w^0)\Pr(w^0) = \left\{1 - \Phi\left[\frac{\ln w^* - \rho^2 \ln w^0 - (1-\rho^2)\mu}{\rho\sigma_u}\right]\right\}\frac{1}{w^0\sigma}\phi\left(\frac{\ln w^0 - \mu}{\sigma}\right), \tag{22}$$

where $\rho^2 = \sigma_w^2/\sigma^2$ represents the share of observed wage variation which is not explained by the measurement error.[7] The resulting likelihood is

$$L_i = \exp\left\{-p\left[1 - \Phi\left(\frac{\ln w_i^* - \mu}{\sigma_w}\right)\right]d_i\right\} \left(p\left\{1 - \Phi\left[\frac{\ln w_i^* - \rho^2 \ln w_i^0 - (1-\rho^2)\mu}{\rho\sigma_u}\right]\right\}\frac{1}{w_i^0\sigma}\phi\left(\frac{\ln w_i^0 - \mu}{\sigma}\right)\right)^{c_i}. \tag{23}$$

Finally we need to allow for the existence of respondents who complete an unemployment spell but do not provide information on their post-unemployment

[7] The assumption that wages are measured with error is used in the estimation of structural search models by Wolpin (1987), Christensen and Kiefer (1994) and Eckstein and Wolpin (1995). An alternative is to assume that the utility derived from jobs is determined by the wage and some non-monetary attributes, i.e. $v = \log w + u$, where v denotes utility from the job and u is its non-monetary component, normally distributed with mean 0, variance σ_u^2, and independent of w. In this case the probability of obtaining an acceptable offer is $1 - \Phi[(\ln w^* - \mu)/\sigma]$, and the joint probability that $v \geq w^*$ and that w is observed is

$$\Pr(v \geq w^*|w)\Pr(w) = \left[1 - \Phi\left(\frac{\ln w^* - \ln w}{\sigma_u}\right)\right]\frac{1}{w^0\sigma_w}\phi\left(\frac{\ln w^0 - \mu}{\sigma_w}\right).$$

This latter approach has been adopted by Manning and Thomas (1997). We also tried to estimate this model but found difficulties in identifying the parameter σ_u, which always had both very high point estimates and standard errors. For this reason we prefer to work with the assumption that post-unemployment wages are observed with error.

wage. The information that is conveyed by these observations is that they have had an offer exceeding their reservation wage, so, taking this into account, our likelihood function generalises to

$$L_i = \exp\left\{-p\left[1-\Phi\left(\frac{\ln w_i^* - \mu}{\sigma_w}\right)\right]d_i\right\}\left\{p\left[1-\Phi\left(\frac{\ln w_i^* - \mu}{\sigma_w}\right)\right]\right\}^{\tilde{c}_i} \left(p\left\{1-\Phi\left[\frac{\ln w_i^* - \rho^2 \ln w_i^0 - (1-\rho^2)\mu}{\rho\sigma_u}\right]\right\}\frac{1}{w_i^0\sigma}\phi\left(\frac{\ln w_i^0 - \mu}{\sigma}\right)\right)^{c_i}, \tag{24}$$

where $\tilde{c}_i$ is equal to one for all completed spells with missing wage and zero otherwise, and c_i is equal to one for all completed spells with a non-missing wage and zero otherwise.

Equation (24) is maximised with respect to p, μ, σ_w and σ_u. Note that in order to deliver both reservation wage and realised wage heterogeneity the model needs to allow for individual heterogeneity in at least one of the parameters p, μ, σ_w, σ_u. We introduce heterogeneity in both p and μ, as explained in the next Section.

Data on both unemployment duration and post-unemployment wages allow us to identify the effect of variables included in p, μ or both separately; see Flinn and Heckman (1982) and Wolpin (1987) for detailed discussions of identification issues in stationary search models. In practice, however, identification may turn out to be a delicate issue when the same covariates are included in the specification of both p and μ, because of missing information on post-unemployment wages due to censoring or non-reporting. With this caveat in mind, we present alternative specifications for p and μ as a check of the robustness of our estimates.

4. Results

The estimates presented here are based on the likelihood function (30), in which σ_w and σ_u are estimated as constant parameters, and p and μ are functions of both individual and labour market characteristics.[8] Either theory or well-established empirical regularities help determine which labour market variables should affect p and/or μ. Search theory predicts that the arrival rate of job offers should depend on labour market tightness $\theta = V/U$, which is therefore included in the determination of p. A well-known stylised fact is the employer size–wage effect, according to which large firms pay higher wages than smaller firms; see Brown and Medoff (1989). As we cannot track down individual information on employer size, we capture the size–wage effect by including the local average firm size in the determination of μ. We estimate the effect of market size with four alternative measures, the number of vacancies by broad skill category, the total number of vacancies, employment, and the number of firms. As mentioned above, no information on the number of firms is available at the TTWA level, so regressors involving this variable can only be included when local labour markets are proxied by counties. Our specification of p and μ is

[8] We attempted to include scale effects in the variance of the wage offer distribution, σ_w, but our estimation program did not achieve convergence. Note, however, that under the log-normal assumptions, the variance of wages depends positively on the mean log wage, i.e. $\mathrm{Var}(w) = \exp(2\mu + \sigma_w^2)[\exp(\sigma_w^2) - 1]$. If there are scale effects in the log of the mean wage offer, these also show up in the dispersion in the level of wages.

$$p = \exp(\alpha_0 + \alpha_1 female + \alpha_2 skilled + \alpha_3 \log age + \alpha_4 \log \theta + \alpha_5 \log size);$$
$$\mu = \beta_0 + \beta_1 female + \beta_2 skilled + \beta_3 \log \text{age} + \beta_4 \log firmsize + \beta_5 \log size.$$

Our estimated model is only semi-structural in the sense that no structural model is imposed to specify p and μ. We restrict the arrival rate of job offers to be non-negative, and its log-linear relationship with market tightness bears close resemblance with most existing matching function estimates. Wage offers are specified as log-linear functions of human capital variables, as it is typically the case in Mincerian wage equations, to which we add size controls.

Local labour market variables are defined at the county-level and at the TTWA-level in turn. We present results on counties first, reported in Table 4. In column 1 we do not include size indicators in either p or μ, and we find a fairly familiar

Table 4

Estimation Results – Local Labour Markets Proxied by Counties (Whole sample)

Variables	1	2	3	4	5	6
μ						
Constant	−1.183***	−1.161***	−1.481***	−1.283***	−1.105***	−0.970*
	(0.434)	(0.430)	(0.408)	(0.396)	(0.404)	(0.755)
Female	−0.345***	−0.343***	−0.337***	−0.339***	−0.344	−0.340***
	(0.052)	(0.052)	(0.050)	(0.050)	(0.052)	(0.050)
Skilled	0.219***	0.219***	0.295***	0.276***	0.221***	0.280***
	(0.060)	(0.060)	(0.067)	(0.057)	(0.058)	(0.058)
log(*age*)	0.514***	0.515***	0.512***	0.510***	0.515***	0.507***
	(0.092)	(0.092)	(0.088)	(0.088)	(0.091)	(0.089)
log(*firmsize*)	0.069	0.057	−0.006	−0.018	0.037	−0.054
	(0.075)	(0.075)	(0.078)	(0.075)	(0.070)	(0.104)
log(V_s)			0.064**	0.045***		0.046***
			(0.028)	(0.017)		(0.017)
log(*acres*)						−0.017
						(0.029)
p						
Constant	−0.205	−0.045	−0.350	−0.259	−0.266	−0.317
	(0.731)	(0.738)	(0.818)	(0.737)	(0.763)	(0.746)
Female	0.200*	0.198*	0.183	0.187*	0.200*	0.190
	(0.114)	(0.115)	(0.114)	(0.112)	(0.115)	(0.112)
Skilled	0.399***	0.883***	0.784***	0.797***	0.872***	0.789***
	(0.128)	(0.210)	(0.223)	(0.227)	(0.212)	(0.227)
log(*age*)	−0.555***	−0.554***	−0.543***	−0.539***	−0.553***	−0.532***
	(0.173)	(0.172)	(0.165)	(0.166)	(0.171)	(0.167)
log(θ)	0.323***	0.334***	0.279***	0.256***	0.309***	0.245**
	(0.087)	(0.089)	(0.086)	(0.094)	(0.082)	(0.097)
log(V_s/V)		0.502***	0.479***	0.429***	0.466***	0.425**
		(0.188)	(0.196)	(0.199)	(0.196)	(0.198)
log(V_s)			−0.063		0.028	
			(0.067)		(0.046)	
σ_w	0.420***	0.422***	0.412***	0.412***	0.422***	0.410***
	(0.030)	(0.030)	(0.027)	(0.027)	(0.030)	(0.026)
σ_u	0.335***	0.334***	0.335***	0.335***	0.335***	0.335***
	(0.016)	(0.017)	(0.016)	(0.017)	(0.017)	(0.017)
log(likelihood)	−6740.7	−6734.4	−6729.0	−6730.1	−6734.0	−6729.8

Notes. Robust standard errors (for clustered data) reported in parenthesis. Significance at 10%, 5% and 1% levels is denoted by *, ** and *** respectively. No. of observations: 2,229. *Source*: SIIOW and NOMIS.

picture of the determinants of the arrival rate of job offers and wage distributions. Men, the highly educated and older workers sample wage offers from a distribution with higher mean (and variance) than the one sampled by women, the less skilled and the young, respectively. Markets in which the average firm size is larger are associated with higher wage offers on average, although this effect is not statistically significant. Arrival rates of job offers are higher for the highly educated, younger workers, and women, although this last effect is only significant at the 10% level. Although it may go against conventional wisdom, the fact that women have (marginally) higher arrival rates than men is consistent with substantial unemployment differentials in favor of women in 1987.[9] In line with much of the matching-function literature, job offers positively depend on labour market tightness, and the elasticity of p with respect to θ, close to 0.3, is comparable with the results obtained by several estimates based on aggregate British data. We also tried versions of our estimated equations that included tightness in the wage-offer equation but it did not turn out to be significant. The standard errors of the estimate on tightness increased in the offer-arrival equation but the estimates clearly suggested that the main impact of tightness is on the arrival of offers.

It may be argued that the relevant tightness measure is not the aggregate one, simply computed as the number of total vacancies to total unemployment in the local market, but one which is skill-specific, i.e., the vacancy/unemployment ratio in the relevant skill segment. Although we have data on vacancies disaggregated by occupation, data on unemployed workers disaggregated by skills are not available at the local level. We therefore tried to pick the effect of tightness by skill by including a measure of relative tightness in p, given by V_s/V. This variable is included in column 2 and is highly significant.

The effect of market size on arrival rates and mean wage offers is obtained from the estimates in columns 3–5. Column 3 includes the number of vacancies among the determinants of both p and μ. Vacancies here are disaggregated into two broad occupational groups, skilled and unskilled (see notes to Table 2). We find that local labour market size has a positive effect on the mean wage offer distribution but not on the arrival rate of job offers. In columns 4 and 5 we test for the effect of vacancies on p and μ separately. The effect of size on μ stays positive and highly significant (column 4), while the one on p does not become significantly different from zero.

We further investigate whether the effects that we estimated are not due to the absolute size of the local market but to its density. In column 6 we drop the size effect from p, which was not significant, and include both the number of vacancies and the geographical size of the local market in μ. If density matters, we expect a negative and significant coefficient on log(acres), once size is accounted for by $\log(V_s)$. If *only* density matters, as opposed to size, the coefficients on $\log(V_s)$ and log(acres) should not differ from each other in absolute value. We find that the effect of $\log(V_s)$ on μ remains largely unchanged from the one in column 4, and that the one on log(acres) is negative but not significantly different from zero. It should also be noted that the coefficients on $\log(V_s)$ and log(acres) do not differ significantly from each other in absolute value (with a p-value of 0.38). But we do

[9] In April 1987 the male unemployment rate in the UK was 13.1%, against an 8.3% rate for women.

not consider this to be convincing evidence that density matters more than size because of the high standard error on the coefficient on log(*acres*), which admits a large range of parameters not significantly different from it. As a final check, we included size and density separately, proxied by $\log(V_s)$ and $\log(V_s/acres)$ respectively (results not reported). Although neither of them was significant at conventional levels, the size effect was more important than the density effect, with t-statistics of 1.14 and 0.81 respectively.[10]

We noted that London is an outlier in our cross-section of counties. In order to check the robustness of the estimated size effect we perform the same set of estimates in Table 4 on a sub-sample which excludes Greater London. The results obtained are reported in Table 5. When we do not include any size indicator in either p or μ (columns 1 and 2), the results are similar to those obtained on the whole sample. But when we include vacancies (disaggregated by occupation) as a proxy for market size, we do not find any size effect in matching rates, coming either through the mean wage offer or the arrival rate of job offers.

Finally, we switch to a narrower concept of local markets, represented by TTWAs, to check for significant differences in the responsiveness of individual return-to-work trajectories to alternative definitions of local markets. When moving to TTWA labour market indicators, specifications that do not include scale effects in p or μ were virtually unchanged from those that used county-level data (and the results are therefore not reported), with the only exception of $\log(V_s/V)$ turning non-significantly different from zero. Results from regressions including size controls are reported in Table 6. Two main differences are worth noting with respect to the results of Tables 4 and 5. First, the positive scale effect in the mean wage offer remains significant also when we exclude observations for London from our sample. But, second, the effect of scale remains significant only when it is included in both the mean and the offer arrival rate, and, in this case, scale appears to affect the offer arrival rate with negative sign. Although this is consistent with the view that in a larger market job offers are slower to arrive because of longer processing time implied by more choice, we do not take it up as an implication of our estimates, because we only found it in one instance.[11]

We have data on a number of other local labour market indicators and, to check robustness, we also estimated the regressions by making use of some alternative measures of size. These are the total number of vacancies (not disaggregated by occupation), the employment level and the number of registered businesses. The results obtained were very similar to the ones reported, so we do not give new tables of estimates. Previous studies (not of search markets) used mainly employment or output measures of size. We chose to report estimates based on vacancies

[10] Size and density effects in economic activity have been previously studied by Ciccone and Hall (1996), who estimate the effect of both county size (proxied by output) and county density (proxied by output per acre) on output per worker in the US. Our study differs in the measurement of the variables of interest, but also in the results, as Ciccone and Hall find that density effects are (slightly) more important than size effects. Density effects were found to be significant by Coles and Smith (1996) in the estimation of a matching function for travel-to-work areas in England and Wales.

[11] Excluding the county 'Greater London' reduces the sample to 1,962 individuals, but excluding the London TTWA reduces it to 2,046 individuals, as Greater London County is larger than the London TTWA.

Table 5

Estimation Results – Local Labour Markets Proxied by Counties (Excluding Greater London)

Variables	1	2	3	4	5
μ					
Constant	−1.071**	−1.055***	−0.891*	−1.047**	−1.103***
	(0.424)	(0.363)	(0.469)	(0.441)	(0.404)
Female	−0.359***	−0.356***	−0.357***	−0.356***	−0.357***
	(0.053)	(0.054)	(0.054)	(0.054)	(0.054)
Skilled	0.210***	0.209***	0.192***	0.208***	0.211***
	(0.044)	(0.043)	(0.046)	(0.044)	(0.043)
log(*age*)	0.512***	0.514***	0.510***	0.514***	0.514***
	(0.091)	(0.0778)	(0.092)	(0.086)	(0.091)
log(*firmsize*)	0.033	0.023	0.021	0.024	0.013
	(0.069)	(0.066)	(0.067)	(0.067)	(0.066)
$\log(V_s)$			−0.019	−0.001	
			(0.027)	(0.022)	
p					
Constant	−0.358	−0.044	−0.519	−0.043	−0.296
	(0.737)	(0.518)	(0.950)	(0.634)	(0.857)
Female	0.255**	0.254**	0.256**	0.254**	0.254**
	(0.119)	(0.122)	(0.122)	(0.122)	(0.122)
Skilled	0.448***	1.014***	1.036***	1.016***	1.009***
	(0.119)	(0.197)	(0.205)	(0.203)	(0.200)
log(*age*)	−0.560***	−0.562***	−0.556***	−0.562***	−0.561***
	(0.175)	(0.132)	(0.175)	(0.157)	(0.174)
$\log(\theta)$	0.279***	0.298***	0.299***	0.299***	0.294***
	(0.090)	(0.082)	(0.086)	(0.084)	(0.086)
$\log(V_s/V)$		0.573***	0.540***	0.575***	0.540***
		(0.187)	(0.206)	(0.195)	(0.207)
$\log(V_s)$			0.058		0.029
			(0.073)		(0.058)
σ_w	0.393***	0.395***	0.396***	0.395***	0.396***
	(0.030)	(0.029)	(0.030)	(0.029)	(0.030)
σ_u	0.322***	0.321***	0.321***	0.321***	0.321***
	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)
log(likelihood)	−5,944.7	−5,936.8	−5,936.4	−5,936.7	−5,936.6

Notes. Robust standard errors (for clustered data) reported in parenthesis. Significance at 10%, 5% and 1% levels is denoted by *, **, and *** respectively. No. of observations: 1,962. *Source*. SIIOW and NOMIS.

disaggregated by skill, as the number of vacancies in one's skill segment should best proxy the volume and variety of job opportunities existing in the local labour market.

Making use of estimates from regression 4 of Table 4, which is our preferred specification for the full sample, we compute the predicted arrival rates and mean wage offers for markets of different sizes. Also, with these estimates we compute the reservation wage that is implied by the optimal search strategy that we used in our estimation, as given by (13). Our predictions are computed setting $r = 0.005$ for the weekly discount rate,[12] for two alternative values of b ($b = 0$ and $b = 40\%$ of

[12] This implies an annual rate of about 30%. In our simple model, the discount factor is the interest rate, however in models with limited job durations it is the sum of the interest rate and the job separation rate. New jobs last about five years in the UK, but because this group of workers is less skilled durations may even be shorter. So an annual job separation rate for these workers of 20 to 25% is reasonable. In case 0.005 is regarded as too high, we note that the smaller the weekly discount rate that we use, the more support there is for the points made in the text that follows.

Table 6

Estimation Results – Local Labour Markets Proxied by TTWAs

Variables	Whole Sample 1	2	3	Excluding London 4	5	6
μ						
Constant	−1.334***	−1.099**	−0.950***	−1.123***	−0.916***	−0.916***
	(0.358)	(0.331)	(0.325)	(0.339)	(0.330)	(0.311)
Female	−0.335***	−0.339***	−0.344***	−0.360***	−0.365***	−0.365***
	(0.049)	(0.051)	(0.053)	(0.047)	(0.047)	(0.047)
Skilled	0.276***	0.246***	0.221***	0.237***	0.212***	0.213***
	(0.048)	(0.048)	(0.053)	(0.037)	(0.038)	(0.040)
log(*age*)	0.513***	0.506***	0.503***	0.504***	0.501***	0.499***
	(0.088)	(0.086)	(0.089)	(0.087)	(0.087)	(0.086)
$\log(V_s)$	0.054***	0.023*		0.030**	−0.001	
	(0.015)	(0.013)		(0.014)	(0.013)	
p						
Constant	0.303	−0.645	−0.299	0.201	−0.665	−0.138
	(0.772)	(0.670)	(0.730)	(0.783)	(0.688)	(0.721)
Female	0.179*	0.192*	0.193*	0.224**	0.241**	0.231**
	(0.110)	(0.112)	(0.116)	(0.115)	(0.114)	(0.114)
Skilled	0.453**	0.420**	0.514***	0.597***	0.583***	0.626***
	(0.197)	(0.214)	(0.194)	(0.195)	(0.193)	(0.194)
log(*age*)	−0.528***	−0.521***	−0.517***	−0.498***	−0.492***	−0.491
	(0.171)	(0.170)	(0.176)	(0.175)	(0.176)	(0.172)
$\log(\theta)$	0.243***	0.211***	0.246***	0.257***	0.234***	0.259
	(0.057)	(0.058)	(0.056)	(0.057)	(0.056)	(0.057)
$\log(V_s/V)$	0.176	0.025	0.152	0.264	0.144	0.253
	(0.175)	(0.168)	(0.175)	(0.175)	(0.160)	(0.174)
$\log(V_s)$	−0.114**		−0.027	−0.115**		−0.065
	(0.046)		(0.039)	(0.051)		(0.041)
σ_w	0.407***	0.407***	0.418***	0.394***	0.395***	0.395***
	(0.026)	(0.026)	(0.029)	(0.027)	(0.028)	(0.028)
σ_u	0.335***	0.336***	0.336***	0.334***	0.334***	0.334***
	(0.016)	(0.016)	(0.016)	(0.017)	(0.017)	(0.017)
log(likelihood)	−6,729.8	−6,736.7	−6,738.7	−6,218.5	−6,222.6	6,220.2

Notes. Robust standard errors (for clustered data) reported in parenthesis. Significance at 10%, 5% and 1% levels is denoted by *, **, and *** respectively. No. of observations: 2,229 in the whole sample; 2,046 excluding London. *Source*: SIIOW and NOMIS.

the average wage). We then use our derived reservation wages to compute acceptance rates, hazard rates and realised wages for the average market and for the largest market in our sample. The results are reported in Table 7.

The Table shows that, when $b = 0$, moving from the average to the largest market size raises the mean wage offer by 10.3%. As predicted by the model of Section 2 for $rb = 0$, the consequent increase in reservation wages completely offsets any effect of better job offers on the re-employment hazard. Higher job offers are simply translated into an equiproportional increase in realised wages. When b is equal to 40% of the average wage, and therefore $rb > 0$, higher job offers translate into a 9.3% increase in realised wages and a 4.4% increase in the re-employment hazard. Noting that b is measuring unemployment income that has to be given up when moving to a job, net of search costs, a number such as 40% is high and above the average replacement ratio for the UK in the late 1980s. Yet, the

Table 7

Comparative Statics for the Effect of Market Size

	$r = 0.005$ $b = 0$			$r = 0.005$ $b = 0.4\mathrm{E}(w\|w>w^{*})$		
	Local market			Local market		
Variables	Average size	London	%	Average size	London	%
Mean wage offer	1.93975	2.14014	+10.3	1.93975	2.14014	+10.3
Arrival rate	0.07029	0.07029	–	0.07029	0.07029	–
Acceptance rate	0.26697	0.26697	–	0.17915	0.18700	+4.4
Hazard rate	0.01693	0.01693	–	0.01143	0.01192	+4.4
Realised wage	3.05379	3.36965	+10.3	3.33019	3.64146	+9.3

Notes. All predictions are based on the estimates in column 4 of Table 4. The average market size is calibrated using the average number vacancies across counties (1,072 skilled and 2,710 unskilled vacancies). The size of London is calibrated using the local number of vacancies (10,559 skilled and 22,335 unskilled vacancies). Arrival, acceptance and hazard rates are values per week. Mean wage offers and realised wages are values per hour.

split between a post-unemployment wage effect and a duration effect of scale is firmly in favour of the post-unemployment wage effect.

The split of the effects of scale in favour of post-unemployment wages may explain why scale effects that are present at the micro level do not show up in matching-function estimation, or indeed in hazard-rate estimation. At reasonable benefit replacement ratios net of search costs, the effect of scale on the hazard is too small to be picked up in reduced-form estimates, at least relative to the observed cross-sectional variations in hazard rates. The effect of size translates mainly into a higher wage rate, which should be picked up in reduced-form estimates of regional wages.[13]

5. Another Look into the Black Box of Matching

Our results lead to an unexpected finding about the properties of hazard rates, and by extension about the structure of the aggregate matching function. The finding that, by influencing the mean of the distribution of wage offers, size affects mainly the post-unemployment wage distribution, but not hazard rates, is more general. Our estimates indicate that shift variables in the distribution of wage offers induce a response from the reservation wage, which shifts the post-unemployment wage distribution, but have virtually no impact on hazard rates. In contrast, variables that influence the mechanics of the meeting technology, which determines the offer arrival rate, have a very small impact on reservation wages and the post-unemployment wage. Their main influence is on the hazard rate.

We illustrate these findings with two more tables. Table 8 shows the impact of tightness on the hazard rate and the post-unemployment wage at net

[13] Tests by Glaeser and Maré (2001) for the US and Combes *et al.* (2004) for France are consistent with this prediction. See also Teulings and Gautier (2002).

Table 8

Comparative Statics for the Effect of Market Tightness

	$r = 0.005$, $b = 0.4\mathrm{E}(w \mid w > w^*)$		
	Local market		
Variables	Mean θ (0.08)	High θ (0.20)	%
Mean wage offer	2.17618	2.17618	–
Arrival rate	0.07300	0.09221	+26.5
Acceptance rate	0.24776	0.21659	−11.4
Hazard rate	0.01743	0.01926	+10.5
Realised wage	3.45158	3.56363	+3.2

Notes. All predictions are based on the estimates of column 4 in Table 4. Arrival, acceptance and hazard rates are values per week. Mean wage offers and realised wages are values per hour.

unemployment income $b = 40\%$ of the average wage. Unlike size, tightness influences the offer arrival rate, and so its main influence is on the hazard rate. A tight market with 26.5% higher offer arrival rate than another ends up with a 10.5% higher hazard rate but only 3.2% higher average wage rate. Perhaps surprisingly, in our estimates tightness influences the mean wage rate only by truncating the distribution of accepted wages, not by influencing each individual's wage. In aggregate matching function estimation tightness is the main independent variable driving the results and our calculations in Table 8 confirm these findings.

In Table 9 we show the effect of the individual's educational level on the hazard, which works through both the wage offer distribution and the offer arrival rate. The Table shows that the effect through the arrival rate is reflected mainly in the hazard rate, whereas the effect through the wage distribution is picked up by the reservation wage and reflected mostly in the average post-unemployment wage rate.

The implications of our findings for the microfoundations of the aggregate matching function are important. Theory needs to concentrate on the mechanics of the meeting technology if it is to understand the structure of matching functions. The structure of the wage offer distribution and the formulas for reservation

Table 9

Comparative Statics for the Effect of Education

	$r = 0.005$, $b = 0.4\mathrm{E}(w \mid w > w^*)$						
	Education level						
Variables	Low	High in p	%	High in μ	%	High	%
Mean wage offer	1.91279	1.91279	–	2.51981	+31.7	2.51981	+31.7
Arrival rate	0.04612	0.10235	+121.9	0.04612	–	0.10235	+121.9
Acceptance rate	0.29378	0.19087	−35.0	0.32859	+11.9	0.21100	−28.2
Hazard rate	0.01264	0.01810	+43.2	0.01424	+12.6	0.02013	+59.2
Realised wage	2.92477	3.24934	+11.1	3.74685	+28.1	4.18808	+43.2

Notes. See Table 8.

wages are not as important. They are important for determining the wage outcomes of search processes, not the duration of search.

6. Conclusions

In this article we argued that the fact that the majority of empirical estimates find that there are no scale effects in aggregate matching functions does not necessarily mean that they are not present at one or more of the structural levels used to derive the aggregate function. We have shown in a simple model of search that scale effects in the quality of job matches or in the arrival rate of job offers can coexist with constant returns at the aggregate level. The reason they may not be observed in the matching function is that workers may raise their reservation wages in markets characterised by scale effects, so as to offset their impact on the probability that they get a job. If this response takes place, the impact of the scale effects is on the mean level of post-unemployment wages.

We estimated a simultaneous system of two semi-structural equations, one for the mean wage offer and one for the probability that the worker gets an offer, and looked for scale effects at either the county level or the travel-to-work area level. Scale effects appear to exist at the level of the distribution of wage offers but not at the level of the arrival of job offers: workers searching in larger markets have to wait as long as other workers to get an offer but the offers they eventually get are better. They respond by raising their reservation wages, such that the impact on the duration of their unemployment is minimal, but the impact on their accepted wage is large. Our findings are consistent with two other branches of the empirical literature, the one that finds constant returns to matching and the one that finds local size effects on wages and labour productivity.

Our findings generalise to other variables, which shed light on the structure of aggregate matching functions. Generally, shift variables in the distribution of wage offers influence the post-unemployment wage distribution but not the hazard rate, through their effect on the reservation wage. But shift variables in the offer arrival rate influence the hazard rate (and by extension the aggregate matching function) with little influence in the expected post-unemployment wage rate.

Our results should be qualified by noting that scale effects depend on the inclusion of London as one of our local markets (representing up to 12% of observations). At the county level London drives the results, whereas at the travel-to-work area level the scale effects are weaker when London is excluded. One possible intuitive reason is that scale effects in the quality of job matches emerge only in very large markets, where choice is really superior to the choice available in smaller markets. More research on different data sets and countries is needed here to uncover the true causes of scale effects. Estimates with data from countries with more than one large local market would be particularly important in this context.

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