Scale Effects in Markets with Search*

Barbara Petrongolo
Centre for Economic Performance
London School of Economics, CEPR and IZA

Christopher A Pissarides
Centre for Economic Performance
London School of Economics, CEPR and IZA

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Abstract

Reduced-form tests of scale effects in markets with search, based on aggregate matching functions, may miss important scale effects at the micro level, because of the reactions of job searchers. We estimate a semi-structural model on a British sample of unemployed people, testing for scale effects on the offer arrival rate and the wage offer distribution. We find scale effects in wage offers but not in offer arrival rates. We also find that reservation wages rise to deliver higher post-unemployment wages but not faster matches, so aggregate matching functions are unaffected by scale.

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1 Introduction

Scale effects in matching models have featured prominently in the economics literature since Peter Diamond's (1982) claim that the complementarities in search models are strong enough to generate multiple equilibria. Theoretically, scale effects appeared "plausible," both to Diamond and others. Yet, despite a small number of exceptions, empirical work has largely supported constant returns (Petrongolo and Pissarides, 2001). The exceptions are not ones that consistently apply to some cases or some periods. Rather, a few diverse estimates support increasing returns, with the vast majority supporting constant returns.[1]

Empirical testing, however, usually proceeds by estimating aggregate matching functions or hazard rates for unemployed individuals. The test for constant returns in the aggregate matching functions is whether a proportional increase in the inputs of both firms and workers into search (at the most basic level, in the total number of vacancies and unemployed workers) increases total matches by a bigger proportion. In hazard-function estimation the test is the equivalent one of whether a proportional increase in local-area unemployment and vacancies increases a typical individual's hazard rate. In both cases, however, the estimation is on reduced forms. But both aggregate matching functions and individual hazard rates conceal more than one structural dimension. They are both a composite of the mechanics of the meeting technology and the willingness of firms and workers to accept the other side's offer.

Our main claim in this paper is that it is feasible for constant returns in aggregate matching functions and hazard rates to coexist with increasing returns at one of the micro levels, because the responses of firms and workers to the increasing returns can cancel out their effects at the aggregate level. The most clear case where this can happen is in the quality of the job match. There may be increasing returns in the quality of job matches, with better matches occurring in larger markets. But if reservation wages increase in proportion to the improvement in the quality of job matches, the aggregate matching function should be independent of scale. The increasing returns would be associated with higher post-unemployment wages but not with shorter durations of unemployment.

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 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 quality of the job match. In both cases optimal reservation wages adjust to offset, partially and sometimes even completely, their effects on the aggregate hazard

[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 generalize from this small number of examples and claim that increasing returns are a feature of all such cases.

rate (and consequently on the aggregate matching rate). But whether they do or not depend on the properties of the distribution of job offers and on the relation between reservation wages and unemployment income.[2]

We estimate our model and look for scale effects at the structural level 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 labor-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 labor-market characteristics on each.

We find scale effects in the quality of the job match (proxied by the mean of the wage offer distribution) but not in the arrival of job offers.[3] 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. Aggregate matching functions derived from our sample would confirm 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" replacement ratios, 40 percent of the mean wage rate net of search costs, imply that the scale effects in the quality 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.[4]

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 some restrictions 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 are reflected mainly in shifts in the post-unemployment wage distribution, with virtually no influence on matching rates. And shifts in variables that act through the mechanics of the meeting technology are reflected in shifts in the matching function, with virtually no influence on the post-unemployment wage distribution. Theoretical studies of the foundations of matching functions will do well to focus on the mechanics of the meeting technology, rather than the structure of the wage offer distribution and the formulas for reservation wages.

[2] Burdett (1981) and van den Berg (1994) derived conditions for signing the effect of changes in the offer arrival rate on hazard rates. Teulings and Gautier (2002) argue that scale effects at the micro level could also be offset by other agent reactions related to the equilibrium process, e.g., labor or job mobility.

[3] In fact, in one of our estimates we find a negative impact of scale on offer arrival rates, which may be consistent with the positive impact on the quality of matches if more choice delays an offer.

[4] Or, alternatively, the remaining effect is offset by other equilibrium adjustments, e.g., those described in Teulings and Coen (2002).

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 on the two alternative measures.

As a test of robustness of our results we re-estimate the model by excluding all observations from London, about 8-12 per cent of our sample, depending on whether we consider countries or TTWAs. In either case, London is an outlier in the size distribution. Compared with London's 3.5m, employment in Birmingham, the second largest county, is 1.1m. We find no scale effects in the smaller sample using county-level data, though they still remain when using TTWA-level data. This opens up the possibility that scale effects in the quality of matches operate only in very large markets, which offer a large choice of diverse occupations. But our sample contains only one very large market, so further tests are needed before either constant returns or non-monotonicity in scale effects can be established as a more general property of search markets. We speculate further on these possibilities in the concluding section of the paper.

The paper is organized as follows. In Section 2 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 3 describes our data set and presents some preliminary evidence. In Section 4 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 labor market characteristics. The results are discussed in section 5. Section 6 draws out more general implications of our estimates for aggregate matching functions. General conclusions are brought together in section 7.

2 Model

We begin by describing the empirical problem. An unemployed individual searches for a job in a local labor market. Offers arrive randomly according to a Poisson distribution with parameter $p(\mathbf{x})$, where $\mathbf{x}$ is a vector of personal and local labor-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 labor-market characteristics, and standard deviation σ_w, which is a fixed parameter. 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 contains 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 labor-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 optimizing 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;[5] formally, whether the vectors $\mathbf{x}$ and $\mathbf{z}$ contain variables for the size of the local labor 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 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 labor 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, neither depends on time or search duration and successive wage offers are independently distributed. A job is an absorbing state, once one is accepted search stops.

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

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

The value of employment 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 exists a unique reservation wage w^* such that $V_n = V_e(w^*) = w^*/r$. The reservation wage satisfies an equation derived from (2),

$$\begin{aligned} w^* &= rV_n = b + p\int_{w^*} \left[V_e(w) - V_n\right] dF(w) && (4) \\ &= b + \frac{p}{r} E(w - w^* | w \geq w^*) \Pr(w \geq w^*). && (5) \end{aligned}$$

Let now x 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,

$$\frac{\partial h}{\partial x}\frac{x}{h} = \frac{xp'(x)}{p(x)} - \frac{w^* F'(w^*)}{1 - F(w^*)}\frac{\partial w^*}{\partial x}\frac{x}{w^*}. \tag{6}$$

[5] If $E()$ is the expectations operator, $\mu = E(\ln w)$. 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.

and from (5),

$$\frac{\partial w^*}{\partial x}\frac{x}{w^*} = \frac{xp'(x)}{p(x)}\frac{w^* - b}{w^*} \geq 0. \tag{7}$$

In general, the sign of $\partial h/\partial x$ is ambiguous, because the two terms in (6) have opposite sign: the worker increases her reservation wage when the arrival of offers improves and this can offset its direct positive impact on the hazard rate.

Burdett (1981) and van den Berg (1994) have shown that it is possible to find distributions that imply $\partial h/\partial x < 0$, although van den Berg's more general analysis shows that empirically reasonable distributions always imply $\partial h/\partial x \geq 0$. Past empirical work also confirmed a positive impact of the offer arrival rate on hazard rates.[6] 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.

Substitution from (7) into (6) yields

$$\frac{\partial h}{\partial x}\frac{x}{h} = \frac{xp'(x)}{p(x)}\left(1 - \frac{w^* F'(w^*)}{1 - F(w^*)}\frac{w^* - b}{w^*}\right). \tag{8}$$

Thus, if the reservation wage is equal to unemployment income, the impact of x on the hazard is as much as its impact on the offer arrival rate. But if the reservation wage is strictly higher than unemployment income, the quantitative impact of x on the hazard depends also on the elasticity of the acceptance probability with respect to the reservation wage. This elasticity, in turn, depends both on the parameters of the distribution and the location of the reservation wage on the distribution.

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

$$\frac{\partial h}{\partial z} = -p\left(\frac{\partial F(w^*)}{\partial z} + F'(w^*)\frac{\partial w^*}{\partial z}\right). \tag{9}$$

By the stochastic dominance assumption made, $\partial F(w^*)/\partial z < 0$, and from (5) 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. However, as in (1), 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.[7]

[6] 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 up. There is overwhelming evidence that they sloe down. See Pissarides (2000) for more discussion of these points, especially chapter 6.

[7] The remarks that follow in the remainder of this section also hold for other distributions, provided z is a multiplicative shift parameter, but given the empirical focus of this paper we derive the expressions explicitly for the lognormal. In the derivations that follow we have used some results derived by Eckstein and Wolpin (1995)

The density of the lognormal is

$$f(w) = \frac{1}{w\sigma_w}\phi\left(\frac{\ln w - \mu}{\sigma_w}\right), \tag{10}$$

where $\phi(.)$ is the normal density

$$\phi\left(\frac{\ln w - \mu}{\sigma_w}\right) = \frac{1}{(2\pi)^{0.5}}\exp\left[-\frac{1}{2}\left(\frac{\ln w - \mu}{\sigma_w}\right)^2\right]. \tag{11}$$

The cumulative density of the lognormal is

$$F(w^*) = \Phi\left(\frac{\ln w^* - \mu}{\sigma_w}\right), \tag{12}$$

where $\Phi(.)$ is the cumulative normal density. By integration we can derive

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

With these expressions the reservation wage equation (5) becomes

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

For any parameter z that influences the mean for the lognormal, (12) yields

$$\frac{\partial F(w^*)}{\partial z} = -\frac{\mu'(z)}{\sigma_w}\phi\left(\frac{\ln w^* - \mu}{\sigma_w}\right) = -w^* F'(w^*)\mu'(z), \tag{15}$$

so (9) implies:

$$\frac{\partial h}{\partial z}\frac{1}{h} = \frac{w^* F'(w^*)}{1 - F(w^*)}\left(1 - \frac{1}{w^*\mu'(z)}\frac{\partial w^*}{\partial z}\right)\mu'(z). \tag{16}$$

To derive the response of the reservation wage to the change in z we differentiate (14) to derive

$$\frac{\partial w^*}{\partial z} = \frac{p\exp\left(\frac{1}{2}\sigma_w^2 + \mu\right)\left[1 - \Phi\left(\frac{\ln w^* - (\sigma_w^2 + \mu)}{\sigma_w}\right)\right]}{r + p\left[1 - \Phi\left(\frac{\ln w^* - \mu}{\sigma_w}\right)\right]}\mu'(z), \tag{17}$$

and so

$$\frac{1}{w^*\mu'(z)}\frac{\partial w^*}{\partial z} = \frac{p\exp\left(\frac{1}{2}\sigma_w^2 + \mu\right)\left[1 - \Phi\left(\frac{\ln w^* - (\sigma_w^2 + \mu)}{\sigma_w}\right)\right]}{rb + p\exp\left(\frac{1}{2}\sigma_w^2 + \mu\right)\left[1 - \Phi\left(\frac{\ln w^* - (\sigma_w^2 + \mu)}{\sigma_w}\right)\right]}. \tag{18}$$

Comparison of (18) with (16) shows that if $rb > 0$ the effect of higher z (noting that by assumption $\mu'(z) > 0$) is to raise the hazard; if $rb = 0$ the hazard is unaffected by changes in the mean of the distribution and if $rb < 0$ the reservation wage overreacts and the hazard is lower.

Now, making use of (14) and (18), we re-write (16) as

$$\frac{\partial h}{\partial z}\frac{1}{h} = \frac{w^* F'(w^*)}{1 - F(w^*)}\frac{rb}{(r+h)w^*}\mu'(z), \tag{19}$$

which, given the argument in footnote 5, is equivalent to

$$\frac{\partial h}{\partial z}\frac{z}{h} = \frac{z\bar{w}'(z)}{\bar{w}(z)}\frac{w^* F'(w^*)}{1 - F(w^*)}\frac{rb}{(r+h)w^*}. \tag{20}$$

Provided $b > 0$, substitution of $w^* F'(w^*)/(1 - F(w^*))$ from (20) into (8) yields

$$\frac{\partial h}{\partial x}\frac{x}{h} = \frac{xp'(x)}{p(x)}\left(1 - \frac{\frac{\partial h}{\partial z}\frac{z}{h}}{\frac{z\bar{w}'(z)}{\bar{w}(z)}}\frac{w^* - b}{b}\frac{r}{r+h}\right) \tag{21}$$

Thus, the effect of the offer arrival rate and the mean wage offer on the hazard are related. They both have their biggest impact when the reservation wage is equal to unemployment income, because in this case the reservation wage is insensitive to changes in parameters. If the reservation wage exceeds unemployment income, the smaller the impact of the mean wage offer on the hazard, the bigger the impact of the offer arrival rate. Without wanting to anticipate too much the empirical results, one of our main conclusions is that empirically the elasticity of h with respect to z is small (i.e., shocks to the mean wage offer do not have a significant impact on the hazard) and consequently the elasticity of h with respect to x (shocks to 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 (5) can be used to construct a likelihood function after a description of the data.

3 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 3003 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 2146 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 and who were out of the labor force at the time of interview. This type of censored spell is measured by the number of weeks that the respondent was on the unemployment register.[8] 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 (see 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.[9] We find that self-reported reservation wages

[8] We assume that once a respondent leaves the unemployment register active search ceases, since once on the register, no active searcher has an incentive to leave it, even if entitlement to benefit ceases. The register for non-recipients of benefit provides free job information which the job seeker is free to use or ignore.

[9] 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).

Table 1: Sample characteristics of the unemployment inflow

Variables	Mean	St.dev.	No.obs.
% uncensored	52.7		2229
% censored	47.3		2229
uncensored duration	12.3	11.1	1174
censored duration	23.9	17.4	1055
females	37.7		2229
age	36.9	11.5	2229
% skilled	43.4		2229
hourly res. wage	2.38	0.98	2229
hourly take-home pay	2.57	1.30	927

Notes. *% 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.

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.[10].

The information on hourly reservation wages is missing for 773 workers. 1445 workers in the sample found a job within the survey period, while 1558 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. The final sample consists of 2229 respondents, the missing ones being the 773 with no reservation wage information and 1 observation with no age information. The 330 cases with missing post-unemployment wage are included in the estimation by making use of the information that they still convey; that the have had an offer exceeding their reservation wage. Some summary statistics of the sample used are presented in Table 1.

We use two alternative characterizations of local labor markets. The first is represented by counties: there are 66 counties in Britain, with an average population slightly above 800,000,

[10]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).

Table 2: Local labor markets in Britain

Variables	Counties		TTWAs	
	Mean	St.dev.	Mean	St.dev.
Unemployed	59986	68698	27057	48484
Vacancies	4140	5639	1772	3773
Tightness	0.08	0.03	0.05	0.05
Skilled vacancies	1072	1614	230	487
Unskilled vacancies	2710	3397	825	1784
Firms	26118	30463	-	-
Average firm size	15.8	4.3	-	-
Area size (acres)	347258	431079	66301	54193
No. of observations	43		64	

Notes. *Unemployed*: number of claimant unemployed, April 1987. *Vacancies*: vacancies notified at Job Centres, April 1987. *Tightness*: vacancies/unemployed. *Skilled vacancies*: vacancies notified 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 notified 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.

and respondents in the SIIOW reside in 43 of them. 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. We then merge individual records from the SIIOW with official labor 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 labor 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 the mean of the wage offer distribution can be gathered by regressing local mean wages on market size. We compute mean wages by 2 educational groups and 43 counties, and regress them on an education dummy, the local labor market tightness (denoted by θ), and the number of vacancies (also disaggregated into 2 occupational groups, denoted by $V_{by\ skill}$) in each county. The results are reported in the first

Table 3: Mean wages and labor market size

Variables	Counties		TTWAs	
	Whole sample	Excl. London	Whole sample	Excl. London
constant	0.237 (0.166)	0.377^{*} (0.194)	0.413^{***} (0.104)	0.456^{***} (0.115)
skilled	0.247^{***} (0.033)	0.233^{***} (0.038)	0.254^{***} (0.031)	0.253^{***} (0.032)
$\log(\theta)$	-0.099^{***} (0.035)	-0.110^{***} (0.036)	-0.058^{**} (0.023)	-0.058^{**} (0.023)
$\log(V_{by\ skill})$	0.042^{***} (0.015)	0.018 (0.023)	0.037^{***} (0.010)	0.030^{**} (0.013)
R^2	0.45	0.45	0.38	0.35
No. Obs.	85	83	127	125

Notes. The dependent variable is the (log) mean wage across 2 educational groups and 43 counties/64 TTWAs. Estimation method: weighted least squares, with weights given by the number of observations in each skill/local labor market cell. Source: SIIOW and NOMIS.

two columns of Table 3. Local wages are positively correlated with the number of job openings, proxying market size, although the size effect is only significant for the whole sample and becomes non significantly different from zero when we exclude Greater London. When using data at the TTWA-level in columns 3 and 4 of the same Table, we detect a significant size effect whether or not we include London in our sample.

We repeat the same exercise using mean completed unemployment duration as the dependent variable. The resulting estimates are reported in Table 4. In no specification can any size effect be detected.

4 Estimation specification

Having modeled 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

$$\begin{aligned} L_i &= \exp\left[-p \Pr(w \geq w^*) d_i\right] \left[p \Pr(w \geq w^* | w_i) \Pr(w_i)\right]^{c_i} \\ &= \exp\left[-p \Pr(w \geq w^*) d_i\right] \left[p f(w_i)\right]^{c_i}, \end{aligned} \tag{22}$$

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, (22) becomes

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

Table 4: Mean durations and labor market size

Variables	Counties		TTWAs	
	Whole sample	Excl. London	Whole sample	Excl. London
constant	1.873*** (0.310)	2.143*** (0.404)	2.006*** (0.201)	1.998*** (0.229)
skilled	−0.169*** (0.062)	−0.192*** (0.072)	−.148*** (0.060)	−0.145** (0.064)
$\log(\theta)$	−0.168** (0.066)	−0.186*** (0.067)	−0.105** (0.045)	−0.105** (0.046)
$\log(V_{by\ skill})$	0.021 (0.028)	−0.023 (0.043)	0.025 (0.020)	0.027 (0.026)
R^2	0.17	0.16	0.11	0.10
No. Obs.	85	83	128	126

Notes. The dependent variable is the (log) mean completed unemployment duration across 2 educational groups and 43 counties/64 TTWAs. Estimation method: weighted least squares, with weights given by the number of observations in each skill/local labor market cell. Source: SIIOW and NOMIS.

The parameters of the model can be estimated by maximizing the log likelihood of a sample of n observations, $\log L = \sum_{i=1}^{n} \log L_i$, with L_i given by (23), with respect to p, w^*, μ and σ_w, under the restriction imposed by (14) 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 realized 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 realized 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 generalize 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 $1 - \Phi\left[(\ln w^* - \mu)/\sigma_w\right]$. 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:

$$\Pr(w \geq w^*|w^0)\Pr(w^0) = \left[1-\Phi\left(\frac{\ln w^* - \rho^2 \ln w^0 - (1-\rho^2)\mu}{\rho\sigma_u}\right)\right]\frac{1}{w^0\sigma}\phi\left(\frac{\ln w^0 - \mu}{\sigma}\right), \tag{24}$$

where $\rho^2 = \sigma_w^2/\sigma^2$ represents the share of observed wage variation which is not explained by the measurement error.[11] The resulting likelihood is

$$L_i = \exp\left\{-p\left[1-\Phi\left(\frac{\ln w_i^* - \mu}{\sigma_w}\right)\right]d_i\right\} \left\{p\left[1-\Phi\left(\frac{\ln w_i^* - \rho^2 \ln w_i^0 - (1-\rho^2)\mu}{\rho\sigma_u}\right)\right]\frac{1}{w_i^0\sigma}\phi\left(\frac{\ln w_i^0 - \mu}{\sigma}\right)\right\}^{c_i}. \tag{25}$$

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

$$L_i = \exp\left\{-p\left[1-\Phi\left(\frac{\ln w_i^* - \mu}{\sigma_w}\right)\right]d_i\right\}\left\{p\left[1-\Phi\left(\frac{\ln w_i^* - \mu}{\sigma_w}\right)\right]\right\}^{\widetilde{c}_i} \left\{p\left[1-\Phi\left(\frac{\ln w_i^* - \rho^2 \ln w_i^0 - (1-\rho^2)\mu}{\rho\sigma_u}\right)\right]\frac{1}{w_i^0\sigma}\phi\left(\frac{\ln w_i^0 - \mu}{\sigma}\right)\right\}^{c_i}, \tag{26}$$

where $\widetilde{c}_i$ 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 (26) is maximized with respect to p, μ, σ_w and σ_u. Note that in order to deliver both reservation wage and realized wage heterogeneity the model needs to allow for individual heterogeneity in at least one of the parameters $p, \mu, \sigma_w, \sigma_u$. 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 separately identify the effect of variables included in p, μ or both (see Flinn and Heckman, 1982, and Wolpin,

[11] 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 $1-\Phi\left[(\ln w^* - \mu)/\sigma\right]$, 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.

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.

5 Results

The estimates presented here are based on the likelihood function (26), in which σ_w and σ_u are estimated as constant parameters, and p and μ are functions of both individual and labor market characteristics.[12] Either theory or well-established empirical regularities help determine which labor market variables should affect p and which μ. Search theory predicts that the arrival rate of job offers should depend on labor market tightness $\theta = V/U$, which is therefore included in the determination of p. A well known stylized fact is the employer size-wage effect, according to which large firms pay higher wages than smaller firms.[13] 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 labor markets are proxied by counties. Having said this, our specification of p and μ is

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

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 labor market variables are defined at the county-level and at the TTWA-level in turn. We present results on counties first, reported in Table 5. In column 1 we do not include size indicators in either p or μ, and we find a fairly familiar 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

[12] We attempted to include scale effects in the variance of the wage offer distribution, σ_w, but our estimation programme 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. $Var(w) = \exp(2\mu + \sigma_w^2)[\exp(\sigma_w^2) - 1]$. If there are scale effects in the log of the mean wage offer, these also show up in the dispersion of the level of wages.

[13] The literature is surveyed by Brown and Medoff (1989).

Table 5: Estimation results - Local labor 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^{***}	-0.942^{***}
	(0.434)	(0.430)	(0.408)	(0.396)	(0.404)	(0.867)
female	-0.345^{***}	-0.343^{***}	-0.337^{***}	-0.339^{***}	-0.344^{***}	-0.338^{***}
	(0.052)	(0.052)	(0.050)	(0.050)	(0.052)	(0.051)
skilled	0.219^{***}	0.219^{***}	0.295^{***}	0.276^{***}	0.221^{***}	-0.299^{***}
	(0.060)	(0.060)	(0.067)	(0.057)	(0.058)	(0.067)
log(age)	0.514^{***}	0.515^{***}	0.512^{***}	0.510^{***}	0.515^{***}	-0.508^{***}
	(0.092)	(0.092)	(0.088)	(0.088)	(0.091)	(0.089)
log(firmsize)	0.069	0.057	-0.006	-0.018	0.037	-0.052
	(0.075)	(0.075)	(0.078)	(0.075)	(0.070)	(0.110)
$\log\left(V_{by\ skill}\right)$			0.064^{***}	0.045^{***}		0.063^{***}
			(0.028)	(0.017)		(0.026)
log(acres)						-0.032
						(0.038)
p						
constant	-0.205	-0.045	-0.350	-0.259	-0.266	-0.374
	(0.731)	(0.738)	(0.818)	(0.737)	(0.763)	(1.113)
female	0.200^{*}	0.198^{*}	0.183	0.187^{*}	0.200^{*}	0.185^{***}
	(0.114)	(0.115)	(0.114)	(0.112)	(0.115)	(0.113)
skilled	0.399^{***}	0.883^{***}	0.784^{***}	0.797^{***}	0.872^{***}	0.782^{***}
	(0.128)	(0.210)	(0.223)	(0.227)	(0.212)	(0.219)
log(age)	-0.555^{***}	-0.554^{***}	-0.543^{***}	-0.539^{***}	-0.553^{***}	-0.538^{***}
	(0.173)	(0.172)	(0.165)	(0.166)	(0.171)	(0.165)
$\log(\theta)$	0.323^{***}	0.334^{***}	0.279^{***}	0.256^{***}	0.309^{***}	0.249^{***}
	(0.087)	(0.089)	(0.086)	(0.094)	(0.082)	(0.091)
$\log\left(V_{by\ skill}/V\right)$		0.502^{***}	0.479^{***}	0.429^{***}	0.466^{***}	0.476^{***}
		(0.188)	(0.196)	(0.199)	(0.196)	(0.197)
$\log\left(V_{by\ skill}\right)$			-0.063		0.028	-0.053
			(0.067)		(0.046)	(0.064)
σ_w	0.420^{***}	0.422^{***}	0.412^{***}	0.412^{***}	0.422^{***}	0.411^{***}
	(0.030)	(0.030)	(0.027)	(0.027)	(0.030)	(0.027)
σ_u	0.335^{***}	0.334^{***}	0.335^{***}	0.335^{***}	0.335^{***}	0.335^{***}
	(0.016)	(0.017)	(0.016)	(0.017)	(0.017)	(0.016)
log(lik)	-6740.7	-6734.4	-6729.0	-6730.1	-6734.0	-6728.4

Notes. Robust standard errors (for clustered data) reported in brackets. Significance at 10%, 5% and 1% levels is denoted by *, **, and *** respectively. No. of observations: 2229. Source: SIIOW and NOMIS.

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.[14] In line with much of the matching-function literature, job offers positively depend on labor 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.

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. In the presence of market segmentation, with skilled and unskilled workers applying to different sets of jobs, the relevant tightness measure for a given worker should be given by 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 county level. We therefore tried to pick the effect of tightness by skill by including a measure of relative tightness in p, given by $V_{by\ skill}/V$. This variable is included in column 2 and is highly significant. As one of our measures of market size is based on the number of vacancies in each worker's skill segment, controlling for relative market tightness is crucial if we are to attain a consistent estimate of the size effect.

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 labor 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 remains non-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 $\log\left(V_{by\ skill}\right)$. If *only* density matters, as opposed to size, the coefficients on $\log\left(V_{by\ skill}\right)$ and log(acres) should not differ from each other in absolute value. We find that the effect of $\log\left(V_{by\ skill}\right)$ 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 $\log\left(V_{by\ skill}\right)$ and log(acres) do not differ significantly from each other in absolute value (with a p-value of 0.38). But we do not consider this to be convincing evidence that density

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

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 $\log(V_{by\ skill})$ and $\log(V_{by\ skill}/\text{acres})$ 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.[15]

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 5 on a sub-sample which excludes Greater London. The results obtained are reported in Table 6. 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 labor 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 $\log(V_{by\ skill}/V)$ turning non-significantly different from zero. Results from regressions including size controls are reported in table 7. Two main differences are worth noting with respect to the results of Tables 5 and 6. 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 offers are slower to arrive because of the bigger choice, we do not take it up as an implication of our estimates because we only found it in one instance.[16]

We have data on a number of other local labor 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. Previous studies (not of search markets) used mainly employment or output measures of size. The results obtained were very similar to the ones reported, so we do not give new tables of estimates.

Making use of estimates from regression 4 of Table 5, which is our preferred specification for the

[15] 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 United States. 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.

[16] Excluding the county "Greater London" reduces the sample to 1962 individuals, but excluding the London TTWA reduces it to 2046 individuals, as Greater London County is larger than the London TTWA.

Table 6: Estimation results - Local labor 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)
$\log\left(V_{by\ skill}\right)$			-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)
$\log\left(V_{by\ skill}/V\right)$		0.573^{***}	0.540^{***}	0.575^{***}	0.540^{***}
		(0.187)	(0.206)	(0.195)	(0.207)
$\log\left(V_{by\ skill}\right)$			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(lik)	-5944.7	-5936.8	-5936.4	-5936.7	-5936.6

Notes. Robust standard errors (for clustered data) reported in brackets. Significance at 10%, 5% and 1% levels is denoted by *, **, and *** respectively. No. of observations: 1962. Source: SIIOW and NOMIS.

Table 7: Estimation results - Local labor markets proxied by TTWAs

	Whole Sample			Excluding London		
Variables	1	2	3	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)
$\log\left(V_{by\ skill}\right)$	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)
$\log\left(V_{by\ skill}/V\right)$	0.176	0.025	0.152	0.264	0.144	0.253
	(0.175)	(0.168)	(0.175)	(0.175)	(0.160)	(0.174)
$\log\left(V_{by\ skill}\right)$	-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(lik)	-6729.8	-6736.7	-6738.7	-6218.5	-6222.6	6220.2

Notes. Robust standard errors (for clustered data) reported in brackets. Significance at 10%, 5% and 1% levels is denoted by *, **, and *** respectively. No. of observations: 2229 in the whole sample; 2046 excluding London. Source: SIIOW and NOMIS.

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 equation (14). Our predictions are computed setting $r = 0.005$ for the weekly discount rate,[17] for two alternative values of b ($b = 0$ and $b = 40\%$ of the average wage). With data on predicted reservation wages, we compute acceptance rates, hazard rates and realized wages for the average market and for the largest market in our sample. The results are reported in Table 8.

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

The split of the effects of scale in favor 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.[18]

6 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 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

[17] This implies an annual rate of about 30 per cent. 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 per cent 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.

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

Table 8: Comparatice statics for the effect of market size

	$r = 0.005$			$r = 0.005$		
	$b = 0$			$b = 0.4E(w \mid w > w^*)$		
	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
Realized 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 5. The average market size is calibrated using the average number vacancies across counties (1072 skilled and 2710 unskilled vacancies). The size of London is calibrated using the local number of vacancies (10559 skilled and 22335 unskilled vacancies). Arrival, acceptance and hazard rates are values per week. Mean wage offers and realized wages are values per hour.

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 9 shows the impact of tightness on the hazard rate and the post-unemployment wage at net 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 9 confirm these findings.

In Table 10 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 wages are not as important. They are important for determining the wage outcomes of search processes, not the duration of search.

Table 9: Comparative statics for the effect of market tightness

	$r = 0.005$ $b = 0.4E(w\|w > w^*)$		
	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
Realized wage	3.45158	3.56363	+3.2

Notes. All predictions are based on the estimates of column 4 in Table 5. Arrival, acceptance and hazard rates are values per week. Mean wage offers and realized wages are values per hour.

Table 10: Comparative statics for the effect of education

			$r = 0.005$ $b = 0.4E(w\|w > w^*)$				
			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
Realized wage	2.92477	3.24934	+11.1	3.74685	+28.1	4.18808	+43.2

Notes. All predictions are based on the estimates of column 4 in Table 5. Arrival, acceptance and hazard rates are values per week. Mean wage offers and realized wages are values per hour.

7 Conclusions

In this paper we argued that the fact that the vast 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 the micro level. We have shown that scale effects in the quality of matches or in the arrival rate of offers can coexist with constant returns at the aggregate level. Specifically, workers raise their reservation wages in markets characterized by scale effects so as to offset their impact on the aggregate matching function. Because of this, the impact of scale effects is primarily on the mean level of accepted wages, and this should be picked up in wage regressions. We have not run wage regressions ourselves but our findings are consistent with the empirical literature that finds local size effects on wages and labor productivity.

Our findings generalize to other variables, which sheds 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 crucially on the inclusion of London as one of our local markets (representing up to 12% of observations). One possibility is that London is characterized by other unique features which drive the results and which we have not identified. But our estimates admit also the intuitive interpretation 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 specifically, comparing say a county of 1 million employed people with one of 0.2 million (say Birmingham and Southampton) we may not be able to find that the bigger choice of jobs available in Birmingham really makes much of a difference to the quality of job matches between it and Southampton. But in a city that supports employment of 3 million people (in reality even more within travelling distance) the available choice is more likely to be rich enough to accommodate specialist talents and push up average wages. More research on different data sets and countries is needed here to uncover the true causes of scale effects, if indeed they exist. Estimates with data from countries with more than one large local market would be particularly important in this context.

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