



**Is There Compelling Evidence against Increasing Returns to Matching in the Labour Market**

Simon Baker, Seamus Hogan, Christopher Ragan

*The Canadian Journal of Economics*, Volume 29, Issue 4 (Nov., 1996), 976-993.

Stable URL:

<http://links.jstor.org/sici?sici=0008-4085%28199611%2929%3A4%3C976%3AITCEAI%3E2.0.CO%3B2-Y>

---

Your use of the JSTOR archive indicates your acceptance of JSTOR's Terms and Conditions of Use, available at <http://www.jstor.org/about/terms.html>. JSTOR's Terms and Conditions of Use provides, in part, that unless you have obtained prior permission, you may not download an entire issue of a journal or multiple copies of articles, and you may use content in the JSTOR archive only for your personal, non-commercial use.

Each copy of any part of a JSTOR transmission must contain the same copyright notice that appears on the screen or printed page of such transmission.

*The Canadian Journal of Economics* is published by Canadian Economics Association. Please contact the publisher for further permissions regarding the use of this work. Publisher contact information may be obtained at <http://www.jstor.org/journals/cea.html>.

---

*The Canadian Journal of Economics*  
©1996 Canadian Economics Association

JSTOR and the JSTOR logo are trademarks of JSTOR, and are Registered in the U.S. Patent and Trademark Office. For more information on JSTOR contact [jstor-info@umich.edu](mailto:jstor-info@umich.edu).

©2002 JSTOR

# Is there compelling evidence against increasing returns to matching in the labour market?

SIMON BAKER National Economic Research Associates  
SEAMUS HOGAN Bank of Canada  
CHRISTOPHER RAGAN McGill University

*Abstract.* Matching models of the labour market have been of particular interest in macroeconomics where the notion of 'thick-market' externalities can lead to multiple equilibria. This has led to some recent interest in constructing empirical estimates of labour-market matching functions. This paper argues that existing estimates do not provide compelling evidence against the hypothesis of increasing returns in matching. The assumption made in several studies, that the relevant pool of job searchers is proportional to the stock of unemployment, is a potentially important source of downward bias in returns-to-scale estimates. We show the source of this bias theoretically and illustrate its magnitude by estimating Canadian aggregate and regional labour-market matching functions over the period 1978–88. This evidence suggests significant increasing returns to labour-market matching.

*Est-ce que les faits remettent sérieusement en question les rendements croissants dans l'appariement sur le marché du travail?* Les modèles d'appariement du marché du travail ont attiré l'attention en macroéconomie: les effets externes de marchés profonds peuvent engendrer des équilibres multiples. Voilà qui a suscité l'intérêt à construire des calibrations empiriques de fonctions d'appariement du marché du travail. Ce mémoire suggère que les calibrations existantes ne fournissent pas un argument fort contre l'hypothèse de rendements croissants dans l'appariement. On fait le postulat dans plusieurs études que l'ensemble pertinent de gens qui cherchent un emploi est proportionnel au stock de chômeurs. C'est possiblement une source importante de biais à la baisse dans les évaluations des rendements à l'échelle. On montre la source de ce biais théorique et on donne une indication de sa taille en calibrant des fonctions d'appariement au niveau national et régional pour la période 1978–88. Ces résultats supportent l'hypothèse des rendements croissants à l'appariement.

We are grateful to Hugh Courtney, an anonymous referee, and to seminar participants at the Bank of Canada for many helpful comments. Baker thanks the U.K. Department of Trade and Industry for financial support during his graduate study at McGill University. Hogan and Ragan thank the SSHRC of Canada for financial support.

## I. INTRODUCTION

In recent years considerable attention has been paid to the process that matches workers and firms and to the returns to scale of that matching process. Matching models of the labour market have been of particular interest in macroeconomics, where the notion of 'thick-market' externalities can lead to multiple equilibria. As Pissarides (1986) argues, when a matching function is used to model the hiring process, a necessary condition for multiple equilibria is that the matching function displays increasing returns; that is, a doubling of the stocks of unemployment ( $U$ ) and vacancies ( $V$ ) must lead to a more than doubling in the flow of hires ( $H$ ).

The interest in models with multiple equilibria reflects the potential these models have for explaining some specific macroeconomic phenomena. For instance, many authors have developed models with hysteresis in key variables (and hence multiple equilibria) to explain the different time-paths taken by North American and European unemployment rates in the early 1980s (e.g., Blanchard and Summers 1986; Lindbeck and Snower 1988). Another example is Diamond's (1982a) model of demand management, in which aggregate-demand policy can be used to move the economy from a low-activity equilibrium to a Pareto-superior equilibrium with higher activity. A key implication of all such models of multiple equilibria is that temporary policies may have permanent effects.

Given the prominent role that matching functions with increasing returns play in this literature, it is not surprising that empirical researchers have been keen to examine the matching process in real-world labour markets. Pissarides (1986) examines the relationship between unemployment exit rates and the levels of unemployment and vacancies. Using aggregate data from the United Kingdom from 1967 to 1983, Pissarides regresses the exit rate out of unemployment against the stocks of  $U$  and  $V$  and the  $U/V$  ratio. If matching displays constant returns, then the  $U/V$  ratio matters, but the levels of  $U$  or  $V$  do not matter. To capture possible shifts in the matching function, Pissarides includes time trends, the unemployment-benefit replacement ratio, and a measure of 'mismatch' as additional right-hand-side variables. Pissarides is unable to reject the hypothesis that labour-market matching is characterized by constant returns.

Blanchard and Diamond (1990) estimate the matching function directly for aggregate U.S. data. Using monthly data from 1968 to 1981, they estimate

$$\ln(H_t) = \alpha + \beta \ln(U_{t-1}) + \gamma \ln(V_{t-1}) + \delta T + \epsilon_t, \quad (1)$$

where  $H$  is the flow of hires and  $T$  is a linear time trend. Unlike Pissarides, who has direct observations on vacancies, Blanchard and Diamond use the Help-Wanted Index as their measure of vacancies. When they estimate equation (1) with OLS, they cannot reject the hypothesis of constant returns ( $\beta + \gamma = 1$ ). When they use an Instrumental Variables estimator, the returns-to-scale estimate increases slightly, but the IV results are very sensitive to the choice of instruments. Overall, they conclude in favour of constant, or perhaps very mildly increasing, returns to scale.

Warren (1992) uses monthly data from the U.S. manufacturing sector from 1969 to 1973, a period for which direct vacancy data are available. He examines the possibility that the Cobb-Douglas assumption used by Blanchard and Diamond may be too restrictive and instead uses the flexible trans-log specification. Warren's OLS estimates suggest a returns-to-scale elasticity of about 1.3.

Though these studies differ with respect to the countries and sample periods, they share one important characteristic. The approach used to generate these estimates – which we refer to as the existing approach – assumes that the stock of unemployment can be used to represent the true pool of job searchers in the matching process. As pointed out by Burgess (1993), however, job-finding by employed workers accounts for a significant fraction of the observed flow of hires. To the extent that the amount of on-the-job search depends on the state of the business cycle, and is thus correlated with unemployment, the existing approach may generate biased estimates of the matching-function parameters.

In this paper we show that, if a rise in unemployment discourages (or at least does not encourage) job search among workers who are either employed or out of the labour force, then using the stock of unemployment to represent the true pool of searchers will lead to returns-to-scale estimates' being unambiguously biased downward. We argue that this problem affects all studies, such as the ones above, which use the existing approach to examine the returns-to-scale of the labour-market matching process.

We illustrate our arguments by estimating aggregate and regional matching functions for Canada over the period 1978–88. The results suggest that simple estimates based on the existing approach lead to a considerable underestimate of the returns to scale in matching; when we use an alternative approach to avoid this downward bias, our evidence points to significant increasing returns to scale.

The paper is organized as follows. In section II we provide a brief review of the matching-function approach to modelling the relationship among unemployment, vacancies, and hiring. We also discuss some of the problems with estimating matching functions that have been raised in the literature. One common theme is that existing estimates of returns to scale should be viewed as lower bounds of the true values. In section III we examine in detail the source of the bias that occurs as a result of assuming that the true pool of job searchers is proportional to the stock of unemployment. We illustrate the magnitude of this bias using Canadian data in section IV. Our estimates suggest that both aggregate and regional matching functions in Canada display significant increasing returns to scale. Some final remarks are presented in section V.

## II. LABOUR-MARKET MATCHING FUNCTIONS

In models of imperfect information in the labour market, workers and firms are assumed to locate each other in some way. Owing to the imperfect information, the meeting of a worker and firm is a random event over which there is typically a well-defined probability distribution. An exogenous matching function models this

random meeting of firms and workers (e.g., Diamond 1982b). This is effectively a production function of the form  $H = m(U, V)$ , in which the inputs  $U$  and  $V$  are the stocks of unemployed workers and vacancies, and the output  $H$  is the flow of worker-firm matches or hires. The matching function is assumed to be increasing in both  $U$  and  $V$ .

The development of matching models in which increasing returns in the matching function plays a prominent role reflects not only its importance in explaining certain macroeconomic phenomena but also a strong prior belief that real-world matching is characterized by increasing returns (see, e.g., Hall 1989). The theoretical argument in favour of increasing returns is the following. Consider a labour market in which the stocks of unemployed workers and vacancies combine to generate a flow of hires equal to  $H$ . Now consider a second identical economy that is physically detached from the first, so that the unemployed workers in one economy cannot match with the vacancies in the other. The replicated economy will also produce  $H$  hires. With replication, then, a doubling of the number of unemployed workers and vacancies leads to a doubling of hires; that is, there is constant returns to scale. If, however, the two economies were merged rather than kept physically detached, so that unemployed workers from one economy could match with vacancies in the other, then there would be a further increase in the number of matches and thus increasing returns to matching.

Given the strong theoretical presumption for increasing returns to matching, there has naturally been some interest in examining the empirical relationship between hires, unemployment and vacancies. The key empirical papers were discussed briefly in the introduction. In the remainder of this section, we examine some of the central problems encountered in estimating the labour-market matching process.

As with empirical research on production functions, one of the major challenges in estimating labour-market matching functions involves controlling for the unobserved changes in the matching function. Hall (1989) argues that OLS estimates of matching functions are likely to understate the elasticities with respect to both  $U$  and  $V$ . The obvious stock-flow relationship between  $U$  and  $V$  and hires implies that any unobserved shock to the efficiency of the matching process in a given month will change the flow of hires for that month and the end-of-month stocks of  $U$  and  $V$  in opposite directions. Therefore, unless all factors that affect the matching process can be included in the regression, OLS will produce estimates of the returns to scale in matching that are biased downwards.

Blanchard and Diamond (1990) attempt to avoid this problem by using as regressors unemployment and vacancies measured at the *beginning* of the month in which the flow of hires occurs. One problem with this approach is that its success requires the unobserved changes in the matching process to be serially uncorrelated. The nature of the factors likely to cause shifts in the matching function, however, are such that considerable serial correlation is probably more likely. For example, one unobserved determinant of the efficiency of the matching process is the search intensity of workers or firms. This search intensity might be affected by the level of unemployment benefits or by the tightness of the labour market. Since there is

strong serial correlation in aggregate economic activity, it would therefore not be surprising to find that search intensity was also strongly serially correlated; in this case, even lagging  $U$  and  $V$  in the estimation process would yield downward-biased estimates of the scale elasticities.

Given the impossibility of including all relevant variables as regressors, an obvious alternative is to estimate the matching function using Instrumental Variables rather than OLS. Blanchard and Diamond (1990) use, alternatively, lagged  $U$  and  $V$  and lagged industrial production as instruments. Given the likelihood that unobserved changes in the matching function are serially correlated, however, it is easy to be sceptical of the suitability of lagged  $U$  and  $V$  as instruments. Measures of real activity such as industrial production may also be inappropriate instruments. In order for such variables to be suitable instruments it must be true that the forces that drive real activity are separate from those that drive the matching process in the labour market. As Hall (1989) argues, however, in many models of aggregate fluctuations, such as those with 'thick-market' effects, such a separation would not be present.

Estimation of labour-market matching functions may therefore be faced with an identification trap: omitted variables are sure to lead to downwardly biased OLS estimates, but convincing IV estimates may be almost impossible to generate, owing to the controversial identifying assumptions that must be imposed.

Aside from issues related to omitted variables and instrumentation, there are two additional reasons why the existing estimates of returns-to-scale elasticities in matching might be viewed as lower bounds of the true values. Burdett, Coles, and Van Ours (1994) argue that temporal aggregation of the data combined with a mean-reverting process in unemployment and vacancies leads to downward bias in estimated returns to scale. As they admit, however, the frequency of the data typically used in estimating matching functions (monthly) relative to the average length of a business cycle suggests that this downward bias is quite small.

Perhaps a more important source of bias is the spatial aggregation of the data. Courtney (1992) argues that the use of aggregate, rather than sectoral, data may lead to bias in the estimates of the scale elasticities. He suggests using data from well-defined geographical labour markets to generate more accurate estimates of the matching function. One piece of supporting evidence for Courtney's views comes from Blanchard and Diamond's own estimate of a single matching function for the combined U.S. manufacturing industries over the period 1969–73. For this less aggregated sample, both OLS and IV estimates suggest a returns-to-scale elasticity of about 1.4.

### III. AN ADDITIONAL SOURCE OF DOWNWARD BIAS

There is a further reason why the existing approach to estimating labour-market matching functions may produce downwardly biased estimates of returns to scale. This concerns the use of the stock of unemployment as the measure of the pool of job searchers, even though many workers who are classified as non-unemployed

(i.e., employed or out of the labour force) also conduct job search. The general implications of on-the-job search for interpreting labour-market flows has been examined by Burgess (1993), who shows that during the 1967–85 period in the United Kingdom the annual flow of hires is about twice as large as the annual outflow from unemployment, thus indicating an important role for search by non-unemployed workers. In this section we examine in detail how job search by non-unemployed workers leads to biased estimates of returns to scale in matching. In the next section we use Canadian data to illustrate the magnitude of the bias.

1. The source of bias

Despite the existence of on-the-job search, recent attempts to estimate labour-market matching functions typically use only the stock of unemployment,  $U$ , to represent the true pool of job searchers,  $S$ . This does not reflect a belief on the part of these researchers that only unemployed workers search for jobs, but is rather a simplifying assumption necessitated by data limitations;  $U$  is readily available in the data, whereas  $S$  clearly is not. Unbiased estimates of the matching-function parameters then requires that the  $S/U$  ratio and the stock of unemployment be uncorrelated within the sample.<sup>1</sup>

To see how the correlation between  $S/U$  and  $U$  biases the estimates of the matching function, consider the case where the true matching function is given by

$$\ln(H_t) = \alpha + \beta \ln(S_{t-1}) + \gamma \ln(V_{t-1}). \tag{2}$$

The true coefficient on  $S$  in the matching function is  $\beta$  which is equal to  $\partial \ln(H)/\partial \ln(S)$ . When estimation proceeds by using  $U$  in place of  $S$ , however, the estimate of  $\beta$  obtained, denoted  $\tilde{\beta}$  is

$$\tilde{\beta} = \frac{\partial \ln(H)}{\partial \ln(U)} = \frac{\partial \ln(H)}{\partial \ln(S)} \cdot \frac{\partial \ln(S)}{\partial \ln(U)} = \beta \eta_{su}, \tag{3}$$

where  $\eta_{su}$  is the elasticity of  $S$  with respect to  $U$ . From equation (3)  $\eta_{su}$  is clearly the complete measure of the extent to which  $\tilde{\beta}$  is a biased estimate of the true parameter,  $\beta$ . If this elasticity is less than (greater than) one, then using  $U$  in the estimate of the matching function in place of  $S$  leads to a downwardly (upwardly) biased estimate of  $\beta$ .

There are two reasons to expect  $\eta_{su}$  to be less than one. First, many of the observed changes in the stock of unemployment are the result of flows between unemployment and employment. The mere change in the *composition* of the pool of searchers caused by such flows means that  $S/U$  will fall as  $U$  rises, and thus  $\eta_{su}$  will be less than one. The second reason to expect  $\eta_{su}$  to be less than one

<sup>1</sup> Blanchard and Diamond (1990) address the issue of the relevant pool of job searchers: they assume that the true pool of searchers is  $X_t = X_{1t} + dX_{2t}$ , where  $X_{1t}$  and  $X_{2t}$  are possible sub-pools and  $d$  is a constant to be estimated. They impose constant returns to matching, however, and so their approach prohibits them from examining the effect that the choice of search pool has on the estimates of the returns-to-scale elasticity.

is due to the endogeneity of search behaviour by non-unemployed workers. If the fraction of non-unemployed workers who undertake job search falls as the level of unemployment rises, then  $S/U$  will be negatively correlated with  $U$  even if there is no change in the number of individuals classified as employed, unemployed or outside the labour force.

To make this argument more explicit, suppose that all unemployed workers are searching for jobs, as are some fraction of the employed workers,  $\lambda_E$ . For simplicity only, assume that individuals who are out of the labour force do not search for jobs; this assumption can be relaxed with no change in the general argument. The true pool of searchers,  $S$ , is then

$$S = U + \lambda_E E, \quad (4)$$

where  $E$  is the stock of employment. Let  $\lambda_E$  vary with the stock of unemployment. This need not be a structural relationship; any correlation within the sample between the stock of unemployment and  $\lambda_E$  affects the estimation bias, whatever the cause of the correlation. Using the identity,  $L \equiv E + U$ , where  $L$  is the size of the labour force,  $\eta_{su}$  is given by

$$\eta_{su} = \frac{1 + E\lambda'_E(U)}{1 + (E/U)\lambda_E}. \quad (5)$$

where  $\lambda'_E(U)$  is the partial derivative of  $\lambda_E$  with respect to  $U$ . The denominator of equation (5) is greater than one as long as some positive fraction of employed workers conducts job search. Whether the numerator is greater or less than one depends on whether a rise in unemployment increases or decreases the fraction of employed workers that chooses to search.

In the case where some positive fraction of employed workers searches for jobs, but where that fraction is constant (i.e., where  $\lambda'_E = 0$ ),  $\eta_{su}$  is less than one, and so  $\tilde{\beta}$  underestimates the true value  $\beta$ . In the more plausible case where a rise in unemployment has the effect of discouraging some employed workers from searching so that  $\lambda'_E$  is negative, this underestimation is intensified. Only in the unlikely case where a rise in unemployment *encourages* job search among employed workers is it possible that  $\tilde{\beta}$  does not underestimate  $\beta$ .

It seems reasonable to expect  $\lambda_E$  to be negatively correlated with unemployment. This might be referred to as the 'discouraged searcher' effect, a natural result in models of on-the-job search (e.g., Burdett 1978). The behavioural story is simply that employed workers are more inclined to search for jobs when the expected pay-off from such search is higher. One possible measure of the probable pay-off to search for employed workers is the ratio of the stock of searchers to the flow of hires or, similarly, the expected duration of an unemployment spell,  $D$ . We then have the relationship  $\lambda_E(D)$ , where presumably  $\lambda'_E(D)$  is negative. The size of  $\eta_{su}$  then depends on the observed sample correlation between  $U$  and  $D$ ; the larger is the correlation between  $U$  and  $D$ , the greater is the extent to which  $\eta_{su}$  is less than

one, and the larger is the downward bias in  $\tilde{\beta}$ . In the Canadian data that we use in the next section, the simple correlation between the stock of unemployment and  $U/H$  (which is a simple measure of expected unemployment duration) is about 0.8, suggesting a significant downward bias in the estimated returns-to-scale elasticity.

## 2. Possible solutions

One possible solution to the problem of downward bias in the estimate of  $\beta$  is to try to estimate the number of non-unemployed searchers. This is essentially the approach taken by Anderson and Burgess (1993) in their analysis of the matching process in five U.S. states. They assume that employed and unemployed searchers are considered identically by firms, so that the ratio of hires out of employment to hires out of unemployment in any period represents the ratio of employed to unemployed searchers in that period. (They make no distinction between unemployed workers and those who are out of the labour force.) Their estimate of the pool of employed searchers,  $\tilde{S}_E$ , is therefore given by

$$\tilde{S}_E = (H_E/H_U)U,$$

where  $H_E$  and  $H_U$  are the flows of hires from employment and unemployment, respectively.

The efficacy of this approach depends on how employed searchers and unemployed searchers are viewed by potential employers. We can imagine two extreme worlds. In one case the two types of searchers are indistinguishable to firms, and thus they compete in the same labour market. In the other extreme, employed searchers and unemployed searchers are perceived completely differently by firms; in this case they effectively search in disjoint labour markets.

Consider the first case: given that employed and unemployed workers are treated identically by firms, it makes sense to estimate the number of non-unemployed searchers and then to estimate a single matching function. Note, however, that matching is inherently a stochastic process. Even if it were the case that employers view the two types of searchers identically, the  $S_E/U$  ratio would equal the  $H_E/H_U$  ratio only *on average*; it would not hold at every point in time. The estimate  $\tilde{S}_E$  from above will therefore contain measurement error, and estimates of the matching-function parameters that use  $\tilde{S}_E$  as a right-hand-side variable will thus be biased downward.

In the second case, employed and unemployed searchers are completely different, and hence the very notion of a matching function determining the flow of hiring of *both* groups of workers is suspect. In this case the ideal approach would estimate separate matching functions for employed and unemployed workers.

Thus, the approach of trying to estimate the true pool of searchers,  $S$ , and then using this estimate as a right-hand-side variable to estimate the matching function can, at best, produce estimates of the matching-function parameters that are downwardly biased. At worst, in the case when unemployed and non-unemployed workers are completely different, this approach produces largely meaningless re-

sults, since the very notion of a single matching function for both types of searcher is questionable.

An alternative approach, which we use in this paper, is to use a dependent variable representing only the flow of hires *from the unemployment pool*, rather than from the entire pool of job searchers. This approach estimates

$$\ln(H_{Ut}) = \alpha + \beta_U \ln(U_{t-1}) + \gamma_U \ln(V_{t-1}) + v_t, \quad (6)$$

where  $H_U$  is the flow of hires from the unemployment pool.

Consider again the two extreme worlds discussed above. In the case where employed and unemployed searchers are completely different, so that they are searching in distinct markets, this approach yields unbiased parameter estimates of the matching function in the market for unemployed workers.

In the other case, where unemployed and non-unemployed workers are viewed identically by potential employers, spillover effects from the presence of non-unemployed searchers to the hiring rate of unemployed searchers again can lead to estimation bias. To see this bias, note that if unemployed and non-unemployed searchers are viewed identically by employers, then the  $H_U/H$  ratio will equal the  $U/S$  ratio. This implies

$$\ln(H_{Ut}) = \ln(H_t) + \ln(U_{t-1}) - \ln(S_{t-1}). \quad (7)$$

Substituting the true expression for total hires from equation (2) into equation (7), the true relationship between  $H_U$ ,  $U$ ,  $S$ , and  $V$  is

$$\ln(H_{Ut}) = \alpha + \ln(U_{t-1}) + (\beta - 1) \ln(S_{t-1}) + \gamma \ln(V_{t-1}).$$

When estimating the matching function using equation (6), the estimated coefficient on unemployment, denoted  $\tilde{\beta}_U$ , is equal to

$$\begin{aligned} \tilde{\beta}_U &= \frac{\partial \ln(H_U)}{\partial \ln(U)} = 1 + (\beta - 1) \frac{\partial \ln(S)}{\partial \ln(U)} \\ &= \beta \eta_{su} + (1 - \eta_{su}). \end{aligned} \quad (8)$$

Equation (8) shows that if  $\eta_{su} < 1$ , then  $\tilde{\beta}_U$  is only an unbiased estimate of  $\beta$  if  $\beta = 1$ ; in general, however,  $\tilde{\beta}_U$  is an estimate of  $\beta$  that is biased towards one.

By estimating the matching function only for unemployed workers, therefore, this approach generates unbiased estimates of the true matching-function parameters in the case where employed and unemployed searchers are completely different. To the extent that these two groups compete in the same labour market, however, this approach generates estimates of  $\beta$  that are biased towards one.

### 3. Demand-side bias

We have examined the relationship between the stock of unemployed workers,  $U$ , and the pool of actual job searchers,  $S$ , and argued that if  $U$  and  $S/U$  are

correlated, then there will be a systematic downward bias in the estimated returns-to-scale elasticity. A similar downward bias is likely to originate in the relationship between measured vacancies and the true pool of searching firms. This paper does not address this second source of bias, not because we think the demand-side bias is less important than that arising on the supply side, but because we are able to distinguish in our data between total hires and hires out of unemployment and so can estimate the magnitude of the supply-side bias empirically. The data do not distinguish between total hires and hires out of measured vacancies, and thus, correcting for the demand-side bias in a similar manner is not possible.

#### IV. RETURNS TO SCALE IN CANADIAN MATCHING FUNCTIONS

##### 1. Estimation approach

Our approach is to draw inferences about the parameters of the true matching function,

$$\ln(H_t) = \alpha + \beta \ln(S_{t-1}) + \gamma \ln(V_{t-1}),$$

by estimating the following regressions:

$$\ln(H_t) = \alpha_H + \beta_H \ln(U_{t-1}) + \gamma_H \ln(V_{t-1}) + \delta_H T + \epsilon_t \quad (9)$$

$$\ln(H_{U_t}) = \alpha_U + \beta_U \ln(U_{t-1}) + \gamma_U \ln(V_{t-1}) + \delta_U T + \nu_t. \quad (10)$$

The  $H$  subscripts on the parameters in equation (9) indicate that the dependent variable is the total flow of hires; the estimation of equation (9) is what we have referred to as the existing approach. The  $U$  subscripts in equation (10) indicate that the dependent variable is the flow of hires only from unemployment. Note in both equations that  $U$  and  $V$  are dated  $t - 1$  to reflect the fact that these stocks are measured at the beginning of the month in which the flow of hires takes place.  $T$  is a linear time trend.

Parameter estimates from either equation (9) or equation (10) taken alone are not particularly informative; recall that the estimate of  $\beta_H$  from equation (9) is a downward-biased estimate of  $\beta$ , whereas the estimate of  $\beta_U$  from equation (10) provides an estimate of  $\beta$  that is biased towards one. Thus, our approach in estimating equations (9) and (10) is to emphasize the *difference* between the parameter estimates in the two equations, rather than to focus on the parameter estimates from either equation individually. This emphasis on the comparison of parameter estimates across equations (9) and (10) is important for two additional reasons, one having to do with the specification of the equations and the other relating to the estimation method.

Equations (9) and (10) are obviously very simple specifications of the labour-market matching process, and there are good reasons to think that this matching process changes in ways that cannot be fully captured by a simple time trend. Indeed, Pissarides (1986) tries to control for some of these shifts by including

additional right-hand-side variables, including a simple measure of mismatch in the labour market. Our approach, instead, is to recognize that adequately capturing these shifts in the matching process is probably impossible; we also recognize, therefore, that, for the reasons discussed in section II, the parameter estimates from either equation will very likely be biased downward.

The second issue is related but concerns the estimation method. Given the simple specifications in equations (9) and (10), the bias introduced by any omitted variables suggests the use of Industrial Variables. If the goal were to arrive at an estimate of the true value of  $\beta$ , we would take this approach, though, as was argued in section II, it might be very difficult to come up with a convincing set of instruments.

Our goal here, however, is simply to show that the existing approach, which estimates equation (9) alone, yields a downwardly biased estimate of the returns to scale for reasons unrelated to the omitted variables. We show the extent of this downward bias by estimating both equation (9) and equation (10). Note that both equations suffer from the same omitted variables problem, but only equation (9) suffers from the bias due to the inappropriate specifications of the search pool. Thus, we use OLS to estimate both equations, cognizant of the likely bias in each equation from omitted variables, but focusing on the difference in parameter estimates across equations.

## 2. Data

Both Pissarides (1986) and Blanchard and Diamond (1990) use aggregate data to estimate labour-market matching functions. As Courtney (1992) argues, however, if the fundamental matching process between firms and workers takes place within well-defined regional or sectoral labour markets, then estimating the matching functions with disaggregated data should yield better estimates of the returns-to-scale elasticities. Given that our data are available regionally as well as for the aggregate economy, we estimate both regional and aggregate matching functions in this paper.

The migration of workers between regions introduces a potential problem for the analysis. For example, suppose that an individual who is unemployed in region  $X$  migrates to region  $Y$  to take up a job. In this case, some of the hiring in region  $Y$  may be from a pool of job searchers from outside that region, a pool that would not be captured in the data for that region. It is clear, however, that this is just another example of the central issue addressed in this paper: that not all hires are from the (region's) unemployment pool, and that maintaining the assumption that the pool of job searchers is proportional to the unemployment pool is a potentially important source of bias. By estimating equation (10), and thus concentrating on hires only from the pool of unemployed workers, the bias emanating from this problem is avoided.

The main source of data for this study is the recently released gross-flows data from Statistics Canada. Beginning in February 1976, monthly flows between employment ( $E$ ), unemployment ( $U$ ), and out-of-the-labour-force ( $N$ ) are computed from the monthly Labour Force Survey (see Jones 1993). Also available are the

monthly values of the stocks of each of the variables  $U$ ,  $E$ , and  $N$ . These data are available separately for each of the ten Canadian provinces. We combine the provincial data to form five regions: the four Atlantic provinces, Quebec, Ontario, the three prairie provinces, and British Columbia.

We construct two different measures for the flow of hires: total hires and hires out of unemployment. The monthly flow of hires out of unemployment,  $H_U$ , is estimated as the monthly flow from unemployment to employment, which is directly available in the gross-flows data. Total monthly hires, following Blanchard and Diamond (1990), is estimated as

$$H_t = UE_t + NE_t + (0.411)qE_{t-1}$$

where  $UE_t$  and  $NE_t$  are the respective monthly flows from unemployment and out-of-the-labour-force to employment,  $q$  is the quit rate, and  $E_{t-1}$  is the stock of employment at the beginning of the month. The term  $(0.411)qE_{t-1}$  is an estimate of the monthly flows of job switchers – those workers who quit one job and move directly to another job within the month. From the 1986 Labour Market Activity Survey, it is estimated that 41.1 per cent of those who quit their jobs do so to take a new job. We use this estimate for the entire sample period. This number is remarkably close to the estimate of 40 per cent for the United States found by Akerlof, Yellen, and Rose (1988) and used by Blanchard and Diamond to construct their measure of total hires. Data on quits are available only annually by province from 1978 to 1988 (see Statistics Canada 1992). We therefore construct annual quit rates for each region and then use the annual quit rate for each month in that year.

Our measure for the stock of unemployment is directly available from the gross-flows data. With respect to timing, we use the stock of unemployment at the beginning of the month in which the flow of hires takes place.

The variable we use to represent vacancies is the monthly Help-Wanted Index. Like the United States, Canada does not have a comprehensive series on actual job vacancies; Canada did have one survey on job vacancies, but this existed only for a few years in the mid-1970s. We therefore follow Blanchard and Diamond in using the Help-Wanted Index as a proxy for actual job vacancies, cognizant of the concerns raised by Abraham (1987) in using such an index. Note, however, that Canada has two help-wanted indices. One index measures the number of *inches* of help-wanted advertisements in eighteen major newspapers across the country; this index was discontinued in 1989. A new index begins in 1981 and measures the number of help-wanted advertisements listed in an expanded set of twenty newspapers. Both indices are available monthly for each of the five regions as well as for the aggregate economy.

Although the gross-flows data is available monthly by province from February 1976 to the present, our sample for the purposes of estimation is restricted by the availability of the quit rates to being 1978:1 to 1988:12. This sample period, in turn, forces us to use the old Help-Wanted Index (based on inches of ads) rather than the new index (based on number of ads). Furthermore, since the Help-Wanted

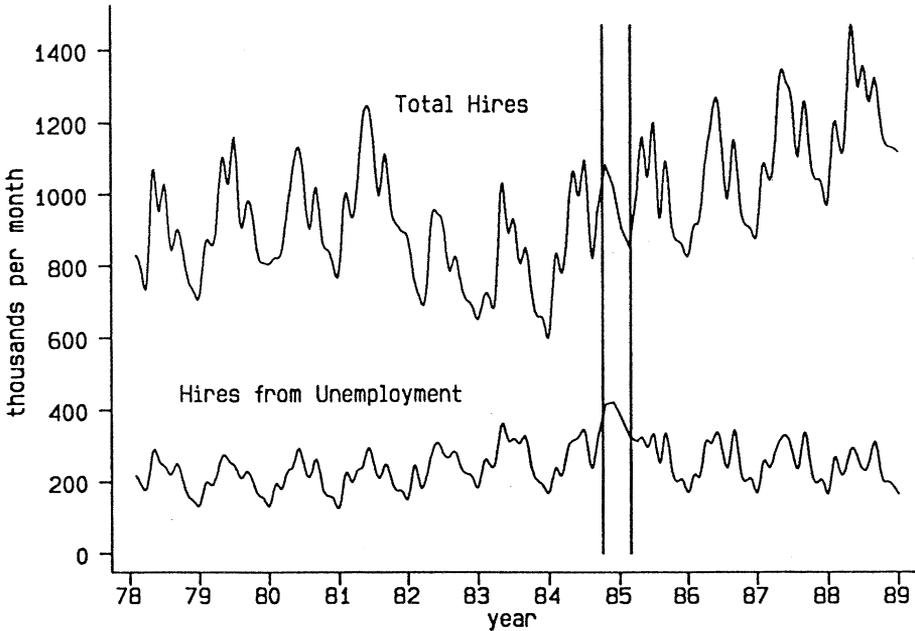


FIGURE 1 Total hires and hires from unemployment, Canada, 1978–88

Index is not available provincially, but rather is available only regionally, we are able to estimate separate matching functions only for each region rather than for each province.

Figure 1 shows  $H$  and  $H_U$  for Canada from 1978:1 to 1988:12. Despite the fact that these years span a business-cycle peak in the late 1970s, the major recession of 1981–3, and the subsequent strong recovery in the late 1980s, the cyclical variation in the flow of hires is not pronounced. There is, however, a clear seasonal component to these flows.

Figures 2 and 3, respectively, show the time series for the stock of Canadian unemployment and the Help-Wanted Index over the same period. The vertical lines in late 1984 and early 1985 in figures 1 and 2 indicate a six-month interval for which the gross-flows data is unavailable. Figures 1 and 2, however, graph the time series with a cubic spline that smooths the data, and these splines continue uninterrupted through the six-month interval. Note the strong seasonal variation, in particular in the unemployment series.

There are two important points that relate our data selection to the issue of estimation bias. The first concerns seasonal patterns in the data; the second is related to measurement error in the estimated flow of total hires.

We use seasonally *unadjusted* data in the estimation of the matching functions for two reasons. The most important reason is that the seasonal variation in  $H$ ,

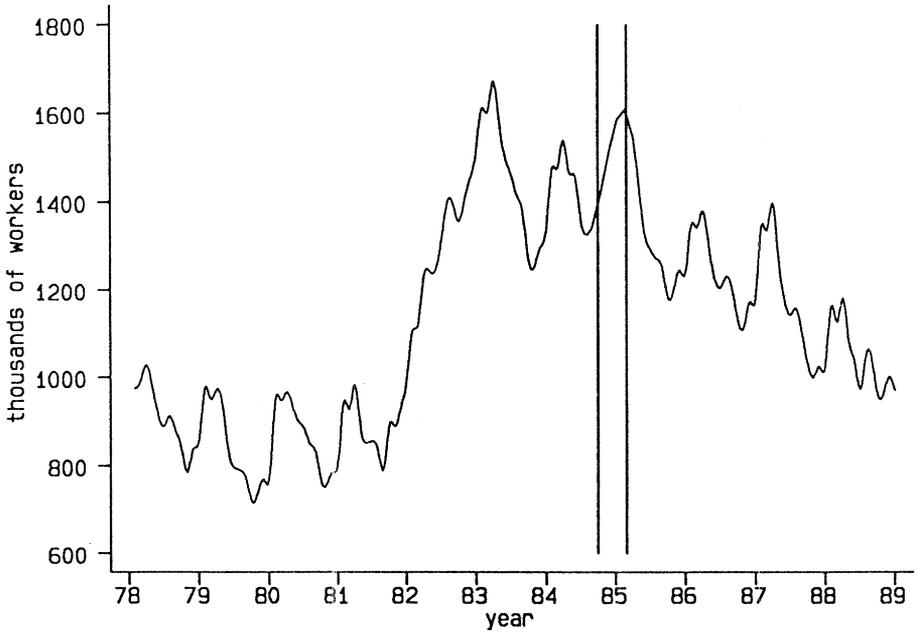


FIGURE 2 Stock of unemployment, Canada, 1978-88

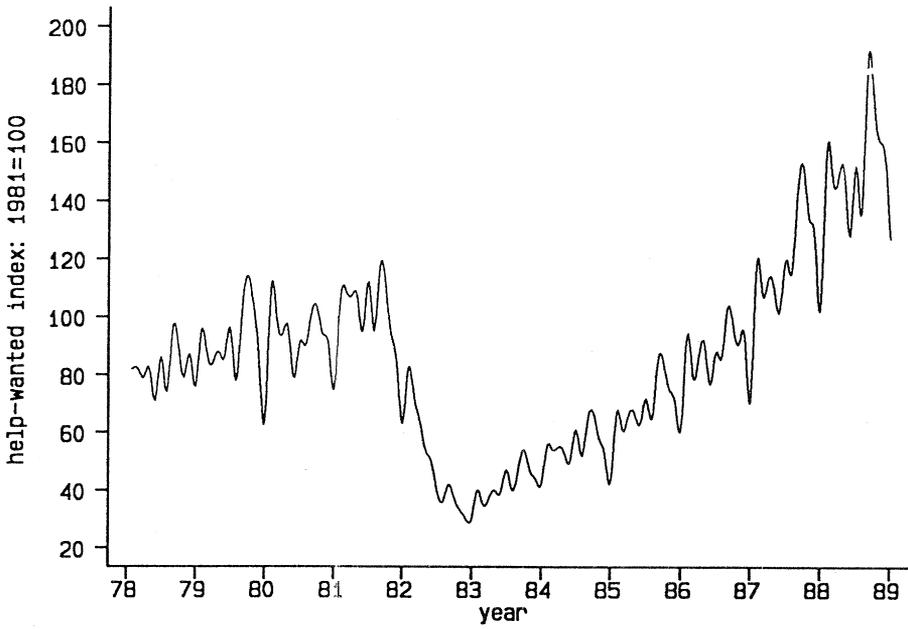


FIGURE 3 Help-Wanted Index, Canada, 1978-88

$U$ , and  $V$  contains information that can be usefully exploited in the estimation of the matching function. The peaks in the flow of hires are closely related to the peaks in unemployment; this is exactly what one would expect if the underlying matching process is relatively stable and if there is a causal relationship from the stock of unemployment to the flow of hires. Seasonal adjustment of the data would eliminate this valuable information. The second reason we choose to avoid seasonally adjusted data is that by removing the seasonal component to the data, which is clearly a large part of the variation, the cyclical component becomes relatively much more important. This cyclical component to the data, however, is likely driven by strongly serially correlated shocks to the matching process, as discussed in section II. By seasonally adjusting the data, therefore, estimation of the matching-function parameters is more susceptible to the problem of downward bias caused by serially correlated unobserved changes in the matching function. Indeed, when we estimated the matching function with all variables seasonally adjusted, the estimated coefficients on  $U$  and  $V$  were less than those generated by the unadjusted data in every specification (i.e., for Canada and for each of the five regions).

The second point about the data is that our estimate of the monthly flow of job switchers clearly contains measurement error. For the estimation of equation (9), this measurement error is not serious, since the error appears only within the dependent variable. But this would present a problem if we were to estimate equation (9) using an estimate of  $S$  to replace  $U$  on the right-hand side. Not only would there be measurement error in the estimate of  $S$ , as discussed in the previous section, but the presence of measurement error in  $H_E$  would introduce further measurement error in the estimate of  $S$ . Thus, given the limitations of our data, there is an advantage to estimating equation (10) rather than a version of equation (9) in which an estimate of  $S$  replaces  $U$ . By using  $H_U$  rather than  $H$  as the dependent variable and by using  $U$  rather than an estimate of  $S$  as a right-hand-side variable, we remove measurement error from the dependent variable rather than add measurement error to the right-hand-side variable. This eliminates an important potential source of downward bias in the estimates of returns to scale.

### 3. Results

Table 1 shows the results of estimating equations (9) and (10) with OLS. The left side of the table shows the results using the existing approach – that is, using the total flow of hires as the dependent variables and the stock of unemployment as a measure of the total search pool. The right side uses hires from unemployment as the dependent variable. The third column in each side of the table shows the estimate of the returns to scale in matching, denoted RTS. The main finding in table 1 is the comparison of the estimated returns to scale between the two specifications. For Canada as a whole and for each of the five regions taken separately the estimated returns to scale is considerably greater when the dependent variable is  $H_U$  than when it is  $H$ . This is the empirical manifestation of the theoretical arguments in the previous section: changes in the  $S/U$  ratio result in a downward bias of

TABLE 1  
OLS estimates of equations (9) and (10)

$$\ln(H_t) = \alpha_H + \beta_H \ln(U_{t-1}) + \gamma_H \ln(V_{t-1}) + \delta_H T + \epsilon_t \tag{9}$$

$$\ln(H_{Ut}) = \alpha_U + \beta_U \ln(U_{t-1}) + \gamma_U \ln(V_{t-1}) + \delta_U T + \nu_t \tag{10}$$

Region	Equation (9)		RTS	<i>p</i>	Equation (10)		RTS	<i>p</i>
	$\hat{\beta}_H$	$\hat{\gamma}_H$			$\hat{\beta}_U$	$\hat{\gamma}_U$		
Canada	0.226 (0.113)	0.357 (0.054)	0.583	–	1.183 (0.167)	0.363 (0.080)	1.546	0.01
Atlantic	0.507 (0.156)	0.498 (0.073)	1.005	0.49	1.233 (0.247)	0.412 (0.115)	1.645	0.02
Quebec	0.089 (0.150)	0.251 (0.053)	0.340	–	0.971 (0.202)	0.208 (0.072)	1.179	0.25
Ontario	0.154 (0.096)	0.338 (0.054)	0.492	–	1.189 (0.149)	0.407 (0.083)	1.596	0.00
Prairies	0.272 (0.063)	0.443 (0.040)	0.715	–	1.411 (0.093)	0.665 (0.059)	2.076	0.00
B.C.	0.097 (0.081)	0.358 (0.046)	0.455	–	1.091 (0.127)	0.428 (0.073)	1.519	0.00

NOTES

All equations are estimated with 126 observations.

RTS is the sum of the estimated values of  $\beta$  and  $\gamma$ .

Estimated standard errors given in parentheses.

*p* is the *p*-value for the test

$$H_0: \text{RTS} = 1$$

$$H_1: \text{RTS} > 1$$

given for those regressions where estimated RTS > 1.

estimates of returns to scale when *H* rather than *H<sub>U</sub>* is used as the dependent variable in matching-function regressions.

All but one of the estimates from the right side of table 1 suggest strongly increasing returns to scale. The last column of each side of the table shows the *p* value associated with testing the null hypothesis that RTS = 1, against the alternative that RTS > 1. In all cases except the province of Quebec, we can reject the hypothesis that there is constant returns to matching at the 98 per cent level. Furthermore, recall that the estimate of  $\beta_U$  from equation (10) provides an estimate of  $\beta$  that is biased towards 1. Since in all regions except Quebec the estimated value of  $\beta_U$  exceeds 1, the estimates of RTS on the right side of table 1 should be viewed as lower bounds of the true values of RTS in those regions. In the case of Quebec, the estimated value of  $\beta_U$  is less than 1, and hence, the evidence in favour of increasing returns in that province is weaker.

V. FINAL REMARKS

The existence of increasing returns in the matching functions by which unemployed workers are combined with job vacancies is crucial in many macroeconomic and

labour-market models. Previous estimates of labour-market matching functions, however, have not provided empirical support for the strong theoretical presumption in favour of increasing returns. We noted in section II that there are many problems in estimating matching functions that are likely to lead to downward bias in estimates of the returns to scale in matching. It is not clear, however, whether these downward biases are economically significant.

In this paper we have identified an additional source of downward bias in the existing approach for estimating the returns to scale in matching. This bias results from the inability to observe the true pool of searching workers. By changing the dependent variable from total hires to hires out of unemployment, it is possible partly to control for this problem and hence to get an estimate of how significantly it biases the estimates of the returns to scale.

Using Canadian gross-flows data, we have estimated matching functions for Canada and for each of five regions. In each case the estimates when hires out of unemployment are used as the dependent variable suggest strongly increasing returns to scale in matching. Furthermore, these estimates are themselves likely to be downwardly biased. This is partly because the correction of using hires out of unemployment rather than total hires is imperfect and results in estimates of the coefficient on unemployment that are biased towards one, and partly because of the various other downward biases that have been discussed in the literature.

The particular estimates obtained, however, are not the main result of this paper. The more important result is that our returns-to-scale estimates are considerably higher when hires out of unemployment is used as the dependent variable than when total hires is used, suggesting that the particular downward bias that is the focus of this paper is economically significant. The theoretical point that the use of total hires (rather than hires out of unemployment) leads to downwardly biased returns-to-scale estimates is not specific to any particular labour market. Therefore, although our empirical results are derived from Canadian data, the magnitude of the *change* in the returns-to-scale estimates when this bias is corrected for may be of general interest.

Finally, although the simple OLS estimates presented here cannot be considered as conclusive evidence of significantly increasing returns to scale in Canadian labour-market matching functions, they do cast doubt on the reliability of empirical estimates using the existing approach that suggest constant returns to scale. Given the sources of downward bias that we have discussed here, together with the solid theoretical basis for expecting increasing returns, any presumption against increasing returns to labour-market matching seems unwarranted.

#### REFERENCES

- Abraham, K. (1987) 'Help-wanted advertising, job vacancies and unemployment.' *Brookings Papers on Economic Activity*, 207–43
- Akerlof, G., J. Yellen, and Rose A. (1988) 'Job switching and job satisfaction in the U.S. labor market. *Brookings Papers on Economic Activity*, 495–582

- Anderson, P., and S. Burgess (1993) 'Job matching and competition among the employed and unemployed: some disaggregated evidence.' Mimeo
- Blanchard, O., and P. Diamond (1990) 'The aggregate matching function.' In *Growth, Productivity, and Unemployment*, ed. P. Diamond (Cambridge, MA: MIT Press)
- Blanchard, O., and L. Summers (1986) 'Hysteresis and the European unemployment problem.' *NBER Macroeconomics Annual*, 15–78
- Burdett, K. (1978) 'A theory of employee job search and quite rates.' *American Economic Review* 68, 212–20
- Burdett, D., M. Coles, and J. Van Ours (1994) 'Temporal aggregation bias in stock-flow models.' CEPR Discussion Paper No. 967
- Burgess, S. (1993) 'A model of competition between unemployed and employed job searchers: an application to the unemployment outflow rate in Britain.' *Economic Journal* 103, 1190–204
- Courtney, H. (1992) 'Regional vacancy-unemployment mismatch and shifts in the U.S. aggregate Beveridge curve.' Mimeo, George Washington University
- Diamond, P. (1982a) 'Aggregate demand management in search equilibrium.' *Journal of Political Economy* 90, 881–94
- (1982b) 'Wage determination and efficiency in search equilibrium.' *Review of Economic Studies* 49, 217–28
- Hall, R. (1989) 'Comment.' *Brookings Papers on Economic Activity*, 61–4
- Jones, S. (1993) 'Cyclical and seasonal properties of Canadian gross flows of labour.' *Canadian Public Policy* 19, 1–17
- Lindbeck, A., and D. Snower (1988) *The Insider-Outsider Theory of Employment and Unemployment* (Cambridge, MA: MIT Press)
- Pissarides, C. (1986) 'Unemployment and vacancies in Britain.' *Economy Policy*, 500–59.
- Statistics Canada (1992) *Worker Turnover in the Canadian Economy: Separations and Hiring, 1978–1989*. Catalogue 71-539 (table 9)
- Warren, R. (1992) 'Returns to scale in a matching model of the labor market.' Mimeo, University of Georgia