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Help Wanted, Job Needed: Estimates of a Matching Function from Employment Service Data

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I estimate a function that matches vacant jobs and unemployed workers to produce new hires. Israeli law requiring vacancy registration yields unique data quality. The literature underestimates matching function coefficients because of a simultaneity bias, as the outflow of hires depletes stocks of unemployed and vacancies. Instruments and a new simulation method address this bias. A new test reveals strong evidence of heterogeneity in unemployed and vacancies. Estimates imply labor market dynamics that absorb shocks completely within only 2 months. Reductions in the hire rate of referrals can explain a 2.1 percentage point increase in unemployment between 1978 and 1990.

I. Introduction

During the 1980s, before the massive immigration from the former Soviet Union, Israel experienced a trend increase in unemployment that

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cannot be explained by a cyclical decrease in labor demand. Between 1980 and 1989 the unemployment rate rose from 4.8% to 8.9% at comparable points in the business cycle. This trend increase in unemployment in the mid-1980s was typical of Western European economies. In this article, I investigate how much of the increase in Israeli unemployment can be attributed to a slowdown in "matching," the process by which unemployed workers and vacant jobs meet each other and create new hires.

Several authors have proposed two-sided search or matching models to explain unemployment, most notably Blanchard and Diamond (1989, 1990) and Pissarides (1985, 1986, 1990). Matching theories of unemployment have two very useful theoretical qualities: they can explain why unemployment exists in equilibrium and can provide a theoretical underpinning for an analysis of unemployment and vacancies that allows structural unemployment to be distinguished from cyclical unemployment. Estimates of a matching function can be used to predict labor market dynamics, informing us of the persistence of unemployment due to labor supply or labor demand shocks, especially in discussions of hysteresis. They also offer the possibility that small improvements in the matching process can yield significant reductions in the steady-state unemployment rate.

A downward-sloping unemployment-vacancy locus, or "Beveridge curve," has been known as an empirical regularity for half a century.[1] Empirical evidence on the size of labor market flows (Leonard 1987; Davis and Haltiwanger 1992) and recent work in search theory have prompted new theories to explain this curve. The evidence suggests that to some extent both unemployment and vacancies can be attributed to high rates of job creation and destruction. This rapid turnover implies a lot of what is sometimes called "frictional" unemployment, as stocks of vacant jobs and unemployed workers are large even when the matching of vacant jobs to unemployed workers takes place quickly. Blanchard and Diamond (1989, 1990) and Pissarides (1990) derive the steady-state levels of unemployment and vacancies from a dynamic matching process based on two-sided search. These models differ from the search unemployment literature by allowing search by firms as well as by workers. The search process is summarized by a matching function $h = m(v, u)$, which produces new hires from stocks of vacant jobs and workseekers. Several attempts have been made in the literature to estimate matching functions. These include Pissarides (1986), Blanchard and Diamond

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at the Bank of Israel, Boston University, Duke, Harvard, the Hebrew University, the Kennedy School of Government, Michigan State, MIT, Rochester, and the Universities of Pennsylvania, Washington, and Western Ontario. Tania Suhoya of the Bank of Israel provided efficient research assistance.

[1] See Beveridge (1944) for the discovery. More recently, Abraham and Katz (1986) use vacancies to diagnose the causes of unemployment.

(1989), Belderbos and Teulings (1990), Christl (1991), Lindeboom and van Ours (1993) and Lindeboom, van Ours, and Renes (1992, 1994).

This article has two purposes. One is to consistently estimate coefficients of a matching function using employment service data. Matching function estimates are subject to simultaneity bias, a problem that has gone unrecognized in the literature. The outflow of hires (the dependent variable) depletes the average monthly stocks of both unemployment and vacancies (the covariates), inducing a simultaneous negative relationship between hires and each of these stocks when the latter are aggregated over time. I introduce two methods of correcting this bias, one using a simulation of the simultaneous equation and the other using inflows of vacancies and unemployed as instruments. Both methods rely on the unique quality of the Israel Employment Service (ES) data, described below. I also introduce a test for heterogeneity in the probability of individual job vacancies or unemployed persons finding a match. This is the first empirical study that I know of to treat matching in two stages, estimating both the outflow of job referrals as a function of unemployment and vacancies, and the proportion of such referrals resulting in hires as a function of labor market "tightness" (a measure of excess demand). The second purpose of this article is to use this estimated matching function to explain increased unemployment in Israel in the 1980s.

Much attention has been given to the trend increase in European unemployment over the last decade. Jackman, Pissarides, and Savouri (1990) survey the increase in unemployment in 14 OECD countries, using vacancies to measure labor demand. They find that the Beveridge curve (unemployment-vacancy locus) is generally downward sloping, but there is a trend increase in unemployment at given levels of vacancies over the 1980s: for an average of the 13 countries (excluding the United States) the vacancy rate was at about the same level in 1986 as it was in 1978 with the unemployment rate some 3 percentage points higher. They interpret this rightward shift of the Beveridge curve as evidence for increased mismatch or friction in labor markets following the recessions of the mid-1970s and early 1980s.

Figure 3 (see below) shows a similar pattern for Israel. The period from 1974 until 1980 is typified by shifts along a downward-sloping curve. While there was no slump in the labor market in the 1970s, the decrease in labor demand in 1980 was followed by a rightward shift of the Beveridge curve by about 3 percentage points of unemployment between 1980 and 1985 and by another 2 by 1989. Yashiv (1994) applies a Beveridge curve analysis to the Israeli economy, using a Beveridge curve derived from a matching function to diagnose the causes of unemployment.

In this article I will attempt to explain shifts in the Israeli Beveridge curve by estimating its underlying matching function. Theory implies that, for a labor force of constant size with worker-job matches breaking up at a constant rate, movements of the Beveridge curve toward higher levels of unemployment must be due to a reduction in the rate at which hiring takes place. One advantage of studying the flow into hires rather than steady-state levels of unemployment and vacancies is that the effects of shocks on flows should be immediate and clear while the full response of levels may take so long that the effect will be hard to identify. Another advantage is that a matching function can be used to predict short-run effects of shocks, such as a wave of immigration, a plant closing, or a cyclical increase in labor demand or unemployment. Estimated returns to scale are also interesting. Increasing returns in matching would indicate that larger labor markets function more efficiently.[2]

Matching models of hiring and unemployment are sometimes criticized for lacking behavioral content. An exception is Pissarides (1990), which offers a dynamic matching model in which optimal search is performed by unemployed workers and by firms with vacancies. Both the unemployed and the vacancies have heterogeneous characteristics, which generate a match specific productivity for each worker-job pair as in Jovanovic (1979). Matching takes place in two stages: referral, and hiring conditional on referral. A worker-job pair may choose to match or to return to search once they learn about their productivity at the job referral. The matching function is then the reduced form of an equilibrium in which reservation wages and reservation productivity levels are chosen optimally by workers and firms. I describe and estimate a variant of the Pissarides model here. The next section presents this two-sided search model of matching. An equilibrium relation between unemployment and vacancies is derived, and its dynamic behavior is examined. The model generates two estimating equations, one for referrals as a function of stocks of unemployment and vacancies and another for the job acceptance rate as a function of the ratio of vacancies to unemployment. While the referral function is treated as a technology describing how the Employment Service works, the acceptance function has behavioral content.

I investigate both simultaneity bias and biases due to heterogeneity in the estimated referral function coefficients. Simultaneity bias is due to the feedback of hires into the monthly stocks of unemployed and vacancies. This feedback equation generates a negative correlation between hires and stocks. The resulting downward bias on ordinary least squares (OLS) coefficients is estimated by simulation. It is about 20% for these data. Since stocks of unemployed and vacancies are reduced by hiring, any heterogeneity in the probability of an unemployed person (vacancy) finding a match will create duration dependence in the probability of hire within the observed stock. I use data on inflows into unemployment and

[2] The studies mentioned in the text all estimate Cobb-Douglas matching functions, finding approximately constant returns to scale. Storer (1994) discusses the choice of functional form.

vacancies to express the stocks as the product of inflows and average duration terms and estimate separate coefficients for each term. Homogeneity implies equality of the coefficients on inflows and durations. I find strong evidence for heterogeneity as inflows have higher coefficients than duration terms for both unemployment and vacancies. The practice of registering vacancies and unemployment spells after a job is found provides a possibly spurious explanation for this apparent heterogeneity. I argue that it is unlikely to provide a complete explanation.

Estimates of the acceptance rate are haunted by high serial correlation of the error term. The strong negative trend in the acceptance rate is not explained by covariates. The ratio of vacancies to unemployed has the expected negative coefficient, but it is tiny, indicating small effects of market conditions on the probability of a referral becoming a hire. In combination, the estimated acceptance rate and referral equations form an estimated function that predicts hires (matches) using unemployment and vacancies. The behavior of the referral function dominates in the short run. Response to changes in the inflow of vacancies is very fast, with most of the long-run adjustment of the unemployment stock completed within a month. Thus, the search-based matching process is far too efficient to generate the observed persistent, high levels of unemployment among immigrants in Israel.

Much of the rightward shift in the Israeli Beveridge curve may be explained by a reduction in the efficiency of the matching function. This reduction is entirely due to a sharp decline in the acceptance rate, from 0.85 to 0.59 between 1978 and 1990. The decline in the acceptance rate accounts for an increase in steady-state unemployment of 2.1 percentage points over the 13-year period, fully half of the trend increase in unemployment.

This article is organized as follows: a model of stochastic job matching is presented in Section II. The Employment Service and the data are described in Section III. Referral and acceptance functions are estimated and impulse-response curves are described in Section IV. Section V concludes.

II. Stochastic Job Matching

This section describes an equilibrium model of job matching in which both workers and firms have individual characteristics. The model is a modified version of one that appears in Pissarides (1990).[3] I describe the equilibrium solution and derive estimating equations for referral and

[3] The original version in Pissarides (1990) includes capital explicitly as a factor of production. This allows for richer business-cycle effects through interest-rate fluctuations and for a long-run growth theory. Capital is omitted here in order to simplify the exposition.

acceptance functions. In this model (fig. 1) the agents are firms and workers. They engage in two activities: search and production. Workers are either employed (E) or unemployed (U). Each firm has one job, which can be either full (E) or vacant (V). Unemployed workers and vacant jobs are searching. Each has a set of characteristics that make some matches more productive than others. Once they meet, in a referral (r), a worker-job pair observes the quality of their potential match. They can then either agree to form a match and engage in production or return to search. A formed match is a new hire (h). There is no further search once matching has occurred. Matches break up at an exogenous separation rate, s.[4]

A. Matching and Production

Matching takes place in two steps: referral and acceptance. Assume that the ES refers workers by drawing at random from the available stocks of vacancies and unemployed. Let u denote the stock of unemployed and v the stock of vacancies. The flow rate of job referrals is given by the function

$$x = x(u, v), \tag{1}$$

where $x(\cdot)$ describes the system used by the ES to refer workers. The values of u and v are set by the optimal behavior of firms and workers. The referral function is assumed (a) to satisfy constant returns to scale, (b) to increase in both terms, and (c) to be quasi-concave. The flow probability that an unemployed worker will be referred is

$$p(\theta) \equiv \frac{x(u, v)}{u} = x(1, \theta), \tag{2}$$

where $\theta = v/u$ describes labor market "tightness." The flow probability that a vacancy will be referred is

$$q(\theta) \equiv \frac{x(u, v)}{v} = x\left(\frac{1}{\theta}, 1\right). \tag{3}$$

Both workers and jobs have heterogeneous individual characteristics that dictate the quality of a worker-job pair in production. Let α be the

[4] More generally, quits and fires could depend on labor market conditions. The composition of the stocks of unemployed and vacancies would then depend on labor market conditions, a point that will return to in the discussion of heterogeneity below.

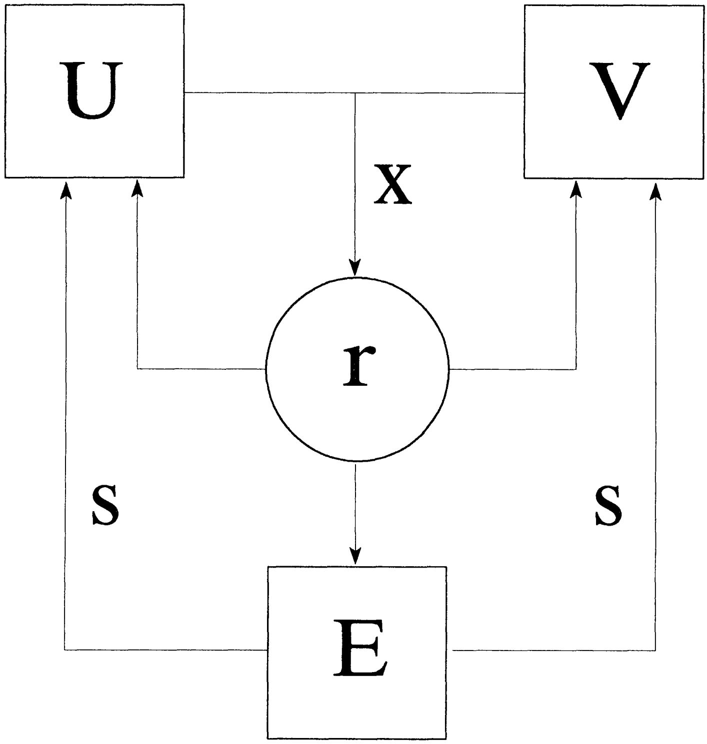

FIG. 1.—Labor market flows

marginal product of a worker-job pair if they decide to form a match and produce. This match quality α is drawn from a nondegenerate distribution $G(\alpha)$, known to both firms and workers. The better the match, the higher is α. This potential marginal product is assumed to be specific to the match in the sense that successive draws of α for a given job or worker are independent.[5] (This assumption serves to rule out any form of observed duration dependence as duration is independent of match-specific heterogeneity.) At a referral, an interview takes place in which α is drawn and observed. If a match is made, the pair will produce α in each period until separation. Once α is revealed, the worker-job pair must decide whether or not they agree to match. If they do not match each returns to search. If they do, production begins, and the stocks of both unemployed and vacancies are reduced by one.

[5] For simplicity, I assume that, even if the same pair is redrawn, the α realizations are independent; α is also assumed to have a finite upper bound. Since α is a marginal product that decreases in employment, the probability distribution is properly written $G(\alpha | E)$.

B. Wage Setting

Worker-job matches negotiate a division of α into wages and profits. Assume a symmetric Nash sharing rule in which workers and firms have equal bargaining strength.[6] This will imply an equilibrium wage-setting rule. It can then be shown that the optimal search strategies of workers and firms are to set reservation wages w_r and profits π_r, respectively, accepting only offers that exceed these reservation levels. Market conditions are reflected in these reservation wages and profits. Matches are formed if and only if α exceeds a reservation marginal product $\alpha_r = w_r + \pi_r$. That is to say, workers and firms will observe α and in equilibrium they will either agree to match or agree not to match. All workers and firms are identical (before α is drawn) so that in equilibrium all worker-job pair referrals share a reservation product α_r. The probability that any referral will result in a match is then

$$1 - G(\alpha_r). \tag{4}$$

Symmetric Nash bargaining implies that, in a match, the surplus $\alpha - \alpha_r$ will be divided equally. The aggregate flow rate of new hires will be the product of $x(u, v)$ and $[1 - G(\alpha_r)]$. Assume that wages cannot be renegotiated so that they remain fixed until separation occurs.

C. Search Costs and Unemployment Income

Firms have the option of searching or not. Searching involves keeping a vacancy posted with the ES. Firms incur search costs at rate γ_0 for vacancies. This flow cost represents the costs incurred in interviewing candidates and the upkeep of idle equipment. If a firm values its reputation with the ES, it will not return referred candidates without an interview so this cost of maintaining a vacancy seems reasonable. An alternative justification of a flow cost of maintaining a vacancy is the alternative cost of holding idle capital. No search implies that no vacancy is measured and no hiring can take place. Assume no adjustment cost for posting or withdrawing a vacancy, so the vacancy rate will adjust instantaneously (i.e., it is a "jump" variable).

Workers have income z while unemployed. This could represent either unemployment insurance, income from casual work, or imputed utility from leisure. Both workers and firms have infinite horizons. They maximize the expected present value of future earnings at discount rate r with rational expectations.

[6] Neither symmetry nor Nash sharing are essential to what follows. All that is required is some rule to divide the surplus which is independent of labor market conditions.

D. Equilibrium

To solve for equilibrium expectations of profits and wages, assume a steady-state rate of unemployment, $\dot{u} = 0$. Let s be the exogenous probability that a match separates. Invoking the law of large numbers, the flow into unemployment is $s(1 - u)$. In a steady state, it will be equal to the outflow to hires, $p(\theta)[1 - G(\alpha_r)]u$. Thus the steady-state unemployment rate is

$$u = \frac{s}{s + p(\theta)[1 - G(\alpha_r)]}. \tag{5}$$

THEOREM (Pissarides, 1990, chap. 5). Under the assumptions listed above there exists a unique equilibrium solution for α_r, u, v, and the expected wage w^e. It is given by equations (5), (6), (7), and (8):

$$w^e = \alpha_r + \frac{1}{2}(\alpha^e - \alpha_r), \tag{6}$$

$$\pi^e = \alpha^e - w^e = (r + s)\frac{\gamma_0}{q(\theta)[1 - G(\alpha_r)]}, \tag{7}$$

and

$$\alpha_r = z + \gamma_0\theta, \tag{8}$$

where α^e is the conditional expectation of product, $\alpha^e = E(\alpha_j | \alpha_j \geq \alpha_r)$, w^e is the conditional expectation of wages, $w^e = E(w_j | w_j \geq w_r)$, and r is the interest rate.

The equilibrium solution has several interesting features. Equation (6) states that the expected wage is the sum of the reservation productivity and one half the expected surplus, as implied by symmetric Nash sharing.

Equation (7) is the firm's break-even condition for search. This is the usual condition defining a firm's labor demand curve, whereby wages equal marginal product, generalized to include search costs and with a stochastic marginal product. In equilibrium, the expected (gross) profit from the match must equal the expected cost of filling a position, the flow cost γ_0 multiplied by the expected duration of search $1/\{q[1 - G(\alpha_r)]\}$, discounted by the interest rate and the probability that the match will be lost due to separation. As for (8), symmetric sharing of the surplus implies that if the firm's expected present value increases by $\gamma_0/\{q[1 - G(\cdot)]\}$ from the hire, then the worker must receive the same amount. Thus the expected flow of earnings of an unemployed workers is the sum of z and $\gamma_0/\{q[1 - G(\cdot)]\}$ multiplied by the probability of hire $p[1 - G(\cdot)]$, which is just $z + \gamma_0\theta$. In equilibrium, this must equal the reservation wage w_r, and the reservation profit must be zero, so that $\alpha_r = \pi_r + w_r = w_r = z + \gamma_0\theta$, which is equation (8).

Since search costs saved by the firm are part of the surplus from a consummated match, workers receive part of these savings as an economic rent. An unemployed person can expect to receive $\gamma_0\theta$, so this is included in her reservation wage. This rent creates a negative relationship between labor market tightness, θ, and the acceptance rate.[7] Tighter labor markets imply higher reservation wages and lower acceptance rates (from [4]). An increase in earnings while unemployed, z, or in the firm's search costs, γ_0, will also slow hiring by raising α_r.

E. Beveridge Curve

A Beveridge curve can now be derived. This curve describes how equilibrium levels of unemployment and vacancies respond to fluctuations in the demand for labor. Substituting (8) in (6) and (6) in (7) yields an expression for expected profit in terms of θ and α_r:

$$\pi^e = \frac{1}{2}(\alpha^e - z - \gamma_0\theta) = (r + s)\frac{\gamma}{q(\theta)[1 - G(\alpha_r)]}\,. \tag{9}$$

Equations (5), (8), and (9) yield a system in θ, u, and α_r. The derivatives of each side of (9) with respect to α_r are equal, as the effect through the expected marginal product is equal to the effect through the change in the proportion of referrals that result in hires. Thus (9) determines the level of labor market tightness independent of α_r. A convenient form for evaluating the comparative statics is derived by substituting (5) in (9) to yield

$$\alpha^e - z - \gamma_0\theta = 2(r + s)\frac{\gamma_0\theta u}{s(1 - u)} \Rightarrow$$

$$\alpha^e - z = \gamma_0 v\left[\frac{1}{u} + \frac{2(r + s)}{s}\frac{1}{s(1 - u)}\right]. \tag{10}$$

This equation describes equilibrium in the labor market in the sense that it defines a steady-state level of vacancies. It is a positively sloped curve in u-v space for suitably small unemployment.[8]

[7] The role of search costs in this dynamic model is similar to that of efficiency wages, which are also a rent and could also be used to derive eq. (8). Search costs are more natural in this context as they explain the existence of vacancies as well as unemployment in equilibrium.

[8] At a given level of vacancies an increase in unemployment will increase labor demand through decreased wages, but will also decrease the rate of new hires through (5), thus increasing hiring costs. These two effects are reflected in the two terms in the square brackets in (10). For a small unemployment rate, the first effect will dominate.

Equation (10) is labeled *VS* (for vacancy supply) in the Beveridge curve diagram (fig. 2). It represents the positive relationship between vacancies and unemployment consistent with profit maximization by firms. A vacancy rate above this line implies expected search costs from a vacancy higher than expected profits. The opposite is true below the line. The downward sloping curve *VU* is equation (5), the steady-state condition for unemployment. In the system, (5), (8), and (10), the matching function is contained only in equation (5), the *VU* curve, which describes the steady state unemployment rate. Decreased efficiency of matching will shift the *VU* curve to the right, increasing the steady-state unemployment and vacancy rates.

Consider the effect of an increase in labor demand due to a drop in interest rates, for example.[9] The decreased cost of financing search costs will result in an increase in vacancies as labor demand expands. This will be reflected in an upward shift of the *VS* curve. The effect in equilibrium of increased labor market tightness on the acceptance rate can be solved through (8). It will shift the *VU* curve slightly to the right, as increased labor market tightness will induce higher reservation wages, a decreased acceptance rate, and an increase in steady-state unemployment. As long as the direct effect of increased labor demand is not overcome by the wage effect on decreased matching, the new equilibrium unemployment rate will be less than the old. This is illustrated in the movement from point *A* to point *B* in figure 2. A locus of points such as *A* and *B* corresponding to possible levels of labor demand trace out the dashed Beveridge curve. It is a downward-sloping curve in unemployment-vacancy space mapped out by fluctuations in labor demand. When labor demand is high, vacancies are high and unemployment is low in the upper-left region. Low labor demand corresponds to the high-unemployment low-vacancy region.

In contrast to movement *along* the Beveridge curve due to fluctuations in labor demand, movements *of* the curve correspond to changes in the rate at which matching (or separation) take place. An increase in the reservation wage due to increased income of the unemployed will shift the Beveridge curve to higher levels of unemployment at each level of vacancies. A decrease in the efficiency of the ES in providing referrals will also shift this curve to the right as any slowdown in the rate of matching will increase the steady-state rate of unemployment.

This distinction between shifts of the Beveridge curve and movements along it can be used to diagnose the causes of increased unemployment. An increase in unemployment accompanied by a drop in vacancies is due

[9] An increase in the rate of labor-augmenting productivity growth would create the same effect if included in the model. The same is true for decreased search costs, γ_0, or a decrease in income from unemployment, z.

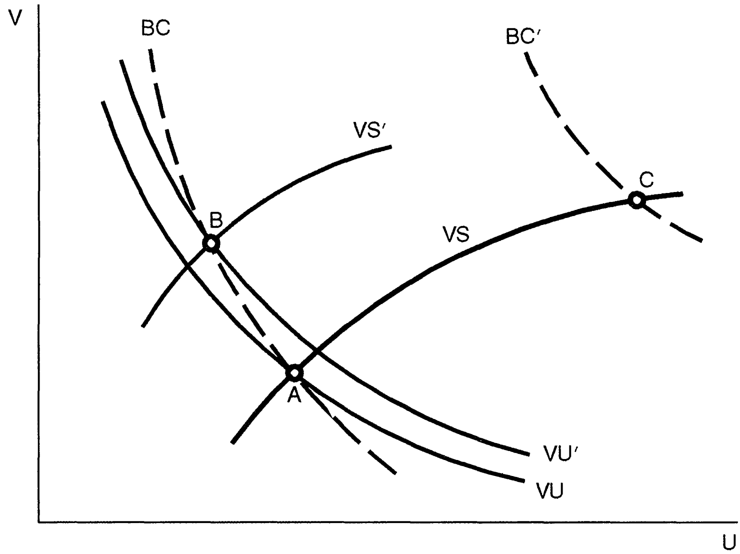

FIG. 2.—The Beveridge curve

to a drop in labor demand, like the movement from B to A. An increase in unemployment not accompanied by a decrease in vacancies is evidence of increased structural or frictional unemployment; simultaneously high levels of vacancies and unemployment produce an unusually low flow of hires and thus remain at high levels. Figure 3 demonstrates that the Israeli Beveridge curve indeed shifted to the right over the 1980s, even when the labor force grew slowly, implying a slowdown in the rate of matching. In the next section I estimate the matching function in order to investigate the causes of that shift.

F. Beveridge Curve Dynamics

How does the adjustment to increases in vacancies or unemployment take place? Unfortunately, the model presented above has not (yet) been solved for equilibrium wage setting out of steady state. A simplified version with a constant acceptance rate and with z and γ_0 proportional to the expected wage is solved in Pissarides (1990). The estimates below reveal that the acceptance rate is actually not very responsive to labor market tightness, so a constant acceptance rate is a mild assumption. Indexing z and γ_0 to expected wages is a long-run assumption necessary to make the model consistent with the observation that the unemployment rate has not decreased with the trend increase in the marginal product of labor. The proportionality of γ_0 to expected wages is a reasonable assumption if search is a labor-intensive activity. The proportionality of the income of the unemployed, z, to the expected wage could reflect the

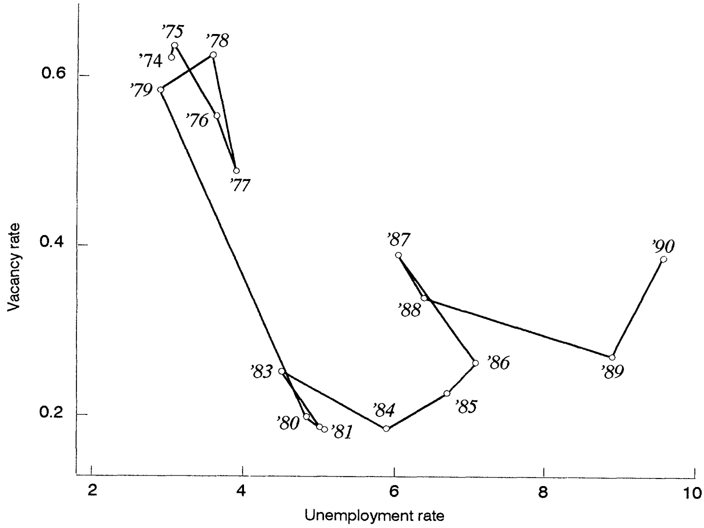

FIG. 3.—Israeli unemployment and vacancy rates, 1974–90. Sources and definitions: the vacancy rate is the Employment Service end-of-month stock of unfilled vacancies *divided* by the sum of itself and the number of employed persons. The unemployment rate is from the Labor Force Survey.

replacement ratio, or the link between wages in informal work to those in employment. I assume

$$z = \lambda w^{e}, \qquad \gamma_0 = \gamma w^{e}, \qquad 0 \leq \gamma < 1. \tag{11}$$

The resulting *VS* curve can be solved by substituting from (11) into (8) and then into (6), then (7), then (9), and then (5) to yield a new equation for the steady-state vacancy supply curve,

$$\frac{1-\lambda}{\gamma} = v\left[\frac{1}{u} + \frac{r+s}{s(1-u)}\right]. \tag{12}$$

This version of the *VS* curve has the long-run characteristic that shifts in the distribution of marginal product are entirely passed on to wages through indexation, so that the steady-state vacancy supply curve is unaffected by α^{e}. Pissarides (1990) shows that even out of steady state, the expected profit condition (9) will hold, yielding a unique value of labor market tightness consistent with profit maximization since at any other value search costs would imply that some adjustment is necessary. Thus all adjustment to (unexpected) shocks is carried out by first jumping to a level of vacancies consistent with the new steady-state level of labor market tightness, θ. Unemployment and vacancies then converge to the new steady state along a ray through the origin on which θ is constant.

Consider first the transition between steady states *A* and *B* (fig. 4). At *A* the inflow of new vacancies is equal to the inflow of new unemployed "(SE)" and to the outflow of new hires. As in the discussion above, an exogenous increase in labor demand is experienced due to decreased interest rates. The result is a single jump in the level of vacancies (to point *C*) followed by convergence to the new steady state *B*. Throughout the process of convergence the vacancy/unemployment ratio θ must be at its new steady state level, thus convergence must be along the line *BC* on the ray passing through the origin and the point *B*. The short-run increase in vacancies will exceed the long-run increase by just enough to ensure that the unemployment rate is reduced to its new, lower, steady-state level at *B*. (Along the convergence path, unemployment and vacancy stocks will be reduced by the same amount through hires; this implies that the level of vacancies will be constantly adjusting to satisfy the break-even condition [10] since in general the line *BC* will not have a 45° slope.) How long does this short-run convergence last? Along the convergence path unemployment is above its steady-state level, so it is important to know if convergence will typically take months or years. This question will be answered below by estimating the matching function and simulating the response of hires and unemployment to an impulse of vacancies.

Because of Israel's recent experience with massive immigration, a

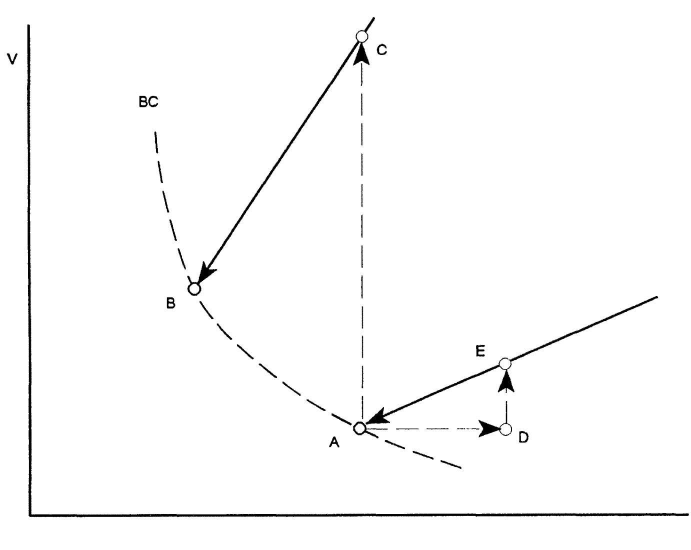

FIG. 4.—Beveridge curve dynamics

dynamic response of particular interest in the Israeli labor market is the response of unemployment to an influx of new unemployed. Consider the case illustrated in figure 4, in which the steady-state inflow of unemployed is augmented with an extra inflow that increases the unemployment stock so as to move it horizontally from steady state A to the point D. Since equation (9) must hold at all times, labor demand will immediately respond to the drop in search costs (implied by an increase in unemployment) by increasing vacancies until the equilibrium level of labor market tightness is restored. This implies an instantaneous vertical jump to the point E on the ray through the origin and the equilibrium point A, followed by convergence along the line AE to the original equilibrium levels of the unemployment and vacancy rates.

Note that the net inflow of new entrants is met with just enough new vacancies to restore the labor market to the old unemployment rate. The only resulting increase in unemployment is the short-run increase during convergence. Lack of a long term unemployment increase depends critically on two assumptions: (i) that the distribution of characteristics of the immigrants is identical to that of the native unemployed, and (ii) that vacancies can be created immediately, with no adjustment costs. (These assumptions are clearly not realistic, but they allow us to see how much of the unemployment during an adjustment period can be explained by a model that allows only search activity as an adjustment mechanism.) As in the previous example, it is important to find out how long this convergence will last. In Section IV below, the estimated matching function is used to simulate the response of hires and unemployment to an impulse of new unemployed accompanied by an increase in vacancies. I find that short run unemployment due to search lasts only 2 months.

G. Estimating Equations

Data are available on unemployment, vacancies, referrals, and hires. Two estimating equations are derived in terms of these variables, one for an aggregate referral function and another for an aggregate acceptance function. The flow rate of new hires is given by their product. The referral function is given by (1), $x = x(u, v)$. It was assumed to exhibit constant returns, positive first derivatives, and quasi concavity. While the property of constant returns is convenient for the derivation of results, it also has some economic meaning. Increasing returns in the referral function imply increasing returns in hiring so that larger labor markets are more efficient. (In this model they would enjoy lower steady-state rates of unemployment because they are "thicker.")[10]

[10] Models that allow "search intensity," in which firms and workers can increase their probability of referral by increasing search effort, can have high-intensity and low-intensity equilibrium if increasing returns in hiring (matching) exist. See Diamond (1982) for details.

The frequency of hire conditional on referral is given by (4) and the solution to α_r:

$$
\begin{aligned}
E(h/x) &= 1 - G(\alpha_r) \\
&= 1 - G(z + \gamma_0\theta),
\end{aligned}
\tag{13}
$$

where h are hires and x are referrals. In Section IV a functional form for $G(\cdot)$ is chosen, and the effect of θ on the probability of hire is estimated. Regardless of the form of $G(\cdot)$, the model predicts that the proportion of referrals that result in hires will be decreased by both the imputed income from unemployment z and labor market tightness θ. In estimating (13) the current value of θ will be used to approximate the equilibrium expected value of θ in the model, essentially using static expectations to approximate rational expectations. Durations of both unemployment and vacancy spells are quite short, so this approximation seems reasonable. (The referral function involves no expectations, so it has no such problem.)

III. Data Description

This is the first attempt that I know of to use the Israeli Employment Service data in estimating of a model. This section describes the institutional setup and compares ES unemployment and vacancies series with data from other sources.[11]

A. Institutions

The main institutional intermediary in the Israeli labor market is the Employment Service. From 1959 until March 1991 private intermediaries were illegal, and all private sector hiring of workers for jobs not requiring a college degree was required by law to pass through the ES.[12] The ES operates labor exchanges for adults, youth (ages 14–17), and college graduates. I use data for adults only. The ES handles large volumes of job seekers and vacancies in about 200 branches throughout the country. It collects job vacancy notifications from firms by telephone. Unemployed workers register in person. Workers are referred to employers, and the

[11] The data source is State of Israel, Employment Service (various issues). Employment service data on unemployment and vacancies are used by the Bank of Israel and the Ministry of Labor as indicators of labor market fluctuations. Both series are considered to be good current indicators of labor market fluctuations. They are especially valuable as they become available before other indicators.

[12] In the 6 months following the authorization of private employment bureaus, 145 firms with 350 branches were established.

status of each referral is monitored. No fees are charged for any of these services.[13]

Unemployment benefits (UI) are paid by the National Insurance Institute for between 138 and 175 days. Eligibility begins after 5 days of unemployment. The benefits range from 48% to 80% of the average wage received by the unemployed in his or her last 75 working days. After the benefit period, a small fraction of the unemployed receives income support. Registration with the Employment Service is necessary both in order to receive unemployment insurance and in order to receive income support.

These two laws—compulsory hiring through the ES and compulsory registration with the ES in order to collect UI—endow the unemployment and vacancy data with uniquely high quality. Even if the actual search for jobs and workers is conducted outside the ES offices, all hires must be registered, at least ex post, to be legal.

B. Unemployment

The ES reports three unemployment series: work seekers, the inflow of unemployment over the month, and the daily average of unemployment. A work seeker is a person who has registered with the ES at least once during a month to apply for work (a work seeker is not necessarily unemployed). This variable includes the stock of individuals seeking work at the end of the last month and the inflow of individuals seeking work during the month. Such a variable is neither a stock nor a flow, so I call it a "count." The inflow of unemployment is the number of work seekers who arrived during the month.[14] The daily average of unemployed is the average stock of work seekers. (The terminology used by the ES is slightly misleading as none of these variables distinguish between unemployed and currently employed work seekers.)

Unemployment data are also available from labor force surveys (LFS).[15] (The LFS unemployment series and the ES daily average of unemployed are comparable variables as they are both stocks.) The two series are plotted in figure 5 for the period 1978–90 (this period was chosen because

[13] The ES is described more fully in app. A of Berman (1992) and in Berman (1993, chap 1). See also State of Israel, Employment Service (1977).

[14] The inflow of unemployment is not recorded in January. It is estimated in this paper for Januaries by constructing a series based on the difference between count of work seekers and the stock of unreferred work seekers at the end of the previous month. An unreferred work seeker is a work seeker not referred to any employer during the month. The true inflows were regressed on the constructed variable, and predicted values were inserted for inflows in Januaries.

[15] The LFS surveys about 12,000 households. An unemployed person is defined as someone who has not worked and has searched for work in the week preceding the survey date.

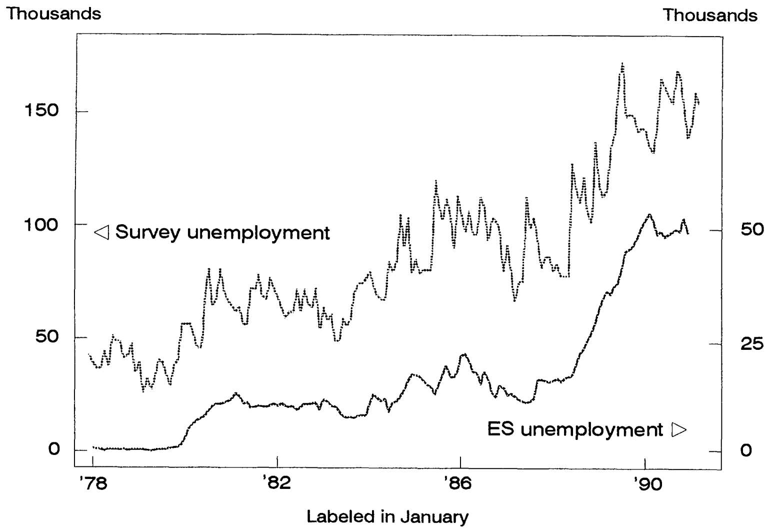

FIG. 5.—Two measures of unemployment

a full set of vacancy data is available). Clearly, only a fraction of the LFS unemployed are registered with the employment service. This proportion increases over time, from 3% in 1978, to 15% in 1980, 18% in 1985, and 30% in 1990. These proportions are much smaller than can be accounted for by the proportion of college graduates and youth in the workforce. Part of the LFS unemployed who are not counted by the ES must be those ineligible for unemployment insurance, either because they are in their first week without work, have not worked enough to fill the eligibility criteria, or have been unemployed long enough to exhaust eligibility.[16]

The increase over time in the proportion of LFS unemployed registered with the ES can be explained by increased benefits and increased eligibility. Benefits were indexed in 1980, and the increased duration of unemployment spells during the 1980s made a larger fraction of the unemployed eligible for benefits.[17] The stock of UI recipients shows the same increase, as does the ES unemployment stock. As a fraction of LFS unem-

[16] One puzzle is that the fraction of LFS unemployed that report the ES as their primary method of work seeking is much larger than the fraction of ES unemployed in LFS unemployed. Reported fractions are for 1978, 38%; for 1980, 57%; for 1985, 52%; and for 1989, 57%. Source: Central Bureau of Statistics (1991), p. 263.

[17] The eligibility criterion for UI is 5 days unemployment (and 180 days of employment in the previous year), whereas the definition of unemployment for the LFS requires no work in the week preceding the survey. Individuals expecting long durations of unemployment are more likely to register immediately at the ES in order to qualify quickly for UI.

ployment, it increases from 2% in 1978, to 11% in 1980, 5% in 1985, and 26% in 1990. For purposes of estimation, the issue is not the completeness of coverage of the unemployed but the consistency of their composition over time. The conclusion from figure 5 is that the unemployed who show up at the ES show the same general trends as the population of unemployed, though their composition may vary over time due to UI eligibility.

After 20 years of relative stability (excluding the 1966–67 depression), unemployment began to rise in 1980. It jumped sharply from 2.9% in 1979 to 4.8% in 1980 and rose steadily afterward to reach 9% by the third quarter of 1989 (in LFS figures). Beginning in the fall of 1989, immigration from the Soviet Union contributed to a further increase to 11.6% in the first quarter of 1992, followed by a decrease to 10% by 1993. Note that over the 10 years between 1979 and 1989, even before the Russian wave of immigration, the unemployment rate in Israel rose by over 6 percentage points.

C. Vacancies

A vacancy at the employment service is defined by a firm's request to receive referrals of workers. Firms typically have a longstanding relationship with the local ES branch. If a firm values its reputation with the employment service, a vacancy represents a commitment to seriously interview candidates referred, so that vacancies are not costless.

Data on vacancies are available from the ES from 1962 on. For subperiods, a help-wanted series from the Advertisers Union and from Manpower Inc. is available to corroborate the ES series. Employment Service data provide three different measures of vacancies registered by firms: total vacancies (tv)—the number of vacancies to be filled over a month: the sum of the inflow over the month (vi), *and* the stock passed on from the previous month (vp); and the number of vacancies left unfilled at the end of the month, (v): the sum of those withdrawn (vw), and active vacancies passed on to the next month (vp). These are stocks, analogous to the level of unemployment. The variables tv and v are available from 1964 on, but the decomposition into vw and vp is available only for 1978–90. The vp series is used for estimation as it reflects the stock of vacancies at a moment in time. A moving average is constructed to measure the average stock of vacancies over the month ($va_t = (vp_{t-1} + vp_t)/2$). Monthly hires are filled vacancies tv-v.[18] The distinction between withdrawn and filled vacancies is a nice feature of the data.

[18] This measure has the advantage that the hire is recorded in the month it is made, even if the start date is deferred. The vacancy and unemployment measures treat the hire date consistently. I thank an anonymous referee for bringing this point to my attention.

One problem with the vacancy stock series is that firms are required to register vacancies in order to hire but not in order to search. This allows the possibility of firms searching outside the employment service and registering the vacancy only when a suitable candidate has already been found, to make the hire legal. To the extent that this is done, reported vacancy stocks will underestimate the true vacancy stock. Possible biases due to ex post reporting of vacancies are discussed below.

The Manpower Inc. vacancy series counts advertisements appearing in major Israeli papers. It is very much like the U.S. Conference Board help-wanted series used by Blanchard and Diamond (1989). Since many advertisements are for positions that require a college degree, this series represents a different mix of vacancies than those registered with the ES. Figure 6 plots the ES and Manpower advertised vacancy series. These two series have different dimensions: *va* is a stock, while advertised vacancies are a monthly count (inflow + lagged stock), which accounts for the difference in levels. The two series seem to share the same general patterns. The vacancy rate implied is slightly higher than that found by Holzer (1994) in U.S. survey data.

The most dramatic feature of the ES vacancy stock is a sharp decline in 1979–80. This decline is corroborated by a quarterly vacancy series from Manpower (not shown). The sharp drop in vacancies in 1979–80 corresponds to a period of contractionary fiscal policy and a decrease in public-sector hiring. (In the 1970s the public sector absorbed 50% of new entrants to the labor force, while in the 1980s it absorbed only 18%.)

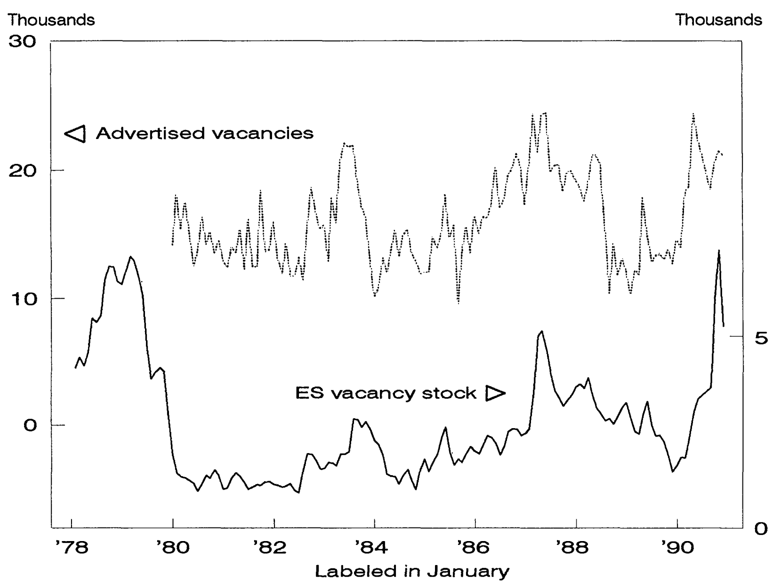

FIG. 6.—Two measures of vacancies

The high level of vacancies in 1987 reflects a cyclical peak in gross domestic products. The spike in vacancies in the final months of 1990 is due to implementation of a building plan to house immigrants. The building industry is a heavy user of the ES, which explains the larger spike in the ES than in the advertised vacancy series.

D. Referrals and Hires

There is no other source of data on referrals in Israel. Data on hires can be compared to gross-flow data from other sources. Table 1 reports the hiring rate constructed by dividing monthly ES hires by employment (using the National Insurance Institute "employee posts" measure). The figure is about 1% in the 1980s. It is comparable to the Blanchard and Diamond (1989) figure of 3% for the United States in 1983. Griliches and Regev (1992) estimate an average annual turnover rate of 4.6% for Israeli manufacturing, which implies a monthly rate of at least 0.4%.[19] Thus, a turnover rate of about 1% seems to have approximately the right size.

Israeli labor market institutions are similar to those of Western European countries. Wage bargaining is highly centralized, and the unionization rate is high. While Western Europe experienced a trend increase in unemployment beginning with the first oil shock, Israel's began only with the second. This difference in timing is generally attributed to the expansion of Israel's public sector, which increased its share in employment from 30%–36% in the 1970s.[20]

IV. Estimation

In this section the referral and acceptance functions are estimated. Before turning to the results, three issues about the estimation of stock-flow relationships require attention. The first is the need to adjust monthly data in order to get flows of comparable size. The second is a simultaneity bias resulting from the fact that the measured stocks of unemployment and vacancies are depleted by hires. This depletion generates two equations simultaneous to the estimated matching function. Finally, I discuss the difficulty in using aggregate covariates to estimate a dissaggregated function.

A. Workdays per Month

The model in Section II was written in continuous time, but the data are available only on a monthly basis. Since months have different lengths, this raises a problem in the estimation of the referral function $x = x(u, v)$. The variables on the right-hand side are stocks, while the number of referrals per month is a flow that varies in proportion to the number of

[19] This figure has a downward bias due to the undersampling of small firms, which tend to have high turnover rates.

[20] My calculation, using the National Insurance Institute "employee posts" measure, 1970–80.

Table 1
Coverage of the Employment Service: Two Measures

	1965	1970*	1980	1990	United States (1980)
% monthly hires of employees	2.9	2.3	1.0	.9	3
% ES unemployment stock as a proportion of LFS unemployed	10	4	15	30	
% UI benefit recipients as a proportion of LFS unemployed	...	...	11	26	

SOURCES.—Employment Service hires and National Insurance Institute employee posts. "ES unemployed" is the Employment Service adult (noncollege graduate) daily average. "UI (unemployment insurance) benefit recipients" is the annual number of benefit days divided by the number of workdays per year (306). Annual number of benefit days is from National Insurance Institute (various issues), table M/1; U.S. data are based on Blanchard and Diamond (1989, p. 23) constructed hires series.
NOTE.—LFS = Labor Force Surveys.
* The definition of ES unemployed changed in 1973; the data are therefore not comparable between periods.

workdays in the month. In order to estimate a coefficient that is constant across months, flow variables such as referrals are divided by the number of days per month. (The conventional solution to this problem is to use indicator variables for months. That method will not work well in Israel as the lunar component of the Hebrew calendar causes Jewish holidays to drift between months.)[21]

B. New Hires Deplete Stocks

Since the outflow of new hires depletes the average monthly stocks of both vacancies and unemployment, there is an identity that must be accounted for in the estimation of (1) and (13) from data in discrete time. I wish to estimate the relationship $x = x(u, v)$ over an interval short enough to allow the possibility of just one job referral per vacancy (or unemployed worker).[22] Referrals are positively correlated

[21] This issue is explored in Appendix B of Berman (1993).

[22] For clarity, assume that this interval is a day. Let t index months and τ days. I wish to estimate $x_\tau = x(u_\tau, v_\tau) + \varepsilon_\tau$, but the variables available are x_t, u_t, and v_t, where

$$x_t = \sum_{\tau=1}^{n_t} x_{t_\tau}, \qquad u_t = \frac{\sum_{\tau=1}^{n_t} u_{t_\tau}}{n_t}, \qquad v_t = \frac{\sum_{\tau=1}^{n_t} v_{t_\tau}}{n_t}$$

where n_t is the number of workdays in month t and t_τ indexes days in month t. The monthly average stocks of unemployed, u_t, and vacancies, v_t, are related to daily hires through the following identities:

$$u_{t_\tau} = u_{t_{\tau-1}} + ui_{t_\tau} - h_{t_\tau}, \qquad \mathrm{v}_{t_\tau} = v_{t_{\tau-1}} + vi_{t_\tau} - h_{t_\tau},$$

with hires through (13) as some referrals become hires. This induces a negative correlation between the error term in referrals and the monthly average stocks of unemployment and vacancies. Thus, direct estimation of (1) by OLS on monthly data will be subject to simultaneity bias as unpredicted referrals ε_t generate hires that will deplete stocks of u and v in (1). Note that this simultaneity bias is generated solely by the aggregation of stock data over days that include the result of an earlier day's hires in their current stock. If the daily stocks and flows were available I could estimate (1) directly from daily data (assuming that a day is a short enough period to have no feedback from flows into stocks).

The same problem exists in the estimation of (13). Conditional on referral, unpredicted hires will deplete stocks of u_t and v_t through the same feedback identity. The direction of the bias of the coefficient on θ ($= v/u$) in (13) cannot be predicted.

A solution to this simultaneity problem is to find an instrument that is not affected by the feedback of hires within the period. The counts of unemployed workers and vacancies are valid instruments (a count is the sum of the stock at the end of the previous month and the inflow over the month). Both are determined before hires and are therefore not subject to the feedback of outflows into stocks. They should also be good instruments since both inflows and stocks at the end of the previous month are inputs into the monthly average stock. This strategy can be used in estimation of equations (1) and (13). The extent of this simultaneity bias will be shown by simulation below.

C. Aggregation within a Function

A third issue that arises from the use of data aggregated over periods within a month is that the covariates in both (1) and (13) are aggregated over time while the function I seek to estimate is the relationship in a single period, say daily. In general, a function of the means is not equal to the mean of the function's values in each period. Equality will obtain if the function is linear or, more generally, if it exhibits constant returns to scale and the ratio of arguments is constant. Aggregation within a function that does not satisfy these conditions will lead to some bias. (This is the same aggregation issue that arises in estimation of production functions or any other function with inputs aggregated over time or across units.)

---

where ui is the inflow of unemployed, vi is the inflow of vacancies, and h is the outflow of new hires. It follows that each hire on day t_τ decreases both u_t and v_t (by $(n_t - \tau + 1)/n_t$).

D. Simulation

The extent of biases due to simultaneity and aggregation within a function is investigated through simulation.[23] Since the feedback mechanism is an identity, the feedback process is known up to the distribution of inflows over days in the month. A simulation was performed assuming that inflows are distributed uniformly over the month. The simulated matching function has a Cobb-Douglas form with elasticities of one on both the unemployment and vacancy stocks. The results of estimation using OLS and instrumental variables (IV) methods with various amounts of equation error are reported in table 2.

The leftmost column reports the true coefficients. Moving to the right, the variance of the error in the estimating equation is increased, yielding worse fits. The result is increased bias in the OLS coefficients of the monthly regression as the negative (simultaneous) coefficient gets more relative weight. When the R^2 of the monthly regression reaches .73, the downward bias is 21% or 22%. At an R^2 of .52, the bias is about 40%. These are typical qualities of fit found in the literature, so estimated coefficients in the literature have a serious downward bias.[24] Instrumental variable estimates reported in the bottom rows of the table are consistent but underestimate standard errors slightly. Instrumental variable estimates from data simulated with the variance of the error in the estimating equation (second column) show very small but significant upward biases. This is evidence of bias due to the aggregation within a function discussed above. Interestingly enough, the size of this aggregation bias is negligible.

E. Functional Form

Since the maximum number of referrals possible in a short period is the product of the two stocks u and v, (1) was estimated using a Cobb-Douglas specification.[25]

[23] I thank Gary Chamberlain for suggesting this technique.

[24] Blanchard and Diamond (1989) propose an alternative solution of using lagged stocks as covariates. This will induce downward bias due to measurement error as the lagged stocks are imperfect measures of current stocks. In a simulation with the ES data like that reported in table 2, regression on lagged stocks generated coefficients with even more bias than those generated using OLS.

[25] I also experimented with a linear form $r_t = \alpha + \beta_t t + \beta_u u_t I(u_t < v_t) + b_v v_t I(v_t < u_t) + \varepsilon_t$, where I is an indicator function. This functional form is motivated by the restriction that in a period so short that only one referral is possible per u or v, the maximum number of referrals possible is the minimum. A simulation confirms that aggregation of this function over a distribution of categories can yield an Cobb-Douglas specification. All of the qualitative results reported below are preserved when this specification is used.

Table 2
Simulated Referral Function Estimation (300 Replications)

	Truth	Standard error of ε .0001	.1	.35	.5	.7
R^2 of daily OLS	. . .	1.00	.78	.28	.21	.20
OLS coefficients:						
log(u)	1	1.00	.98	.78	.60	.37
		(.00)	(.1)	(.4)	(.4)	(.05)
log(v)	1	1.00	.98	.79	.61	.38
		(.00)	(.01)	(.03)	(.04)	(.05)
R^2 of monthly OLS	. . .	1.00	.98	.73	.52	.26
Monthly IV coefficients:						
log (u)	1	1.007	1.01	1.00	1.00	1.00
		(.000)	(.02)	(.07)	(.10)	(.17)
		[.003]	[.02]	[.06]	[.09]	[.14]
log(v)	1	1.006	1.01	1.00	1.01	1.00
		(.000)	(.02)	(.06)	(.08)	(.14)
		[.002]	[.01]	[.05]	[.08]	[.12]

NOTE.—The data are generated by the equation $\ln(x_\tau) = -10 - 0.016t + 1\ \ln(u_\tau) + 1\ \ln(v_\tau) + \varepsilon_\tau$, where τ indexes days and t months; ε_τ has a normal distribution. Daily hires are generated by $h_\tau = 0.75x_\tau$. Monthly data are aggregated over days each 25 days for 149 months. The feedback from daily hires to the monthly stocks of vacancies and unemployed is such that each hire on the τth day of the month depletes both u_t and v_t by $(25 - \tau + 1)/25$. Actual monthly data for u and v are used to generate referrals. Instrumental variable (IV) estimates are computed using actual monthly inflows of unemployed and vacancies in both logs and levels as instruments as well as a constant and a time trend. The IV estimates are generalized method of moments estimates. The R^2 coefficients and estimated standard errors reported are averages across 300 replications. Actual standard errors are of the 300 estimated coefficients. Actual standard errors are in parentheses; estimated standards errors are in brackets. OLS = ordinary least squares.

A functional form for the acceptance rate (13) requires proposing a form for $G(\alpha)$. A convenient form is

$$G(\alpha) = \frac{\alpha}{1 + \alpha}, \quad \alpha \geq 0.$$

This is a logistic distribution for the logarithm of α, so I have assumed that match quality has a nonnegative support. This form has the useful property that $G(\alpha)/[1 - G(\alpha)] = \alpha$, so in terms of the reservation productivity,

$$\frac{G(\alpha_r)}{1 - G(\alpha_r)} = \alpha_r.$$

Note that none of the elements in this equation are observed, but it nevertheless provides a link between new hires and factors that determine the reservation wage.

Define $P_t = h_t/x_t$, the proportion of referrals that result in hires in period t. Then

$$\frac{1 - P_t}{P_t} = \frac{G(\alpha_{r_t})}{1 - G(\alpha_{r_t})} + \eta_t \quad E(\eta_t) \approx 0,$$
$$= \alpha_{r_t} + \eta_t,$$

where the approximation is a first-order Taylor expansion.[26]

From equation (8) we have

$$\alpha_{r_t} = z_t + \gamma_0\theta_t, \tag{8}$$

in which θ is observable while z and γ_0 are not. Substituting for α_r and linearizing, we get an estimating equation:

$$\frac{1 - P_t}{P_t} = z_t + \gamma_0\theta_t + \eta_t \tag{14}$$
$$= \gamma_0\theta_t + \zeta_t$$

The error term ζ includes both the error term η and the missing z.[27]

F. Estimation of a Referral Function

I turn now to estimation of the referral and acceptance functions (eqq. [1] and [13]). The variables in the referral function are plotted in figure 7 and descriptive statistics are given in table 3.

In figure 7 we see that the stock of work seekers rose from about 1,000 in 1978 to 50,000 in 1990. The stock of vacancies decreased sharply in 1980 from an average level of 5,400 before to an average of 2,100 afterward. (This is concurrent with the contractionary fiscal and employment policy discussed above.) These data offer a rare opportunity to compare the actual levels of unemployment and vacancy stocks. While the unemployed far outnumber vacancies in the 1980s, the 1970s in Israel were a period of low unemployment in which at one point there were over 30 vacancies for each unemployed worker. The higher of the two remaining curves is the flow of referrals, which averages about 18,000 per month and increases slowly over the period. Directly below it is the flow of

[26] $P/(1 - P) \approx (1 - G)/G + [P - (1 - G)]/G^2$ and $E(P) = 1 - G$.

[27] It is common in this type of estimation to estimate using weighted least squares since the variance of η can be estimated. In this case the variance of ζ will be likely to dominate that of η since the number of referrals is high, so the weighing is not performed.

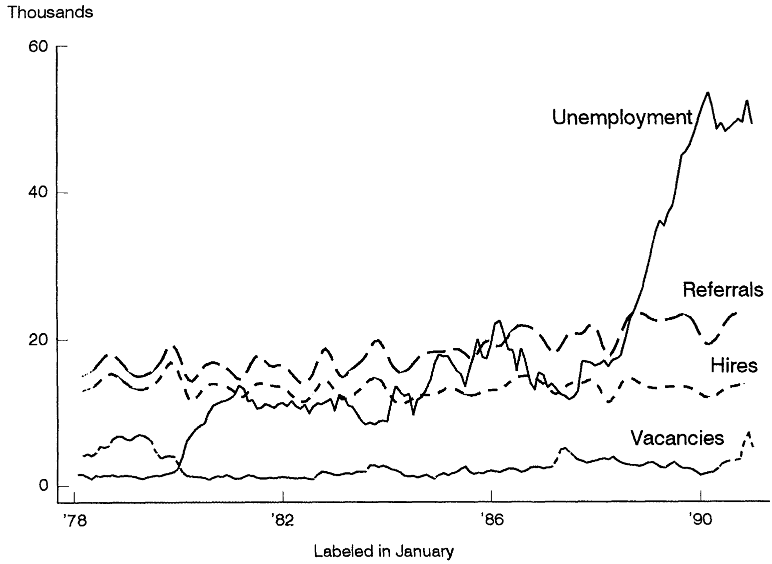

FIG. 7.—Vacancies, unemployment, referrals, and hires, 1978–90

hires. (These two flow series have much more variation than the stocks. They have been smoothed with a cubic spline in the graph.)

The referral function is estimated in logarithms. Figure 8 displays the natural logarithms of unemployment, vacancies, and referrals/day for 1978–90. Note that fluctuations in vacancies are negatively correlated

Table 3
Descriptive Statistics for Estimating Equations, February 1978–December 1990 (N = 148 observations)*

	Mean	SD	Minimum	Maximum
Referrals/day	709.7	125.3	404.5	1,153.2
Workdays/month	25.5	1.3	22	27
Vacancy stock	3,168.3	1,591.6	1,401.4	7,935.8
Unemployment stock	16,902.2	13,183.9	1,306.3	53,925.1
N	78	43.7	2	156
Vacancy count/day	685.1	121.4	439.8	1,141.9
Unemployment count/day	1,607.3	704.2	498.6	3,677.0
Vacancy inflow/day	580.2	79.6	380.6	870.2
Unemployment inflow/day	635.4	178.6	310.9	1,267.3
Hires/day	511.8	61.3	345.9	682.3
P = hires/referrals	.73	.09	.57	.88
θ = vacancy/unemployment (stocks)	.60	1.12	.04	5.24

* July 1978 and January 1988 are missing in the ES reports. July 1990 and August 1990 are missing due to work stoppages at the ES. Since the vacancy stock is constructed as a moving average of end-of-month stocks, the month immediately following each of the three gaps in the data is not used in estimation.

FIG. 8.—Vacancies, unemployment, and referrals, 1978–90

with fluctuations in unemployment. This is the "Beveridge curve" phenomenon. The doubling of unemployment between 1988 and late 1990 is mostly due to a massive increase in the size of the labor force due to immigration from the former Soviet Union, which began in the fall of 1989. The lowermost line in figure 8 is the logarithm of the monthly average of referrals per day (referrals per month divided by the number of workdays in the month). This series seems to follow the lower of the two stocks in the graph: unemployment till 1980 and vacancies afterward.

Estimates of the referral function are reported in table 4. The dependent variable is the flow of referrals per day, while the covariates are a trend term and the stocks of vacancies and unemployment. (A set of month indicators is included in all specifications with December omitted.) Column 1 reports OLS estimates. The coefficients on both v and u are very low, at .19 and .14, respectively, suggesting sharply decreasing returns to scale. This specification is subject to simultaneity bias, as the stocks are depleted by outflows of hires, which causes a downward bias on coefficients of u and v. I treat this simultaneity by instrumenting with counts of vacancies and unemployment, which are not subject to the stock-flow identity. Column 2 reports estimates obtained using counts as instruments. Here coefficients on v and u are about twice as large. This implies a simultaneity bias of 50%, much larger than the bias indicated in the simulation in table 2. These coefficients are also much smaller than those typically estimated in the literature, a point discussed below.

The Durbin-Watson statistic in column 2 indicates positive serial correlation of the error term. Since the counts include stocks from the end of

Table 4
Referral Function Estimates Using Various Instruments
Dependent Variable: log (Referrals/Day)

	Method			
		IV Using:		
	OLS (1)	Counts (2)	Inflows (3)	Lagged Stocks (4)
Constant	3.76	1.14	.89	3.90
	(.37)	(1.02)	(1.42)	(.39)
Trend	.00007	.0026	−.0027	.0003
	(.00049)	(.0011)	(.0017)	(.0005)
log(v)	.19	.36	.39	.17
	(.02)	(.07)	(.09)	(.03)
log(u)	.14	.29	.29	.13
	(.03)	(.06)	(.09)	(.03)
R^2	.77	.70	.67	.77
D-W	2.25	1.69	1.59	2.26
p-CRS	.00	.01	.07	.00

NOTES.—Estimated standard errors are in parentheses. They are robust to heteroskedasticity and first-order autocorrelation. Instrumental variables (IV) include both levels and logarithms; IV estimates are overidentified. Generalized method of moments estimates are reported with the estimated covariance matrix used for weights. The p-CRS is the p value of a χ^2 test that the coefficients on unemployment and vacancies sum to one. A full set of month indicators are included in all specifications with December omitted. The sample contains 148 monthly observations in the period between February 1978 and December 1990. Inflows are all unemployed and vacancies that arrive during the month. Counts are all unemployed and vacancies available during the month. A count is the sum of the inflows and the stock at the previous month's end. OLS = ordinary least squares; D-W = Durbin-Watson statistic.

the previous month, serial correlation of errors makes them inadmissible instruments. (Recall that the correlation of the error term with the contemporaneous stocks is the reason for instrumenting at all.) Positive serial correlation of the errors would cause a negative correlation of lagged stocks with the current error term implying a downward bias on coefficients. Inflows of u and v during the month remain admissible instruments in the presence of serial correlation. Column 3 reports the results of using inflows of unemployment and vacancies rather than counts as instruments. Estimated coefficients on both vacancies and unemployment are much higher, indicating returns to scale of 0.7 and a downward bias on the OLS coefficients of over 50%. Standard errors on these estimates are high, indicating that inflows are not nearly as correlated with stocks as are the counts (which include the lagged stocks). The specification in column 3 shows symptoms of even stronger serial correlation than that in column 2, with a Durbin-Watson statistic of 1.59.

Why should the error term be serially correlated? The referral process at the ES is a closed system. Vacant jobs and unemployed workers are inputs, and referrals are the output. Since these are accounted for the presence of serial correlation suggests that some other persistent effect is creating a systematic pattern. One possibility is that the "intensity" of search by the unemployed or by firms varies over time in response to changes in the wage level or in the level of unemployment benefits. Another possible explanation is that there are persistent changes in the productivity of the Employment Service clerks.

G. Heterogeneity

A more likely explanation for serially correlated errors is that the internal composition of both unemployment and vacancy stocks changes over time. For instance, if an influx of hard to refer workers arrives in a given month, they are likely to generate an unexpectedly low flow of hires and be carried over into the next month's stock to again generate a low flow of referrals. This explanation involves ex ante heterogeneity since a "hard-to-match" worker must show correlated match-specific productivities α between referrals, in contradiction to the assumption of the model. Ex ante heterogeneity is one of the common explanations of observed negative duration dependence in duration data. Such duration dependence would appear here as serially correlated residuals.

Heterogeneity in the stocks may also explain why the bias in OLS estimates is greater than that predicted by the simulation. If it exists, the use of either inflows or lagged stocks as instruments imply different experiments. Instrumenting with inflows implies varying the stock by changing the number of new, easily matched vacancies or unemployed. Instrumenting with lagged stocks implies varying the stock by varying old vacancies or unemployed. Heterogeneity in referral probabilities would make old stocks less likely to be matched than new as the easy to refer are selected out over time. Column 4 reports the results of instrumenting with lagged stocks rather than inflows. The estimated coefficients are (insignificantly) smaller than those obtained by OLS. This is consistent with simultaneity bias due to a serially correlated error process but could also be interpreted as a symptom of two different kinds of experiments due to negative duration dependence. Simultaneity aside, OLS coefficients could then be interpreted as weighted averages of coefficients from these two experiments.

To test for heterogeneity, I can use the inflow variables (described above) to decompose the stocks of both vacancies and unemployed into the products of inflow and duration terms: $v = vid^v$ and $u = uid^u$, where vi and ui are the inflows to the vacancy and unemployment stocks over the month. Variables d^v and d^u are the (derived) average durations of a vacancy or unemployment spell in a steady state. The Cobb-Douglas referral function

$$\log(x_t) = \alpha + \beta_t t + \beta_v \log(v_t) + \beta_u \log(u_t) + \varepsilon_t$$

can then be rewritten as

$$\begin{aligned}\log(x_t) = \alpha + \beta_t t + \beta_{v1}\log(vi_t) + \beta_{v2}\log(d_t^v) \\ + \beta_{u1}\log(ui_t) + \beta_{u2}\log(d_t^u) + \varepsilon_t.\end{aligned} \tag{15}$$

If vacancy and unemployment spells are homogeneous, each will have the same probability of receiving a referral, independent of a spell's past duration. Then the restrictions $\beta_{v1} = \beta_{v2}$ and $\beta_{u1} = \beta_{u2}$ will apply, as there are no composition effects. Negative empirical duration dependence will be evident if the coefficient on duration is smaller than that on the inflow, indicating that an increase in the vacancy (unemployment) stock due to the inflow of new vacancies (unemployment) creates more referrals than an equal increase in the vacancy (unemployment) stock due to increased duration of existing vacancies.

The inflow-duration version of the referral function is subject to simultaneity in the duration term due to the feedback of hires to monthly stocks. Since the inflows are covariates, I need another variable to instruments duration terms. I use inflows from mutually exclusive occupation/industry groups below.

The Employment Service classifies both workers and job vacancies into occupation/industry groups for processing. Data on seven aggregate groups is available. These seven groups are treated as mutually exclusive by the service and are processed by separate divisions. Referrals between divisions are rare. I interpret this as evidence that these groups have a natural logic to them and estimate referral and acceptance functions within each group as if they were completely separate markets. The unskilled category is the largest, with 67% of referrals in the sample period. The clerical category accounts for 16% and the rest have no more than 7% each.

Table 5 reports the results of estimating a referral function for each category. Inflows of vacancies and unemployed are used as instruments.

Table 5
Referral Function Estimates: Seven Occupation/Industry Groups (Using Inflows as Instruments)
Dependent Variable: log(Referrals/Day)

	Total	Building	Industry	Transport	Clerical	Professional	Service	Unskilled
Constant	.89	−3.84	−.55	−1.39	−3.08	−1.75	−3.73	−2.07
	(1.42)	(1.05)	(.51)	(.98)	(1.71)	(.88)	(.80)	(2.33)
Trend	−.0027	−.0095	−.0041	−.0032	−.0084	−.0030	−.014	−.0068
	(.0017)	(.0016)	(.0009)	(.0018)	(.0032)	(.0029)	(.003)	(.0003)
log (v)	.39	.71	.36	.65	.68	.44	.89	.55
	(.09)	(.14)	(.05)	(.14)	(.11)	(.09)	(.08)	(.15)
log (u	.29	.68	.39	.30	.65	.39	.67	.52
	(.09)	(.11)	(.04)	(.11)	(.19)	(.11)	(.12)	(.17)
R^2	.67	−.17	.46	−.04	.04	.76	.53	.33
D-W	1.59	.96	.79	.71	.49	.88	.90	.87
p-CRS	.07	.10	.00	.84	.25	.38	.00	.82

NOTE.—Estimated standard errors are in parentheses and are robust to heteroskedasticity and first-order autocorrelation. Instrumental variables (IV) include both levels and logarithms of inflows and the logarithm of workdays per month; IV estimates are overidentified. Generalized method of moments estimates are reported with the estimated covariance matrix used as a weighing matrix. A full set of month indicators are included in all specifications with December omitted. The p-CRS value is the p value of a χ^2 statistic testing for constant returns for scale. The sample contains 148 monthly observations in the period between February 1978 and December 1990. D-W = Durbin-Watson statistic.

The coefficients in the categories tend to be higher than those in the aggregate, presumably because aggregation induces some measurement error. Constant returns to scale is rejected in only two of the seven categories, once in favor of decreasing returns and once in favor of increasing returns. Thus, as labor markets increase in volume (over time) there is evidence for neither congestion nor increased efficiency in the matching of new vacancies and newly unemployed workers.

The constants are negative and there are small negative trends. (The constant in this equation can be interpreted as the logarithm of the probability that a given u, v pair will get referred to each other in January 1978, when $v = 1$, $u = 1$ and the trend equals zero. Thus the estimated constant should be negative so that its exponent is less than one.) All trend terms are negative. All seven estimated functions show evidence of positive serial correlation of the error term. As in table 4, this may be a symptom of heterogeneity in individual referral probabilities.

Since seven groups are available, we can now test for heterogeneity by estimating equation (15) for each group using inflow terms in the other six as instruments. These will be valid instruments if unexpected referrals in one group are independent of inflows in the others. Since these inflows are predetermined, this independence seems plausible. Estimates are presented in table 6.

Table 6
Referral Function Estimates Including a Duration Term
Dependent Variable: log(Referrals/Day)

	Building	Industry	Transport	Clerical	Professional	Service	Unskilled
Constant	−.02	1.61	.52	.29	.78	−.93	.85
	(.33)	(.28)	(.20)	(.14)	(.41)	(.27)	(.26)
Trend	−.0004	.0035	.0041	.0057	.0064	−.0009	.0013
	(.0011)	(.0005)	(.0005)	(.0005)	(.0011)	(.0010)	(.0003)
log (vi)	.55	.49	.73	.87	.46	.87	.74
	(.05)	(.05)	(.06)	(.04)	(.04)	(.03)	(.04)
log (d^v)	.09	−.18	−.02	−.01	.01	.23	−.06
	(.04)	(.03)	(.03)	(.03)	(.04)	(.04)	(.02)
log (ui)	.34	.30	.12	.09	−.07	.34	.15
	(.06)	(.04)	(.03)	(.03)	(.05)	(.03)	(.03)
log (d^u)	.10	−.10	−.06	−.01	.08	.14	−.01
	(.06)	(.04)	(.03)	(.02)	(.05)	(.04)	(.02)
R^2	.61	.79	.82	.90	.87	.92	.92
D-W	2.08	1.33	1.59	1.40	1.28	1.44	1.35
p-homogeneity	.00	.00	.00	.00	.00	.00	.00
p-CRS inflows	.08	.00	.01	.09	.00	.00	.01

NOTE.—The variables vi and ui are the inflows of vacancies and unemployment respectively over the month; d^v (d^u) is the average duration of a vacancy (unemployment) spell in a steady state in which the outflow rate equals the inflow rate ($d^v = v/vi$). Estimated standard errors are in parentheses are robust to heteroskedasticity and first-order autocorrelation. Instrumental variables (IV) include both levels and logarithms of inflows and logarithms of inflows from each of the other six occupation/industry groups and the logarithm of workdays per month; IV estimates are overidentified. Generalized method of moments estimates are reported with the estimated covariance matrix used as a weighing matrix. The p-homogeneity value is the p value of the χ^2 test that coefficients are equal on inflow and duration terms. The p-CRS value is the p value of a χ^2 statistic testing for constant returns to scale in the two inflow variables. The sample contains 148 monthly observations in the period between February 1978 and December 1990. D-W = Durbin-Watson statistic.

In all seven occupation/industry groups the estimated coefficient on inflows is much larger than that on duration, indicating that old vacancies and unemployed are much less likely to generate referrals than inflows. This is strong evidence for heterogeneity. The estimated coefficients on durations hover around zero. They often have implausible negative coefficients. Allowing for these separate coefficients on old and new spells reduces the serial correlation in the error term. This may be because the high serial correlation of stocks makes adding the duration term (without an instrument) much like adding a lagged dependent variable, but it is also consistent with the explanation given above that heterogeneity caused the observed serial correlation. Beyond their use as a test for heterogeneity, the coefficients on duration have no structural interpretation.

Heterogeneity in vacancies and unemployed can explain why the OLS estimates in the first column of table 4 are so much smaller than those found in the literature using similar methods but annual rather than monthly observations. In the low frequency variation of the stocks, the variation in incidence (which is quite productive) may dominate, while in the high frequency variation the duration may dominate. In their study of Dutch employment service matching, Lindeboom et al. (1994) found a comparably low coefficient on the stock of workseekers, though they estimated a coefficient near unity on vacancies. The low estimated coefficient on vacancies in table 4 may be due to the high quality of the Israeli data since mandatory registration of vacancies may allow measurement of many vacancies with low hazards that are not observed in the literature. Indeed, many of these vacancies are withdrawn without being filled.

Heterogeneity in vacancies and the unemployed in their probability of gaining referrals implies a serious complication in modeling an aggregate matching function. If individual agents are aware of different probabilities of gaining referrals, they will search with different reservation wage or productivity levels. They must be somewhat aware of their individual characteristics as their duration of search provides information on their probability of gaining a referral. Thus, the assumption of ex ante homogeneity in the model is formally inconsistent with the evidence for heterogeneity in table 6.

The fact that veteran unemployed have a far smaller probability of gaining referrals also implies that unemployment composed largely of veteran unemployed will be slow to reduce itself through new hires. The estimated coefficients can give no indication how long it will take for these long-term unemployed to be hired as they have no structural interpretation.

A possible spurious explanation for the heterogeneity result is due to the ex post registration of vacancies. If matches made outside the ES are then registered as vacancies by sending the worker to the ES to register both himself as unemployed and the job as vacant (with an understanding that a referral and hire would follow), then these new vacancies and unemployment spells will appear to be extremely productive. This is a form of heterogeneity—the stocks will be composed of those that have already been matched and those that have not—but it is artificial. While ex post registration of vacancies may have been occurring, there is some evidence that its extent is limited. In 1978 and 1979, the inflow of vacancies far exceeded the inflow of unemployed, so that many vacancies must have arrived that were not ex post registration.

H. Estimation of an Acceptance Function

The aim of this research is to estimate an aggregate matching function, the product of a referral function and an acceptance rate. Figure 9 plots the proportion of referrals that resulted in hires over the 1978–90 period. The striking feature of this graph is that the acceptance rate dropped sharply over the 1980s, from 85% in 1979 to only 59% in 1990. Aside from a slight leveling off in 1985–86, the acceptance rate dropped consistently in each year from 1979 to 1990. This decrease in the acceptance rate shows that part of the increase in unemployment in the 1980s in Israel is associated with a trend slowdown in the hiring process. A simple calculation using the steady-state unemployment equation (5) at the implied mean values of s, and assuming that the national unemployment rate applies to the ES sample, reveals that the 26 percentage point drop in the acceptance rate implies a 2.1 percentage point increase in steady-state unemployment.

Table 7 reports on the change in acceptance rates within each group. Surprisingly, none of the drop in the aggregate referral rate can be attributed to changes in the composition of referrals. While there is considerable

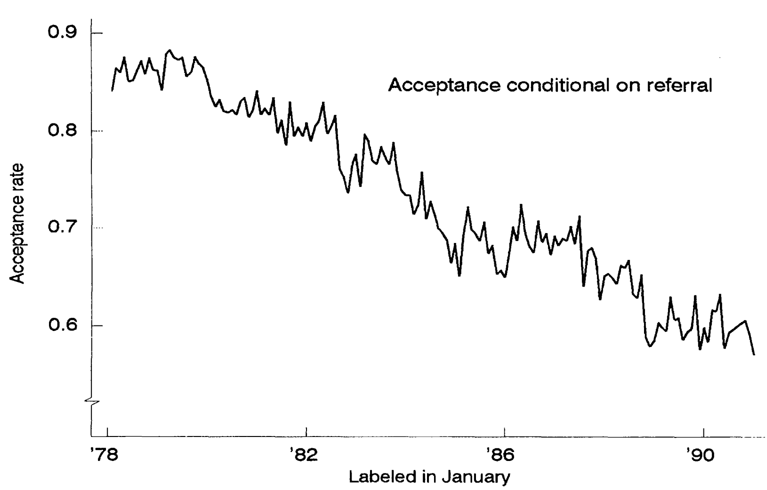

FIG. 9.—The acceptance rate

Table 7
Acceptance Rate in Seven Occupation/Industry Groups

	Average P, 1978–90	Change in P, 1978–90	Share in Referrals		Change in Share, 1978–90
			1978	1990	
Total	.72	−.26	1	1	. . .
Building	.77	−.31	.01	.01	.00
Industry	.74	−.25	.07	.07	.00
Transport	.70	−.31	.02	.02	.00
Clerical	.61	−.46	.18	.14	−.04
Professional	.61	−.37	.01	.02	.01
Service	.67	−.30	.04	.05	.01
Unskilled	.75	−.21	.66	.68	.02

NOTE.—P is the acceptance rate (hires/referrals). The average is a weighted average of 152 months between January 1978 and December 1990. Changes are calculated as the difference between the 1978 and 1990 annual averages.

variation in average rates and in changes between groups, the share of each group in total referrals remained virtually unchanged over the 13-year period. Among occupation/industry groups, the clerical and professional groups have low acceptance rates.

Another striking aspect of the table is the high level of acceptance. Seventy-two percent of all referrals result in hires. Even in relatively complex jobs like clerical and professional, where we would expect the variance of α to be high and thus the acceptance rate to be low (due to option value considerations in search), the acceptance rate averages 61%. A possible explanation of this high success rate in referrals is ex post registration of vacancies, which result in a formal referral of an already matched worker. This can only provide a partial explanation, as the inflow rate of vacancies actually exceeds that of work seekers in 1978–80, when the acceptance rate was highest (88%).

Table 8 presents estimates of the acceptance function (eq. [14]) for each occupation/industry group. Since (14) is nonlinear in P and in the coefficients, the partial derivatives of P with respect to covariates vary with P. Estimates are reported for the partial derivatives evaluated at the sample mean.[28] (Note that while the model requires that θ be set with perfect foresight rational expectations, the measured θ is the current value. Static expectations are being used to approximate rational expectations. Since durations of unemployment and vacancies are short and θ changes very little over time, this should be a good approximation.)

Five of the seven groups show evidence of positive serial correlation

[28] Reported coefficients are partial derivatives $d(h/x)/dc$ with respect to covariate "c" evaluated at the mean of the dependent variable h/x. This is a linear function of the coefficients of eq. (13): if $(1 - P)/P = \pi c + E$, then $dP/dc = \pi/\{(-1/P^2)\} = -\pi P^2$. The mean of P is 0.73 in the pooled sample.

Table 8
Acceptance Function Estimates
Dependent Variable: Hires/Referrals

	Method							
	OLS Total	IV Building	IV Industry	IV Transport	IV Clerical	IV Professional	IV Service	IV Unskilled
Constant	−.04	.06	−.03	−.06	.07	.02	−.001	.016
	(.01)	(.02)	(.01)	(.02)	(.02)	(.02)	(.012)	(.017)
Trend	−.0021	−.0028	−.0020	−.0022	−.0042	−.0032	−.0028	−.0036
	(.0001)	(.0002)	(.0001)	(.0001)	(.0002)	(.0002)	(.0001)	(.0001)
θ (= v/u)	−.0051	−.0079	−.0007	.0151	−.0788	−.0143	−.0338	−.0372
	(.0019)	(.0023)	(.0008)	(.026)	(.0152)	(.0058)	(.0073)	(.0087)
R^2	.94	.50	.85	.75	.90	.78	.83	.84
D-W	.90	1.72	1.03	1.65	.56	1.05	1.06	1.09

NOTE.—Reported coefficients are partial derivatives $d(h/x)/dc$ with respect to covariate "c" evaluated at the mean of the dependent variable h/x. This is a linear function of the coefficients from eq. (10): if $(1 - P)/P = \pi c + E$, then $dP/dc = \pi/[(-1/P^2)] = -\pi P^2$. The mean of P is 0.73 for the pooled sample. Estimated standard errors are in parentheses and are robust to heteroskedasticity and first-order autocorrelation. Instrumental variables (IV) are the v/u ratios for inflows from all seven groups and the inflows from the same group; IV estimates are overidentified. Generalized method of moments estimates are reported with the estimated covariance matrix used as a weighing matrix. A full set of month indicators are included in all specifications with December omitted. At a 5% significance level the Durbin-Watson (D-W) lower bound is 1.55. OLS = ordinary least squares.

of the error term, so that any inference from this regression is tenuous. Six of the seven groups report the negative coefficients on θ predicted by the model. Labor market tightness increases search costs for firms and thus increases the firms surplus from a match of given quality. Some of that surplus must be shared with the workers, so that the reservation level of productivity increases, resulting in a lower acceptance rate (this negative effect of tightness on the acceptance rate is also consistent with efficiency wage theory). The key finding in table 8 is that the effect of labor market tightness is quite small, making its effect on the matching function through acceptance rates negligible.

Since the trend decrease in acceptance rates may have caused a large increase in unemployment, it is worth speculating on its possible causes. None of the trend decrease in the acceptance rate can be explained by labor market tightness since θ decreased over the sample period, which should increase acceptance rates. One possible cause is mismeasurement. If the proportion of hires registered ex post with the Employment Service decreased, then the proportion of hires in referrals would also decrease (a smaller proportion of referrals would be mere formalities). Ex post referrals could decrease over time either because of increased use of the ES from the beginning of a firm's search or due to decreased enforcement of regulations. Administrators at the ES report neither increased use nor decreased enforcement. Another possibility is that increased unemployment insurance benefits, z, decreased the surplus from a hire by increasing the reservation wage. While there were several large increases in UI benefits over the sample period, examination of the residuals from estimates of the acceptance function (not shown) reveal that there is no pattern of decreased acceptance corresponding to periods of increased benefits. Decreased separation rates and increased variation in match-specific productivity are also possible causes of decreased acceptance rates. While this model predicts that these effects should act through θ, in a more general model they may not. A decrease in separation rates can probably be ruled out since it would coincide with decreased unemployment. Increased variation in α is a possible culprit, as it would increase the option value of search, thus increasing reservation wages and profits.

Another possibility is that exogenously set real wages are a binding lower bound on wages, in contradiction to the unrestricted surplus splitting assumed in the model. In that case, real wage increases not matched by increases in the mean of α would both decrease the inflow rate of vacancies and under fairly general assumptions decrease the probability of a given referral resulting in a hire. Yet another possibility is that the average quality of a referral dropped due to the increased workload of the ES staff. The ES expanded its staff only slightly over this 13-year period, so that the ratio of work seekers to ES clerks increased substantially. A final possibility is that the Israeli labor market experienced increased mismatch between the characteristics of vacancies and those of the unemployed. This may have been reflected in a reduction in the potential marginal product of the average referral, leading to a reduction in the acceptance rate.

I. Impulse-Response Functions

The product of the estimated referral and acceptance functions is the estimated matching function. This function can be used to predict the dynamic response of levels of unemployment and vacancies to changes in their inflow rates. Here I demonstrate two experiments from the discussion of Beveridge curve dynamics in figure 4 above: an increase in labor demand due to an additive shift in the distribution of marginal products, and an increase in the inflow of unemployment due to immigration. Impulse-response functions are shown for two specifications of the estimated matching function (for unskilled workers) in order to illustrate the effects of correcting simultaneity bias. These responses depend not only on the parameters but also on the starting values of u and v. Initial values were chosen such that unemployment and vacancies were equal and represented steady states for both specifications (this was possible with minor adjustment to one estimated constant).

Figure 10 shows the response of unemployment to an additional inflow of 100 vacancies over and above the steady state inflow rate, corresponding to the movement from A to B via C in Figure 4. Figure 11 shows the response to an additional inflow of 100 unemployed and the resulting increase in vacancies, corresponding to the movement from A to A through D and E in figure 4. Three main points stand out in these figures.

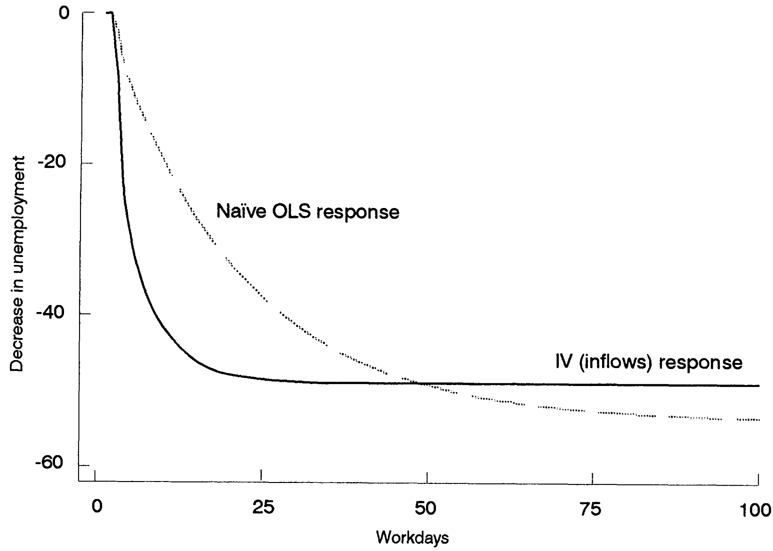

FIG. 10.—Response to additional inflow of 100 vacancies. See note to fig. 11 below

One is that responses are extremely rapid. Even in the slowest case, most of the long-run effect is worked out within 2 months (50 working days). A second point is that adjustment for simultaneity reduces estimated response time. The low elasticities in the OLS referral function give the slow response, while the higher elasticities in the referral function instrumented with inflows give a response completed within a month. Finally, the long-run response to an inflow of unemployed is zero since any inflow of unemployed in this model will decrease search costs to firms and generate an immediate increase in vacancies.

The speed of convergence to steady state in both of these simulations has an important implication for how we think about short-run unemployment. The speed at which inflows to unemployment and newly created vacancies find matches determines that short-term unemployment due to search cannot explain the high unemployment rates experienced by immigrants to Israel. Matching occurs too fast. The short-term adjustment to increased inflows is generally finished in less than a month, indicating either that immigrants are matching more slowly than the other unemployed or that there has not been a concurrent increase in vacancies, as predicted by the model, or both. Both explanations are supported by data. The simulations suggest a more general conclusion that matching occurs much too quickly to generate adjustment dynamics lasting longer than about a month.

V. Conclusions

This article provides two solutions to the problem of simultaneity in estimation of an aggregate matching function and introduces a test for

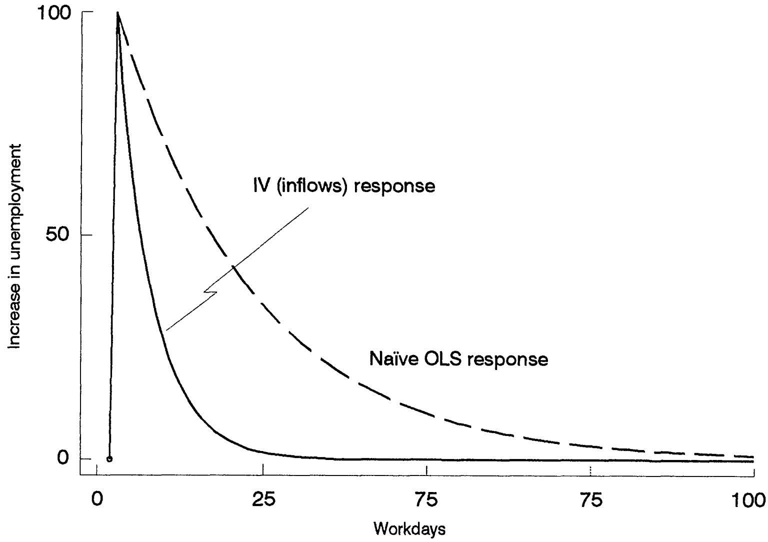

FIG. 11.—Response to additional inflow of 100 unemployed. Note: Simulated impulse response functions are generated using matching functions estimated for unskilled workers. The "naive ordinary least square" curve uses the referral function $\ln(r_t) = 3.55 + 0.17 \ln(v_t) + 0.13 \ln(u_t)$ estimated as in table 4, col. 1. The "instrumental variable inflow" curve uses the referral function $\ln(r_t) = -0.27 + 0.55 \ln(v_t) + 0.13 \ln(u_t)$ reported in table 5. All three curves use the starting values $\log(v) = 7.3$ and $\log(u) = 7.3$, the inflow rates $ui = 234$, $vi = 234$, and the acceptance rate $P = 0.75$.

heterogeneity in the probabilities that individual unemployed persons or vacant jobs will gain referrals. The estimated matching functions from Israeli ES data show rapid dynamic adjustment to increases in vacancies and unemployment. A decrease in the efficiency of matching over the 1980s can explain part of the trend increase in unemployment experienced in the Israeli labor market, a trend that is common to many European countries.

Matching functions are subject to simultaneity bias due to the depletion of stocks by outflows of hires and to aggregation in measuring these stocks. Two techniques have been demonstrated to correct for this bias: instrumentation with inflows and simulation of the (simultaneous) depletion equation. While the first technique requires data on gross inflows of unemployment and vacancies, an uncommon feature of the Israeli ES data, the second is generally applicable. Downward bias due to the depletion of stocks by outflows is about 20% for OLS estimates in these data. This is an issue of general interest in the matching function literature. Estimates of constant returns to scale may suffer from the downward biases of about 40%. Increasing returns to scale in matching would imply that large labor markets are more efficient. Estimates corrected for simultaneity bias in this data set have slightly decreasing or constant returns to scale.

A test for heterogeneity in the probability of both vacancies and unemployed persons finding a referral was introduced. The result is dramatic: newly arrived vacancies have a much higher probability of gaining referral than older vacancies and the same is true of the unemployed. While negative duration dependence is a familiar phenomenon in unemployment, this is a new finding for vacancies. To some extent, this observed heterogeneity may be due to a spurious effect, the reporting of vacancies after a match has already been consummated. I argue that the extent of the resulting bias is limited.

Heterogeneity in vacancies and among the unemployed exposes an important weakness of matching models. The estimating equation for the acceptance function is derived from a model in which all vacancies have equal probabilities of gaining a referral, as do the unemployed. If there is heterogeneity in these probabilities, it will be observed by agents (who are aware of their own duration), and they will search with heterogeneous reservation wages, contradicting equation (13). The development of a theoretical model of heterogeneity capable of producing an estimating equation for referrals is a key to future research. Heterogeneity in the composition of the stocks of vacancies and the unemployed allows a different interpretation of shifts in the Beveridge curve. A reduction in the quality of the stocks or of the extent to which they suit each other will appear as a reduction in the efficiency of matching and a rightward shift of the curve to higher levels of unemployment at a given level of vacancies.

Impulse-response functions reveal that the matching process has extremely rapid dynamics. Adjustment to an impulse of new unemployment or vacancies is complete within 2 months. Matching cannot generate even medium-term dynamics in adjustment to a steady state. In Israel's case that would imply that 2 months after the inflow of immigrants stops, a steady-state level of unemployment will be reached. Clearly, an alternative explanation for the period of high unemployment in Israel is that the skills of the immigrants were not well matched to the requirements of job vacancies. This suggests that retraining of the unemployed and investment by firms in different technologies must take place if unemployment rates among immigrants are to be further reduced. Retraining and appropriate investment should shift the Beveridge curve back to lower levels of unemployment.

The proportion of job referrals resulting in new hires declined sharply, from 0.85 to 0.60 over the 1978–90 period. This decline could account for a 2.1% increase in the unemployment rate among job seekers in the sample. Its underlying causes remain unexplained. I have argued that increased labor market tightness, a possible decrease in separation rates, and increased UI benefits are unlikely to account for the drop in acceptance rates. More likely explanations are increased real wages (over and above productivity gains), increased variation in match-specific marginal products, or a decrease in the average of these marginal products. These explanations are consistent with mismatch and with the fact that inflows of unemployed were not accompanied by equal inflows of vacancies over the decade. Since exogenous variation in real wages is available due to national wage indexation agreements, it may be possible to estimate the effect of changes in real wages on acceptance rates. That investigation is left to future research.

The picture that emerges of the causes of Israeli unemployment in the 1980s is as follows. A drop in labor demand, evident from the drop in vacancies in 1979–80, may account for the 2 percentage point increase at the beginning of the sample period. Between 1980 and 1989 the unemployment rate rose sharply, from 4.8% to 8.9%. Assuming that the ES sample is representative, I have shown that 2.1 points of this 4.1 percentage point increase can be explained by the decrease in acceptance rates, leaving a 2 percentage point increase in unemployment unexplained. None of the further 2% increase in unemployment following the massive immigration that began in 1989 can be attributed to short-term adjustment due to job search. The matching function estimates indicate that the adjustment of the unemployment rate to an inflow of new unemployed is completed within 2 months, suggesting that longer-term adjustments such as retraining and investment were necessary to decrease unemployment among immigrants.

The empirical results of this article have two important implications beyond the Israeli labor market. The first is that small changes in the efficiency of the matching process may cause large changes in steady-state levels of unemployment. The second is that job search is too efficient to generate dynamics lasting longer than a few months, so transitory shocks cannot generate European style hysteresis combined with slow matching of jobs to workers.

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