NBER WORKING PAPER SERIES

AN ESTIMATE OF A SECTORAL MODEL OF LABOR MOBILITY

Boyan Jovanovic

Robert Moffit

Working Paper No. 3227

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
January 1990

This paper is part of NBER's research program in Labor Studies.

NBER Working Paper #3227
January 1990

AN ESTIMATE OF A SECTORAL MODEL OF LABOR MOBILITY

ABSTRACT

This paper develops a model of sectoral labor mobility and tests its main implications. The model nests two distinct hypotheses on the origin of mobility: (a) sectoral shocks (Lucas and Prescott, 1974) and (b) worker-employer mismatch (Jovanovic, 1979, Miller, 1984, Flinn, 1986). We estimate the relative importance of each hypothesis, and find that the bulk of labor mobility is caused by mismatch rather than by sectoral shift. We then try to put a value on society's match-specific information. That is, we ask to what extent the availability of the option to change jobs raises GNP. We find that the mobility option raises expected earnings by roughly between 8.5 percent and 13 percent of labor earnings, which translates to an increase in GNP of between 6 percent and 9 percent.

Boyan Jovanovic
Department of Economics
New York University
269 Mercer St.
New York, NY 10003

Robert Moffit
NBER
269 Mercer St.
New York, NY 10003

1. Introduction

The modern approach to labor mobility examines it in two different ways. One approach focuses on explaining the existence of unemployment as a frictional phenomenon, a byproduct of labor movements that respond to shifts in the demand for labor in different sectors of the economy. These demand-shifts are in turn the result of shocks to tastes or technology. Lucas and Prescott (1974) provide a theory, and Lilien (1982) applies it to some recent data on unemployment. The work of Long and Plosser (1983) is also a theory of sectoral labor relocation over time that abstracts from unemployment.[1]

But certain detailed features of mobility itself call for a richer theory. Two such features are (1) that workers tend to move mostly <u>within</u> sectors, not <u>across</u> sectors, and (2) that net labor mobility across sectors appears to be dwarfed by gross mobility -- most moves between sectors cancel out. The model of Jovanovic (1979), extended and estimated with micro data by Miller (1984) and Flinn (1986), was designed to explain such movements of labor. This second approach, however, says nothing about sectoral flows of labor.

This paper merges these two views in one model, which is then estimated with data on individuals. This exercise allows us to measure the relative importance of each hypothesis. Moreover, it helps one avoid certain pitfalls. For instance, Bull and Jovanovic (1987) argue that if sectoral shifts are ignored when looking at micro data, downward bias will result in the estimated coefficient of job-tenure in the wage equation, and to avoid such bias, more attention should be paid to the firm's product-market. More generally, the importance of matching will be overstated if every job separation is attributed to a perceived mismatch.

The macro data, too, will be misinterpreted if sectoral demand-shift is viewed as the only cause of unemployment. In the Lucas-Prescott view, each unemployed worker is in transit from one sector to another, in response to a demand shift, and a constant rearrangement of sectoral-demands is thus necessary to generate a positive natural rate of unemployment. Because their theory rules out all other reasons for labor mobility, it implies that gross flows of labor should equal net flows. Instead, gross flows are in fact much larger, and contrary to their assumption that unemployed workers are in transit from one sector to another, following a spell of unemployment most workers return to the same sector.

The paper also quantifies the social value of match-specific information at between 6% and 9% of GNP. One arrives at this number by valuing, at equilibrium prices, the output that would be lost if agents <u>could not</u> act on their match-specific information by exercising their option to change jobs. This number measures what society would lose if it, in effect, threw away its match-specific information.

In the next section, we briefly lay out the magnitudes of the gross flows and net flows in the data set we will be using to test our hypotheses; this will motivate the paper, and it will highlight some of the facts that we are trying to explain. Section 3 develops a simple model of labor mobility that incorporates both matching considerations and sectoral shocks. Section 4 then uses the model together with some properties of the data, to arrive at an estimate of the social value of job-specific information. Empirical tests of the model are reported in Section 5, as well as an estimate of the relative importance of matching and sectoral shocks in the determination of labor mobility over the period 1968-1980. Our empirical test is based on our demonstration that the matching model predicts a positive effect of the standard deviation of the log wage distribution on mobility -- this test of the matching model is new, and contrasts with prior tests such as that of Flinn (1986) which was based upon the covariance structure of earnings predicted by the model.

2. Gross and Net Flows

Table 1 shows the magnitudes of gross and net flows in the data set which we will use for our testing in Section 5, the National Longitudinal Survey of Young Men (NLS). For the purposes of this section it need only be said that the NLS is a panel data set which allows us to observe young men in their 20s and early 30s at the pairs of years shown in the table, and to determine whether they had or had not changed sectors. In Table 1 we use a simple three-sector classification with manufacturing as one sector, services and trade as another, and the remaining industries as a third. This sectoral partition roughly divides the employed labor force into equal sectors.[2]

As Table 1 indicates, gross flows -- the fractions of workers changing sectors -- are quite high in these data, no less than 14 percent of men changing sectors between any of the two-year periods. In part this high percent is a result of the relatively young age of the sample (the mobility rates in the table are standardized to age 28 and thus represent mobility at that age) -- it is well known that mobility declines with age. Mobility rates for the male labor force as a whole range from 6 percent to 10 percent over one-year periods (Murphy and Topel, 1987, Table 11) and is probably less than we find in Table 1 even over two-year periods. On the other hand, our crude three-sector classification no doubt greatly understates gross flows relative to that which would be obtained with a finer industrial classification. In the figures of Murphy and Topel just cited, for example, a two-digit sectoral classification was used, which is probably part of the reason that their mobility rates are fairly high relative to ours (if, for example, theirs are doubled to approximate two-year mobility rates).

In any case, the gross flow data in Table 1 show an unmistakable downward trend over time (recall that this is not a result of aging of the sample, since the rates are standardized to age 28). Once again, this downward trend does not appear to be a result of either the crudeness of the sectoral classification scheme or the young mean age of the sample, for a similar decline over the same period has been found for the male workforce as a whole and for a two-digit industrial classification (Murphy and Topel, 1987, Table 11). The causes of this downward trend in mobility have not been investigated, to our knowledge, anywhere in the literature.[3] One of the important issues we examine in our empirical work is the degree to which this decline can be explained by matching considerations rather than sectoral shocks.

The net flows shown in the second column are computed from the data as follows, where π_{st} is the fraction of employment in sector s at time t:[4]

$$(1/2)\sum_s |\pi_{st} - \pi_{s,t-1}|.$$

There is no obvious trend in the net flows, with those in the 1968-1971 range exceeding those earlier and later to some degree. However, that the net flows are completely dominated by gross flows holds for all years. As we noted previously, this relationship is not explained by the Lucas-Prescott and other sectoral shift models.[5, 6]

The third column shows the ratio of the second to the third, and thus shows the fraction of all moves that are "sectoral" moves. This figure thus shows that sectoral shocks, to the extent that they are responsible only for the sectoral moves, have been responsible for no more than 26% of all moves in each year and generally much less.

Table 2 shows some simple regression evidence on the statistical significance of the trends in Table 1. The flows are broken down by sector as well. The decline in gross flows is not only statistically significant overall but equally so by sector, though largest in manufacturing (sector 2). But no statistically significant trend appears in either net flows or in the proportion of all moves due to net flows.[7]

Loosely speaking, then, this rough evidence suggests that matching determinants of mobility are much more important than sectoral shift determinants. However, obviously no direct test has been performed for the degree to which this evidence, particularly that on the gross flows, can be attributed to mismatch. The main object of our paper is to construct a model that will allow us to test this hypothesis and measure its magnitude.

3. The model

There are N sectors in the economy. Each sector has a constant number of identical, price-taking firms, whose number is normalized at unity. The production function for the output, y_{st}, of sector s at time t is

$$y_{st} = f^s(x_{st}, z_{st}),$$

where x_{st} is total labor employed in efficiency units, and z_{st} is a shock, common to all firms in that sector. We abstract from capital. Let p_{st} be the output-price in sector-s, and w_{st} the price per efficiency-unit of labor hired in sector s. The firm takes both prices as given in solving the problem:

$$\max_x \{p_{st} f^s(x, z_{st}) - w_{st} x\},$$

which leads to the first-order condition

$$p_{st} f_1^s(x, z_{st}) - w_{st} = 0,$$

which in turn implicitly defines the factor-input demand x_{st}, in efficiency units, for sector s:

(1) $$x_{st} = \psi^s(w_{st}/p_{st}, z_{st}),$$

where ψ^s is the "inverse marginal product" function is sector s.

The efficiency units contributed by a given worker, or just the worker's "productivity", for short, is specific to the match between him and his employer, and is denoted by m.[8] In the population of all potential pairings of workers and employees, the distribution of m is denoted by the cumulative distribution function $F(\cdot)$, with mean $\bar{m}$. The productivity of the match, m, is not known ex ante. Rather, the worker must work for the employer for a period before m is discovered. Except for the differences leading to the dispersion in m, workers (and employers in a given sector) are observationally all alike.

Workers are risk-neutral. They live and work for two periods. Generations overlap, and in each period there are young and old workers in each sector. The young worker is with his first employer, while the old worker may have changed employers, depending on the first-period realization of his match-value m.

Let n'_{st} be the number of old workers in sector s who choose to remain with their employer, and n''_{st} the number in that sector (either old or young) who start out with a new employer (i.e., the "new hires" in sector s). Then if n_{st} is total employment in sector s at t,

$$(2) \qquad n_{st} = n'_{st} + n''_{st} \qquad \text{all} \quad (s,t).$$

The analysis will proceed on the assumption that workers are paid their marginal products.[9] This means that workers on a good match earn more than workers in a poor match. Let m^*_{st} be the reservation value for m, i.e., the lowest m at which workers in sector s will choose to remain with their employers. Then total efficiency-units of labor supplied in sector s are to

$$(3) \qquad x_{st} = n''_{st}\bar{m} + n'_{st}E(m|m > m^*_{st}).$$

The value m^*_{st} is to be determined in equilibrium from the condition that the worker be indifferent between staying and leaving.[10]

If w_{st} is the price per efficiency-unit of labor in sector s, and if $w_{st} > w_{jt}$ for some pair of sectors (s,j), all young workers and all the old movers would flow to sector s and none to sector j. A "corner solution" of this sort is not to be expected except at the most extreme values of the sectoral shocks. Thus we shall look for equilibria in which payments across sectors per efficiency-unit of labor, are equalized:

$$(4) \qquad w_{st} = w_t \qquad \text{all } (s,t).$$

This does not mean, however, that (observed) sectoral <u>wages</u> are equalized. The wage per worker in sector s is $w_t x_{st}/n_{st}$; we shall show presently how wages across sectors can differ.

If (4) holds, expected second-period earnings are equalized in all sectors, and are equal to $w_t\bar{m}$. If a cost c is incurred by those who move, the expected value of moving is $w_t\bar{m} - c$. Since this must equal $w_t m^*_{st}$, we obtain

$$(5) \qquad m^*_{st} = \bar{m} - c/w_t = m^*_t, \qquad \text{all } (s,t).$$

Therefore, given w_t, the probability that an old worker in sector s will leave his job is

$$(6) \qquad q_t = \Pr(m \leq m_t^*) = F(\bar{m} - c/w_t),$$

which does not depend on s. Thus we have arrived at

Proposition 1: Given his age, the probability that a worker will leave his job depends only on w_t.

If m is normally distributed (see footnote 10), then $F(\bar{m} - c/w_t) = \Phi(-c/\sigma w_t) = q_t$, so that we have

Corollary 1: If m is normally distributed with mean $\bar{m}$ and variance σ^2, the probability that a worker will leave his job depends only on the ratio of the cost of moving to the standard error of the wage distribution.

The proposition and its corollary are strong, and testable. Although the standard error of the matching distribution (σ) will not be directly observable, the standard error of the earnings distribution (σw_t) will be. If the theory is correct, we should expect it to affect mobility positively.[11] Note that the level of the wage does not affect mobility independently of the standard error of the wage-distribution.

The next immediate implication of (6) is, (since q_t is increasing in w_t)

Corollary 2: The economy-wide separation rate will be procyclical if w_t is.

Conditions under which w_t is procyclical will be spelled out later.[12] Let us normalize the size of the population to equal 2, so that the measure of old and young each equals 1. Then

$$\sum_s n'_{st} = 1 - F(\bar{m} - c/w_t), \quad \text{and} \quad \sum_s n''_{st} = 1 + F(\bar{m} - c/w_t).$$

Summing in (2) over s yields the following expression for aggregate labor efficiency:

$$(7) \qquad X_t \equiv \sum_s x_{st} = 2\bar{m} + [1 - F(\bar{m} - c/w_t)][E(m|m > \bar{m} - c/w_t) - \bar{m}]$$
$$= 2\bar{m} + \int_{\bar{m}-c/w_t} (m-\bar{m})dF(m) \equiv S(w_t).$$

In the case when m is normally distributed (see footnote 10), the supply function assumes the following simple form:

$$(7)' \qquad X_t = 2\bar{m} + \sigma\phi(-c/\sigma w_t) \equiv S(m, \sigma, c, w_t).$$

It helps to think of $S(\cdot)$ as the aggregate supply function of X_t. Now define the economy-wide average wage as $W_t^* \equiv w_t X_t/2$, i.e.,

$$(8) \qquad W_t^* = w_t\bar{m} + (w_t/2) \int_{\bar{m}-c/w_t} (m-\bar{m})dF(m).$$

Evidently, W_t^* is increasing in w_t. Thus, following on from Corollary 2, we obtain

Proposition 2: The real wage, W_t^*, and and the separation rate, q_t, are positively correlated over the business cycle.

This proposition squares well with the evidence, which is that wages and separations are both procyclical[13] (Keane, et al., 1988, Parsons 1977). It remains to be shown, however, that W^* is itself procyclical in our model; that is, that it moves together with GNP. This will be shown presently.

Although workers' earnings are different, and their services are supplied to different sectors, it is helpful, as we said, to think of the right-hand side of (7) as the aggregate supply curve for X_t as a function of w_t. The supply curve slopes up because $\partial X_t/\partial w_t = cf(\bar{m} - c/w_t)/w_t > 0$. If c falls, the supply curve shifts to the right, from S to S'. The same rightward shift in S takes place, under normality, when σ increases. This rightward shift is illustrated in Figure 1.

The aggregate demand curve is obtained by substituting w_t for w_{st} in eq. (1) and then summing over s. Letting $p_t = (p_{1t},\ldots,p_{nt})'$, and $z_t = (z_{1t},\ldots z_{nt})'$, we can write the aggregate demand curve as

$$(9) \qquad D(w_t, p_t, z_t) = \sum_{s=1}^{n} \psi^s(w_t/p_{st},\ z_{st}).$$

The intersection of $S(m,\sigma,c,\cdot)$ and $D(\cdot,p_t,z_t)$ determines the "market clearing" w_t.[14] The dichotomy of supply and demand is useful here because each parameter-change shifts only one of the curves, so that the effects on

w_t can be immediately deduced. In fact, the model implies the following restriction:

Proposition 3: The only effect that p_t and z_t have on q_t is through their effect on w_t.

We shall now show that w_t or W_t^* move together with GNP as the evidence indicates. Consider Figure 1. There are no aggregate supply shocks, only aggregate demand shocks, z_t. If we assume that an increase in z_{st} raises not only total product, but also the marginal product of x_{st}, it follows that when GNP is high, the curve $D(\cdot)$ will shift to the right.[15] Hence GNP and w_t move together. Thus q_t, w_t and W_t^* all move together with GNP.

The effect of sectoral shocks on job separations. The only effect of sectoral shocks, z_{it}, on job separations is through their effect on w_t, as asserted in proposition 3. When the values of the z_{it} are far away from their average values, one's intuition says that mobility ought to be higher. Thus one may look for restrictions that will ensure that a mean-preserving spread of the distribution of z's over sectors, will cause w_t to rise, and hence lead to an increase in mobility. Figure 1 shows that since the z's do not affect S, it suffices that a mean preserving spread of the z's should shift D to the right. From eq. (9), a sufficient condition for this is that ψ^s be convex in z_{st}. Thus we have proved

Proposition 4: If ψ^s is convex in z_{st} for each s, a mean-preserving spread in the realized distribution of the z_{st} over sectors will raise w_t and raise job separations. The opposite is true if ψ^s is concave in z_{st}.[16]

While the only effect of sectoral shocks on job separations is through their effect on w_t, these shocks may still have a direct effect on sectoral separations. The nature of this effect will depend on the ratio of young workers to mismatched old workers (from other sectors) flowing into an expanding sector. If, however, c were slightly less if a worker finds a new job in the same sector as his previous job, then we would expect that small changes in the distribution of employment over sectors will be effected by incoming workers alone, but that more dramatic shifts in this distribution will require that some experienced workers change sectors as well. Based on this logic, one would expect that the probability that a worker will change sectors will be positively affected by changes in z's. Our empirical results show that, in fact, it is the unforeseen changes in z's that cause people to change sectors, and that the foreseen changes in the sectoral demand for labor appear to be met by labor-force entrants.[17]

Sectoral Wage Differentials. Although a unit of productivity gets the same reward, w_t, in all sectors, observed wages will generally differ over sectors. Letting W_{st} denote the (average) payment per unit of labor time supplied in sector s at t, equations (2), (3) and (5) imply that

$$W_{st} = w_t x_{st}/n_{st} = w_t\left[\bar{m} + \theta_{st}[E(m|m > \bar{m} - c/w_t) - \bar{m}]\right]$$

where $\theta_{st} = n'_{st}/n_{st}$ is the fraction of old workers in sector s. Since w_t is common to all sectors, the only source of sectoral wage differentials is θ_{st}. A contracting sector in which θ_{st} would tend to be high, will therefore have higher wages than an expanding sector in which θ_{st} would tend to be low.

The above scenario more or less describes U.S. experience over the past 15 years or so: The manufacturing sector has shrunk while services have expanded, but manufacturing wages have tended to exceed those in the service sector.

Our model uses quits as the mechanism to generate separations, and when comparing the model's implications to the data, we shall use separations, not quits. Our reason for doing so is that layoffs too could have been used in our model as a mechanism for separations, and it would have led to the same amount of separations that the quits mechanism generates.[18] The only difference is the behavior of wages. Our tests of the model will recognize the possible difference in wage-behavior when layoffs are the mechanism used to obtain separations. This is a point that we shall return to in section 5.

4. The Contribution of Match-Specific Information to Aggregate Output.

Under the interpretation that there is just one kind of output, but many sectors in which it can be produced, we can take $p_{st} = 1$ for all (s,t); that is, we can use the price of output as the numeraire. Real GNP is then

(10) $$Y_t = \sum_s f^s(x_{st}, z_{st}).$$

The planner's problem is to maximize Y_t net of the moving cost $cF(m^*)$ subject, using (7), to the constraint

$$(11) \qquad \sum_s x_{st} \leq 2\bar{m} + \int_{m^*}(m-\bar{m})dF(m), \qquad x_{st} \geq 0.$$

His decision variables are the x_{st} and m^*, where m^* is the poorest-quality match that the planner will tolerate. The right-hand side of (10) is strictly concave in the vector $x = (x_1, \ldots x_S)$. We form the Lagrangian

$$L(x, m^*, \lambda) = \sum_s f^s(x_s, z_s) - cF(m^*) + \lambda[2\bar{m} + \int_{m^*}(m-\bar{m})dF - \sum_s x_s].$$

For simplicity we omit time-subscripts here. While this is a one-period problem, it is indexed by the time-varying vector z, and the solution for x and λ will depend on t as well.

The first-order necessary (saddle point) conditions for optimality are

$$\partial f^s/\partial x_s = \lambda, \qquad s = 1, \ldots, S,$$

$$c = \lambda(\bar{m}-m^*),$$

and that the constraint (11) must hold. Thus we have shown that if for each t

$$(12) \qquad \lambda = w_t \quad \text{and} \quad m^* = \bar{m} - c/w_t,$$

equilibrium coincides with the output-maximizing solution. Moreover, w_t is the social opportunity cost of human capital, human capital generated by labor mobility.

Mobility can be valued by comparing the solution to the above program to what the planner could attain if he could not relocate badly matched workers, but if he still could locate young workers freely over sectors. This, of course, is just the value of the job-specific information collectively accumulated by workers on their first jobs. He would then have $\int_{m^*}(m-\bar{m})dF$ less human capital to work with, but he would be saving $cF(m^*)$ in moving costs. Current income-accounting practice values quantities at market prices which for us means w_t. Using (12), the social value of information is

$$w_t \int_{\bar{m}-c/w_t} (m-\bar{m})dF - cF(\bar{m} - c/w_t) = \int_0^\infty \max\{-c,\ w_t(m-\bar{m})\}dF(m) \geq 0.$$

The inequality follows because $\int(m-\bar{m})dF = 0$, and the latter is a lower bound for the expression displayed above. Assuming normality for m, the expression for the value of information can be shown to reduce to

$$\sigma w_t[\phi(-c/\sigma w_t) - (c/\sigma w_t)\Phi(-c/\sigma w_t)],$$

where ϕ and Φ are the standard normal p.d.f. and c.d.f., respectively. Dividing both sides through by mean earnings allows us to write the value of information as a percentage of earnings as:

$$v[\phi(-c/\sigma w_t) - (c/\sigma w_t)\Phi(-c/\sigma w_t)],$$

where v is the coefficient of variation of earnings. Thus the value of information in percentage terms is a function only of this coefficient of variation and of $-(c/\sigma w_t)$, but the latter can be inferred from the observed value of mobility, q_t, as given in expression (6). For example, Murphy and Topel (1987, Table 11) show that q_t ranged from .06 to .11 from 1970 to 1985, and in Section 5 we find in our data on U.S. males that the coefficient of variation of (residual) earnings is approximately .40. Thus, the social value of information as a percent of labor earnings ranges from 8.5% to 13%. And since labor's share in GNP is about two-thirds, the contribution of information to GNP is roughly 5.7-8.7% of GNP.

This estimate is certainly a rough one. The two main refinements would, however, cause revisions that would adjust our estimate in opposite directions. The first refinement would push our estimate up. It stems from the possibility that wages move less than one-to-one with productivity.[19] If so, then v understates the coefficient of variation of m, and would imply that our measure understates the true value of information. But a second refinement would push our estimate down. Flinn (1986, p. S102) finds that only 38% of (residual) wage variability is caused by what we in this paper call m, and that the rest is attributable to individual-specific heterogeneity and to white noise. This implies that our estimate overstates the true value of information. Thus these two refinements pull in opposite directions, and we leave it to future work to disentangle them.

5. Tests Against the Data

The data we use to test the model are drawn from the National Longitudinal Survey of Young Men (NLS), a panel data set containing information on a group of males who were 14-24 in 1966, the first year they were interviewed, and who were 29-39 in 1981, the last year they were interviewed. Interviews were conducted in only 12 of the 16 years from 1966 to 1981; hence a fully year-to-year study of mobility cannot be conducted. We instead select only those interview years which can be paired with an interview two years prior or two years hence, and therefore study two-year mobility patterns.[20] There are seven two-year matches, whose years are shown in Table 1. For each two-year pair, we select all men who were employed in both those years and who also met several exclusion criteria: were at least 21 years of age, had completed schooling and military service, and who had complete data on the variables in the analysis.[21] The resulting sample contains 9963 observations, each constituting a two-year match for an individual male. The distribution of the observations over the years is shown in Appendix Table A-1.

The means of the variables we use in our analysis are also shown in the Appendix Table. The sector of employment is that obtaining at the time of the interview and hence sectoral mobility is defined as change of sector between the two interview dates. The real hourly wage rate (1967 CPI) is that obtaining at the time of interview, and is calculated as the straight-time hourly wage for hourly workers and as current earnings divided by usual or actual hours worked for those who are salaried. Variables for age, education, years of labor force experience, and race are straightforwardly defined.

We shall conduct two exercises in this section to test the consistency of our model with the data. First, we shall consider the basic question of whether movers are drawn from the lower portion of the wage distribution as our theory predicts. Matching models of labor mobility have this prediction as a fundamental characteristic, and if it is not shown in the data, the matching model must be suspect to begin with. Relatedly, we shall wish to determine if individual wages increase after a move, a question that has been examined by others as well (e.g., Mincer and Jovanovic, 1981; Bartel and Borjas, 1981; Mincer, 1986).

Second, we shall consider whether the probability of a move is positively affected by the standard error of the wage distribution, a key prediction in our model. We shall also be interested in examining the magnitude of the influence of sectoral shocks on mobility after that standard error is controlled for. The time series evidence will be used to examine these propositions.

Evidence from the first of our exercises is provided in Table 3, which shows the results of three log wage regressions containing a dummy variable for whether the individual changes sector between the two years. Recall that the model predicts that stayers ought to do better than movers. A mover's expected wage is $w_t\bar{m}$, because his second-period employer is chosen at random. A stayer's second-period earnings are, on average equal to $w_t[\bar{m}+\sigma h(-c/\sigma w_t)]$. Hence a stayer ought to do better by an amount $w_t\sigma h(-c/\sigma w_t)$. But expected first-period wages of those who move, $w_{t-1}[\bar{m}-\sigma\tilde{h}(-c/\sigma w_{t-1})]$, are less than those of stayers, $w_{t-1}[\bar{m}+\sigma h(-c/\sigma w_{t-1})]$, where $\tilde{h}(x) = f(x)/F(x)$. Hence, in column (1) of Table 3 we regress the log wage at the <u>first</u> point in time on the mobility dummy. Of course, mobility cannot have affected the wage prior to the move, so the effect we wish to measure here is in fact the heterogeneity associated with mobility. As the table shows, movers indeed have wage rates almost 8 percent below those of non-movers with the same levels of education, experience, and other characteristics. Thus, the basic characteristic of matching models is consistent with the data.[22]

Log wage regressions analogous to those of column 1 but on the second period wage (not shown in the table) continue to show negative coefficients on the mobility variable. This is unquestionably an indication that movers continue to be in the lower part of the wage distribution after the move, as predicted by our theory -- movers receive $w_t\bar{m}$ after the move whereas nonmovers receive $w_t\bar{m}$ plus a truncated error. But the wage gap between movers and stayers widens a bit. This is also shown in column (2) of Table 3, where the change in the log wage is regressed on the mobility variable.[23] The results indicate that wages of movers appear to fall relative to those of non-movers between the two periods. A similar finding was reported by Mincer (1986) who found the same (though insignificant) qualitative effect of mobility on the wage-change when selection bias was not controlled for.[24]

This result is quite probably a consequence of errors-in-variables bias and heterogeneity in wage growth rates. With initial wages measured with error, simple regression-to-the-mean effects will result in wage decreases for some fraction of the sample between the two years. Alternatively, if there is heterogeneity in wage growth rates and if movers are drawn disproportionately from the lower portion of the growth rate distribution, the negative mobility effect we observe in column (2) will result.

These two explanations are statistically indistinguishable with our data and neither can be directly controlled for.[25] However, column (3) of the table, which reports the results of a regression with an interaction term for the initial log wage and the mobility variable, provides indirect evidence in support of this interpretation. Here the uninteracted mobility dummy has a positive and significant coefficient. The negative coefficient on the interaction term implies that individuals with low initial log wages have wage increases, while those with sufficiently high initial wages have wage decreases.

The second test of our theory concerns the expected positive relationship between the standard error of the wage distribution and mobility rates. In section 3, σ could well have been allowed to depend on t; all the expressions remain unchanged. Similarly, nothing was assumed about the distribution of the z's -- equilibrium behavior is described conditional on the realized z's. Tables 4 through 7 test whether mobility is affected by shifts in σ (the standard deviation of m) or in σ_z (the standard deviation of the sectoral shocks).

A simple examination of whether our data support the hypothesis that mobility should be positively related to $w_t\sigma$ is afforded by Tables 4 and 5, which show mobility rates and wage-error variances by year and experience in the data. Reading down its columns, Table 4 shows that mobility rates have fallen over time, confirming our initial examination of gross flows in Section 2 above. Although there is considerable noise in the data, it is apparent that the decline over the entire period is greater for those with more experience than those with less. Cross-sectionally, reading across rows, the pattern of mobility with experience seems to have changed over time, moving from quadratic to monotonic.

For present purposes, we are interested in discerning whether the mobility rates in Table 4 are positively correlated with the log wage variances in Table 5. A simple OLS regression of the entries in Table 4 on the entries in Table 5 yields a positive though insignificant coefficient on the log wage variance (coefficient = .172, s.e. = .222). Thus, some support for the expected relationship is found. Visual inspection of the tables shows the reason for the statistical weakness of the coefficient, for wage variances generally rise with experience while mobility falls. However, since wage profiles typically diverge for other reasons (e.g., human capital), this negative relationship does not necessarily contravene our theoretical model.

Tables 4 and 5 are, in any case, too crude to provide an accurate test of the hypothesis. Neither the log wage variances nor the mobility rates control for other individual characteristics such as education and race, and the wage variances are also unadjusted for selectivity bias. Further, we obviously have not tested for the presence of sectoral shocks as an explanation for mobility over the period.

To address these issues, we use the time-series dimension of the data to construct variables for mobility, wage variances, and shock variances by year. First, to construct a time-series of mobility rates standardized by experience level, we estimate probit equations for sectoral mobility separately by year as a function of several demographic variables, including experience. The fitted probabilities at 5, 8, and 11 years of experience are shown in the first three columns of Table 6. As should now be expected, mobility appears to fall over time for all experience groups. The results also show that mobility falls much faster from 1968 to 1973 than from 1973 to 1981, especially for the more experienced workers.

Second, to obtain a selectivity-bias-adjusted time series of wage variances, we estimate log wage equations by year as a function of education, experience, and race. The standard error of the regression for each year is shown in the fourth column of Table 6. These standard errors, and those in column 5, are the basis for the calculation of v in section 4. The standard error rises in the late 1960s but falls on average over the the 1970s. However, these standard errors understate the dispersion in the latent wage distribution because, while the variance of wages for movers is indeed $w_t^2\sigma^2$, that for non-movers is the smaller variance of a truncated distribution:

$$w_t^2\sigma^2[1 + z(p)\lambda(p) + \lambda^2(p)],$$

where $z(p) = F^{-1}(p)$, $\lambda(p) = f[F^{-1}(p)]/p$, and p is the probability of not moving. The term in brackets is less than one. To correct for this heteroskedasticity we reestimate our log wage equations with a standard heteroskedasticity adjustment for the term in brackets using the rate of non-moving in each year for p. The resulting standard errors of regression are shown in the fifth column of Table 6. They exceed those in the previous column, as expected, and fall at a faster rate over time.[26, 27]

Finally, to compute a measure of sectoral shocks we estimate log employment equations for each sector on annual US data from 1946 to 1985 as a function of one- and two-period lags and a time trend.[28] The standard errors across the three sectoral residuals for each year in our sample are shown in the last column of Table 6. As it is based on residuals from an autoregression, this series can be interpreted as measuring the extent of surprises in the sectoral shocks. The series shows relatively large surprises in the late 1960s and in the middle 1970s, as accords with most estimates of macro disturbances.

The results of regressing the three mobility probabilities on the wage and sectoral shock standard errors are shown in Table 7. For all three experience levels the coefficient on the standard error of the matching distribution is positive, and it is significant at the 10% level for all experience levels when our preferred adjusted wage variable is used. Thus the evidence provides support for our matching explanation of the decline in labor mobility in the US economy over the 1968-1980 period, especially when our preferred wage-error measure is used. The strength of the positive correlation is apparent from Table 6, for both labor mobility and the standard error of log wages were, on average, high in the 1968-1973 period relative to their levels in the 1973-1980 period.

The results also show significant and positive effects of the sectoral shock variables on mobility. These effects are to be expected in our model because our log wage standard error does not hold the wage level constant; sectoral shocks affect the wage and hence mobility, as we demonstrated in Section 3 above.[29] Nevertheless, it is of interest to determine the relative importance of matching and sectoral shocks in contributing to the secular decline in gross flows. Since their coefficient magnitudes are not comparable, the table shows partial correlation coefficients as well. The partial correlation coefficients for the adjusted wage variable are always higher than those for the shock errors. This is especially so for the more experienced workers, implying that the relative importance of shocks to mobility, though smaller than that of wages, appears to be stronger on less experienced cohorts of workers, a result that should accord with intuition. Of course, both matching influences as well as those of sectoral shocks are smallest in absolute value on the most experienced workers.[30]

The lesser importance of the shock variable may be a result of its definition. In Table 8, we test two alternative variables, one being the standard deviation of sectoral growth rates across sectors -- the variable used by Lilien -- and the other being our net flows index shown in Table 1 (one-half the sum of absolute changes in sectoral employment percentages). Interestingly, both of these measures have negative effects on mobility. Inspection of the values of the two measures by year reveals that both trended upward strongly in the 1968-1971 period -- unlike our preferred shock variable -- which runs counter to the strong declines in mobility in that period. The negative effect represents an implausible behavioral relationship and, in fact, all the shock measures here are insignificant. We suspect that the reason why these alternative measures do poorly is that they include the foreseen components of the changes in the z's, unlike our preferred measure reported in Tables 6 and 7.

Finally, a remaining issue is whether our results are in any way special to the relatively young sample we have used in our analysis, for young workers have relatively high mobility rates. As we noted in section 2, other evidence indicates that gross mobility is still quite high in the male workforce as a whole and, furthermore, that such mobility has declined over time just as that for young workers has. A separate question is whether our results in this section indicating the greater relative importance of matching rather than sectoral considerations in determining mobility would also extend to the workforce as a whole.

In Table 9, we show the regression coefficients and partial correlation coefficients for several experience levels, based upon a specification identical to that shown in table 7 (the columns for experience levels 5, 8, and 11 are the same in both tables).[31] Our interest in Table 9 is in discerning how the coefficient patterns change with levels of experience and therefore, by extrapolating in a simple way, what they would be for the workforce as a whole. As the Table indicates, the regression coefficients and partial correlation coefficients for the wage standard error initially rise with experience but later begin to decline. Those for the shock variable decline monotonically over all experience levels. Thus the influence of both matching and shock variables on labor mobility declines with experience. However, the ratios show less evidence of decline. The ratios of regression coefficients rise up to 9 years of experience and the (more meaningful) ratios for partial correlation coefficients rise up to 10 years of experience. While the ratios begin to decline thereafter, the wage-error partial correlation coefficient nevertheless remains 4.6 times as great as that for the sectoral-shock partial correlation coefficient even at our highest experience level. Thus, our result would fail to hold for the workforce as a whole only if there were a drastic decline in this ratio for older workers.

6. Conclusions

This paper has provided a detailed examination of the data on economy-wide labor mobility, and it has developed a model to interpret this data. The model, which nests two dominant hypotheses advanced to explain mobility -- mismatch and sectoral shift -- has been found, for the most part, to be consistent with the data. Changes in mobility over time are explained fairly well by movements in the standard deviation of wages. Sectoral shocks retain some explanatory power, however, even when the standard deviation of wages is controlled for. Surprises in the sectoral demand for labor are in fact the variable that works best. This may mean that labor force entrants bear the brunt of the adjustment in the distribution of employment over sectors, but only when such shifts in the distribution are foreseen, or it may simply mean that this variable is just a proxy for the unmeasured part of the standard-deviation of wages. All in all, the model ascribes most mobility to mismatch, the remainder to sectoral shift.

The paper has also estimated the contribution of match-specific information to GNP and labor productivity, and has found it to be somewhere between 6% and 9% of GNP. This estimate is rough, and is conditioned on a host of special features of the model and of our data, features that future work will need to relax.

REFERENCES

Bartel, Anne P., and Borjas, George J. " Wage Growth and Job Turnover: An Empirical Analysis." in Studies in Labor Markets, edited by Sherwin Rosen. Chicago: The University of Chicago Press (for NBER), 1981.

Bull, Clive, and Jovanovic, Boyan. "Demand-Shift Versus Mismatch as Causes of Labour Mobility." Review of Economic Studies 55, (January 1988): 169-76.

Dagsvik, John, Jovanovic, Boyan, and Shepard, Andrea. "A Justification for Three Popular Assumptions in Job-Matching Analysis." Journal of Labor Economics 3, no.4 (October 1985): 403-20.

Flinn, Chris. "Wages and Mobility of Young Men." Journal of Political Economy 94, no. 3, pt. 2 (August 1986): S88-S109.

Greenwald, Bruce. "Adverse Selection in the Labour Market." Review of Economic Studies 53, (July 1986): 325-48.

Jovanovic, Boyan. "Job Matching and the Theory of Turnover." Journal of Political Economy, 87, no. 5 (October 1979): 972-90.

Jovanovic, Boyan. "Work, Rest, and Search: Unemployment, Turnover, and the Cycle." Journal of Labor Economics 5, no. 2 (April 1987): 131-48.

Keane, Michael, Moffitt, Robert, and Runkle, David. "Real Wages Over the Business Cycle: Estimating the Impact of Heterogeneity with Micro Data." Journal of Political Economy 96, no. 6(December 1988): 1232-66.

Lilien, David. "Sectoral Shifts and Cyclical Unemployment." Journal of Political Economy 90 (1982): 777-93.

Long, John, and Plosser, Charles. "Real Business Cycles." Journal of Political Economy 91, no. 1 (February 1983): 39-69.

Lucas, Robert, and Prescott, Edward. "Equilibrium Search and Unemployment." Journal of Economic Theory 7, (February 1974): 188-209.

Miller, Robert. "Job-Matching and Occupational Choice." Journal of Political Economy 92, no. 6 (December 1984): 1086-1120.

Mincer, Jacob. "Wage Changes in Job Changes." in Research in Labor Economics, edited by Ron Ehrenberg, Greenwich, Conn: JIE Press, 1986.

Mincer, Jacob. "Education and Unemployment." (May 1988), unpublished paper.

Mincer, Jacob, and Jovanovic, Boyan. "Labor Mobility and Wages." in Studies in Labor Markets, edited by S. Rosen, Chicago: The University of Chicago Press (for NBER), 1981.

Murphy, Kevin, and Topel, Robert. "The Evolution of Unemployment in the US: 1968-1985." NBER Macroeconomic Annual, 1987.

Parsons, Donald. "Models of Labor Market Turnover: A Theoretical and Empirical Survey." in Research in Labor Economics, edited by Ron Ehrenberg. Greenwich, Conn.: JAI Press, 1977.

Rob, Rafael. "Labor Movements in a Two-Sector Economy with Switching Costs." unpublished paper, University of Pennsylvania, July 1989.

FOOTNOTES

Part of this research was completed while Robert Moffitt visited the C.V. Starr Center of Applied Economics at New York University. We thank the Starr Center for financial and technical assistance, and Chris Flinn, Mike Keane, Jacob Mincer and Ed Prescott for helpful discussion.

[1] Although in the special case that they solve explicitly, the amount of labor allocated to each sector does not change over time. In the general case, however, it clearly would.

[2] Unemployed workers are not included as a separate sector. One reason for excluding them is our attempt at a simple model of mobility. Effectively, our theory will assume that movement from one job to another involves no intervening unemployment. For a (more complicated) model of cyclical unemployment, see Jovanovic (1987). This is in contrast to Lucas and Prescott (1974) in which <u>every</u> job change involves an intervening spell of unemployment. The truth seems to be half-way in between: Mincer (1988) finds that 47% of separations involve no intervening unemployment, although this number is much higher for quits than it is for layoffs.

[3] Murphy and Topel, for example, noted the downward trend only as evidence against the hypothesis that sectoral shifts have increased the unemployment rate. They noted a downward trend in net flows for the same reason.

[4] The (1/2) term is to adjust for double counting. The percentages are adjusted for age and represent those at age = 28.

[5] Of course, a finer sectoral classification would produce more net flows. But it would also produce more gross flows, and the ratio of the two, as denoted by our index, has no determinate relationship to the fineness of the classification: Even with the finest classification in which each firm is a

sector unto itself, the ratio will be less than one because firms lose some workers while at the same time replacing them with others. Moreover, while the index must be zero when there is just one sector, and while it will increase on average, this increase need not be monotonic. In any case, though we experimented with four-sector classifications with no change in our results, we are limited by sample size considerations from proceeding very far in this direction.

6 Once again, the age composition our sample could affect these results but is unlikely to in a major way. Net flows are, indeed, smaller for older workers than for younger workers (Murphy and Topel, 1987, Tables 9 and 10). Since both gross and net flows fall with age, there is no reason to expect that their ratio would significantly fall.

7 If the net flows were generated by iid shocks z_t, this lack of significance would be expected. However, below we construct a more direct measure of sectoral shocks.

8 Bull and Jovanovic (1988) assumed that productivity depended on a match-specific and a firm-specific term. They, however, treated firms' prices as exogenous processes, and moreover, did not define "sectors" -- the price of a firm was treated as independent of the prices of all other firms.

9 This "assumption" is really a <u>consequence</u> of our earlier assumption that efficiency-units of labor in a given sector all trade at the same price. Because of risk-neutrality, this assumption about wages can be justified by appealing to an implicit contract view of wage-determination: If employers acquire reputations about the way the compensate their workers, then a pure piece-rate scheme (which is what we assume here) is an equilibrium wage contract. See Jovanovic (1979, theorems 1 and 2). Other compensation schemes will leave certain properties of the equilibrium intact -- see footnote 18.

[10] If m were normally distributed, with $F(m) = \Phi((m-\bar{m})/\sigma)$ (denoting by Φ and ϕ the standard normal CDF and pdf respectively), we would have $E(m|m > m^*_{st}) = \bar{m} + \sigma h[(m^*_{st}-\bar{m})/\sigma]$, where $h = \phi/(1-\Phi)$ is the hazard-rate of the normal distribution. Eqs. (2) and (3) would then imply that

$$x_{st} = \bar{m}n_{st} + \sigma h[(m^*_{st}-\bar{m})/\sigma]n'_{st}.$$

For a justification for the normal distribution in this context, see Dagsvik, Jovanovic and Shepard (1985). Aside from the theoretical arguments in favor of normality that were advanced there, data on the physical productivities of some low-skill workers revealed that after controlling for observed characteristics, the distribution of productivity was indeed normal for those workers. Of course this conclusion held only for these workers, and not necessarily for the population at large.

[11] This model can explain the temporal decline in sectoral mobility (discussed in Section 2) by either (a) a temporal decline in σw_t, or by (b) a temporal decline in the cross-sectional variance of sectoral shocks (see proposition 4 and the ensuing discussion), or by some combination of the two. Indeed, the aim of Tables 7 and 8 below is to assess the relative importance of (a) and (b) in explaining the temporal decline in mobility. That part of the analysis, however, is an accounting exercise only, because the paper offers no explanation of why σw_t or the variance of sectoral shocks behaved as they did.

[12] Note that w_t is not quite the economy-wide real wage. See eq. (8) below.

[13] Keane et al. (1988) supply evidence that wages are procyclical. Parsons (1977) provides evidence that quits are procyclical. Layoffs, on the other hand, are countercyclical, but since the constitute somewhat less than half of all separations, the tendency since the war has been for separations

to be weakly procyclical. Our model implies that W_t will be positively correlated with GNP -- see the argument following proposition 4.

[14] The equilibrium w_t is conditioned on p_t (as well as on z_t). In this sense the model is not a general equilibrium one because the product market has been left out. The model has a general equilibrium interpretation, however, if we assume that a single consumption good is produced in several "sectors," (say, with different technologies whose relative productivities fluctuate over the business cycle). Then the consumption good can be made to be the numeraire, and one can set $p_{st} = 1$ for all s and t. In this case equilibrium evidently maximizes aggregate output, and under risk-neutrality allocations are Pareto optimal. If workers were risk-averse, the welfare properties of this type of equilibrium would hinge on the type of income-insurance that a worker could get. Rob (1989) treats this issue in a related context.

[15] This would happen if, for instance, the z_{st} entered $f^s(\cdot)$ multiplicatively.

[16] Convexity of ψ^s in z_{st} is, unfortunately, not an intuitive restriction on the primitives. When ψ^s is twice differentiable, its convexity in z_{st} requires that (dropping the superscript from f),

$$\partial^2 x_s/\partial z_{st}^2 = -(f_{12}/f_{11}^2)(f_{111}f_{12}/f_{11} + 2f_{112} + f_{11}f_{122}/f_{12}) > 0.$$

Although this is a complicated condition, it appears to be met in reasonable cases. For instance, $f^s(x,z) = x^\alpha z$ for $\alpha \in (0,1)$, then $\psi^s(w/p_s, z_s) = (p_s\alpha z/w)^{1/(1-\alpha)}$, which is indeed convex in z as required by proposition 5.

[17] See the discussion in the next section of Tables 7 and 8. The inter-

pretation of these tables is motivated by the results of Corollary 1, and Proposition 4.

[18] To show this, assume for the moment that the z_t are constant and that $w_t \equiv 1$. One might follow Greenwald (1986) and assume that firms are restricted to single-period noncontingent (i.e., independent of m) wage offers. Then the following is a zero-profit equilibrium: Second-period movers receive $\overline{m}$, second period stayers get $\overline{m}$-c, and first-period workers get $\overline{m}+\beta[E(m|m > \overline{m}-c) - (m-c)]$. In this equilibrium firms fire anyone whose productivity is less than his wage, and the same people get fired as quit in our model. This is exactly what Greenwald's two-period equilibrium would look like if his unobserved heterogeneity were match-specific (instead of worker-specific, as he assumes).

[19] This may be for income-smoothing reasons, or because the labor market is in a Greenwald-type equilibrium described in note 18.

[20] Interviews were conducted annually from 1966-1971 and in 1973, 1975, 1978, 1980 and 1981. We performed some testing with a one-year mobility sample, but the set of one-year matches is disproportionately concentrated in the late 1960s and early 1970s. Combining one-year and two-year time frames would be possible if we were to put more structure on our estimating equations but we are reluctant to do this and, in addition, it would be extremely cumbersome.

[21] The data set is the same as that used by Keane et al. (1988) but not all the exclusion criteria reported in Appendix Table B-1 of that paper are applied here. Of those reported in that table, those applied here are the exclusions if the individual is a full-time student, self-employed, working without pay or by piece-rate; if he had not finished school and the military; if his age were less than 21; and if he had missing data for WAGE1, the

completion date for the school or military, interview month, education, or marital status.

22 We subjected this equation to considerable sensitivity testing by estimating models with different sets of regressors and with differently-defined wage variables for the dependent variable. The negative and significant coefficient on the mobility variable is extremely robust to the specification.

23 We wish to stress that the mobility effects we measure here do not measure the effect of moving on the latent matching distribution or wage distribution (i.e., of m or $w_t m$); that distribution is fixed by assumption and not affected by the mobility rate. Indeed, non-movers have unchanging wage rates according to our model and continue to be drawn from the upper part of the matching distribution. Our estimates instead measure only selection effects -- that is, only the nature in which individuals sort themselves across the wage distribution before and after moves.

24 Mincer found that the coefficient turned positive when movers' wages were compared to those of individuals who moved one period later.

25 Because these data do not allow us to identify structural selection bias models non-parametrically, we do not estimate them.

26 One virtue of this procedure is that, in contrast to Flinn (1986), it relies on the time-change of σ to test for the presence of matching effects on mobility. This means that if our assumption that wages equal productive efficiency is not true so that in the levels our estimate of $w_t\sigma$ are inaccurate, (say biased downward), the movement <u>over time</u> in our estimate of this parameter should correspond, roughly, to the movement over time in the parameter $w_t\sigma$.

27 These trends are consistent with the recent literature showing an in-

crease in the variance of male earnings in the US workforce in the late 1970s and early 1980s. As the fourth column of Table 6 indicates, that variance increased after 1973.

[28] Thus, three regressors appear in each of the three time-series log employment regressions. This lag structure is the shortest one which generates DW statistics acceptable at the 95% level for all sectors.

[29] That is, individual log earnings for individual i in year t are $\log(w_t m_{it}) = \log(w_t) + \log(m_{it})$. Since our matching-error variances are computed separately by year -- that is, they are cross-sectional variances of the residuals in the log earnings equation by year -- they represent the variances of the log of m_{it}, not the log of earnings.

[30] Of course, since the two standard errors in the regression may be correlated, their relative contributions are not uniquely assignable. To obtain a lower bound on the contribution of matching, we regressed the matching standard error on the shock standard error and used the residuals from this regression instead. The results were virtually identical to those in Table 7 because the R-squared from the first-stage regression was only .02.

[31] Unfortunately, sample sizes do not permit us to go beyond 11 years of experience. The ages of the sample members go as high as 38.

TABLE 1

Gross Flows, Net Flows, and Index for Three-Sector Model

	Gross Flows	Net Flows	Index (net/gross)
1966-1968	.217	.019	.089
1967-1969	.205	.008	.039
1968-1970	.190	.050	.262
1969-1971	.151	.023	.155
1971-1973	.158	.014	.089
1973-1975	.160	.009	.057
1976-1978	.151	.019	.123
1978-1980	.146	.017	.117

Notes: Gross flows are predicted probabilities of changing sector obtained from probit equations for mobility containing variables for ln(age-20) and year dummies. Figures in table evaluated at age = 28. Net flows are as discussed in text. Sector definitions: see Appendix Table A-2.

TABLE 2

Time-Trend Regression Coefficients

Gross Flows	
All Sectors	-.0051*
	(.0015)
Sector 1	-.0030*
	(.0010)
Sector 2	-.0045*
	(.0012)
Sector 3	-.0028*
	(.0012)
Net Flows	
All Sectors	-.0007
	(.0012)
Sector 1	-.0008
	(.0008)
Sector 2	.0023
	(.0017)
Sector 3	-.0015
	(.0015)
Index	
All Sectors	-.0011
	(.0065)
Sector 1	-.0017
	(.0065)
Sector 2	-.0047
	(.0118)
Sector 3	.0025
	(.0048)

Notes: Standard errors in parentheses

*: Significant at 10% level

Sector definitions: See Appendix Table A-2.

TABLE 3

Mobility Coefficients in Log Wage Regressions

	Dependent Variable		
	Log Wage (t-1)	Log Wage (t) - Log Wage (t-1)	Log Wage (t)
Mobility dummy (=1 if moved from t-1 to t)	-0.079* (0.011)	-0.016* (0.008)	0.124* (0.018)
Log Wage (t-1)	-.-	0.656* (0.008)	0.681* (0.008)
(Mobility dummy) × Log Wage (t-1)	-.-	-.-	-0.143* (0.017)

Notes: Standard errors in parentheses

*: Significant at 5% percent level

All regressions include education, experience, experience squared, and year dummies.

TABLE 4

Fractions of the Sample Changing Sector by Year and Experience

	Experience Level (years)							
Year[a]	All	1-3	4-6	7-9	10-12	13-15	16-18	19-21
1968	.26	.23	.31	.24	.25	-	-	-
1969	.24	.17	.22	.27	.23	-	-	-
1970	.22	.20	.25	.21	.20	-	-	-
1971	.17	.10	.14	.19	.20	.20	-	-
1973	.18	.20	.16	.18	.16	.20	-	-
1975	.17	.20	.19	.15	.17	.17	.16	-
1978	.15	.17	.14	.14	.17	.14	.12	.14
1980	.13	-	.12	.12	.14	.13	.13	.17

[a] Second year of the two-year pair. Sample sizes by year are shown in Appendix Table A-1.

TABLE 5

Log Wage Variances by Year and Experience

Year[a]	Experience Level (Years)							
	All	1-3	4-6	7-9	10-12	13-15	16-18	19-21
1968	.185	.187	.184	.176	.159	-	-	-
1969	.219	.141	.194	.264	.171	-	-	-
1970	.224	.156	.208	.262	.181	-	-	-
1971	.211	.189	.182	.238	.215	.160	-	-
1973	.185	.185	.155	.188	.235	.167	-	-
1975	.187	.147	.169	.206	.202	.219	.170	-
1978	.182	.138	.142	.186	.208	.225	.200	.115
1980	.190	-	.159	.168	.201	.216	.212	.177

[a] Second year of the two-year pair.

TABLE 6

Trends Over Time in Mobility, Matching, and Sectoral Shocks

	Prob. of a Sectoral Move, by Experience Level[a]			Standard Deviation of Log Wage Distribution[b]		Standard Deviation of Sectoral Shocks (Surprises)[c]
	5 yrs.	8 yrs.	11 yrs.	Unadjusted	Adjusted	
1968	.25	.23	.23	.380	.496	.020
1969	.25	.28	.20	.402	.520	.017
1970	.22	.20	.17	.408	.517	.004
1971	.18	.20	.17	.395	.487	.005
1973	.20	.16	.15	.363	.450	.017
1975	.21	.17	.15	.368	.462	.031
1978	.19	.18	.17	.376	.454	.008
1980	.15	.15	.14	.381	.455	.006

[a] Predicted from a probit mobility equation estimated separately for each year as a function of education, experience, experience squared, and race. Mean values of education and race are used.

[b] Standard error of log wage regressions estimated separately by year as a function of education, experience, experience squared, and race; adjusted and unadjusted for heteroskedasticity.

[c] Across-sector standard deviation of residuals from sector-specific AR(2) log annual US employment regressions.

TABLE 7

Regression Coefficients in Move-Probability Equations, by Experience Level

	5 Years		8 Years		11 Years	
	(1)	(2)	(1)	(2)	(1)	(2)
Standard Dev. of Wage Dist.:						
Unadjusted	1.61*	-	2.50*	-	1.05	-
	(0.69)		(0.78)		(0.79)	
	(.51)		(.67)		(.26)	
Adjusted	-	0.91*	-	1.26*	-	0.66*
		(0.23)		(0.30)		(0.31)
		(0.76)		(0.76)		(0.47)
Standard Dev. of Sectoral Shocks (Surprises)	3.28*	2.21*	2.78*	1.05	1.39	0.72
	(1.17)	(0.71)	(1.32)	(0.93)	(1.33)	(0.96)
	(0.61)	(0.66)	(0.47)	(0.20)	(.18)	(0.10)
Intercept	-0.46	-0.26	-0.80	-0.42	-0.28	-0.48
R-squared	.64	.82	.68	.78	.28	.48

Notes: Standard errors in first parentheses, partial correlation coefficients in second parentheses.

* Significant at 10% level.

TABLE 8

Regression Coefficients in Move-Probability Equations
Using Two Alternative Sectoral-Shock Variables

	5 Years		8 Years		11 Years	
	(1)	(2)	(1)	(2)	(1)	(2)
Standard Dev.						
of Wage Dist.	0.80*	0.99*	1.19*	1.51*	0.60*	0.75*
(Adjusted)	(0.38)	(0.39)	(0.30)	(0.20)	(0.28)	(0.33)
	(0.47)	(0.57)	(0.76)	(0.92)	(0.49)	(0.50)
Standard Dev.						
of Sectoral	-4.51	-	-7.40	-	-8.23	-
Growth Rates	(7.98)		(6.22)		(5.77)	
	(0.06)		(0.22)		(0.29)	
Net Flows						
(Influx)	-	-0.96	-	-1.54*	-	-0.64
		(0.85)		(0.43)		(0.73)
		(0.20)		(0.72)		
Intercept	-0.17	-0.25	-0.36	-0.50	-.10	-.17
R-squared	.49	.57	.78	.92	.59	.50

Notes: Standard errors in first parentheses, partial correlation coefficients in second parentheses.

*: Significant at 10 percent level.

TABLE 9

Wage and Shock Coefficients and Partial Correlations

by Detailed Experience Level

	Experience Level (Years)						
	5	6	7	8	9	10	11
Regression Coefficients:							
Std. Dev. of Wage Dist. (adjusted)	.91	1.14	1.26	1.26	1.16	.95	.66
Std. Dev. of Sectoral Shock	2.22	1.73	1.34	1.06	.86	.74	.72
Ratio	.41	.66	.94	1.12	1.36	1.28	.91
Partial Correlation Coefficients:							
Std. Dev. of Wage Dist. (adjusted)	.76	.84	.81	.78	.75	.69	.47
Std. Dev. of Sectoral Shock	.66	.55	.34	.20	.15	.13	.10
Ratio	1.15	1.52	2.41	3.82	5.10	5.48	4.63

APPENDIX TABLES

TABLE A-1

Means of the Variables Used in the Analysis

Variable	Mean	Standard Deviation
Move dummy		
(=1 if moved,	0.17	0.38
=0 if not)		
Log hourly wage rate		
(1967 dollars)	$1.11	$0.44
Education (years)	12.52	2.80
Experience (years)[a]	8.52	3.98
White Dummy		
(= 1 if white,		
= 0 if not)	0.76	0.43

Notes:

All variables defined as of the second year.

No. of observations = 9963. By year: 492 (1966-1968), 628 (1967-1969), 754 (1968-1970), 887 (1969-1971), 1357 (1971-1973), 1846 (1973-1975), 2032 (1976-1978), 1967 (1978-1980).

[a] Years since left military or school, whichever came later.

TABLE A-2

Employment Distribution by Sector (Percent)

	Sector[a]		
	1	2	3
<u>All Years</u>	23.7	34.3	42.0
<u>By Year</u>			
1966	24.1	42.9	32.9
1967	24.2	42.0	33.9
1968	23.4	41.4	35.2
1969	23.5	39.8	36.7
1970	24.1	36.0	39.9
1971	24.6	34.7	40.7
1973	25.3	35.7	39.0
1975	23.8	32.1	44.0
1976	22.5	31.7	45.8
1978	22.2	32.8	45.1
1980	23.8	31.8	44.4
1981	23.8	30.7	45.5

Notes: Computed on complete sample, n = 24,050.

Sector 1: Agriculture, Mining, Construction, Transportation.

Sector 2: Manufacturing.

Sector 3: Trade, Finance, Insurance, Real Estate, Services, Government.

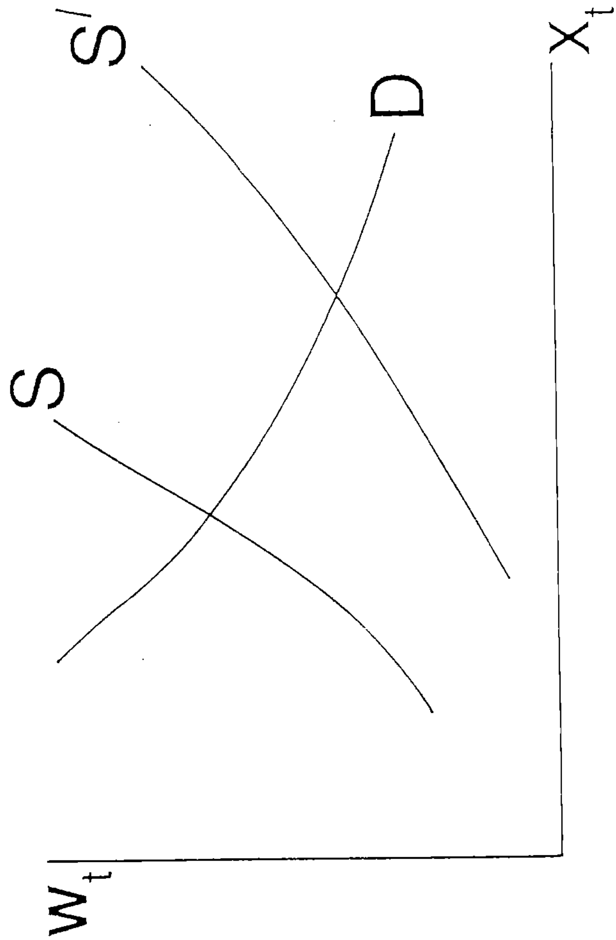

Figure 1: Determination of w_t and X_t.