Review of Economic Studies (1991) **58**, 971-991 0034-6527/91/00560971 $02.00

Estimation and Testing of the Union Wage Effect Using Panel Data

GEORGE JAKUBSON
Cornell University

First version received October 1986; *final version accepted September* 1990 (*Eds.*)

We present estimates of the union wage effect controlling for unmeasured individual effects, and subject the conventional fixed-effects model to specification tests. For PSID men the union wage effect is 5-8% after controlling for person effects, as opposed to 20% in cross-section. Omnibus tests based on an unrestricted reduced form and instrumental variables tests based on differencing are consistent with conventional models. Tests based on comparing those who enter and leave union coverage provide evidence against the usual model. We find evidence for interactions between union status and other variables even after controlling for person effects.

1. INTRODUCTION

Whether unions truly raise wages is a longstanding question in labour economics. A considerable body of empirical work, based on cross-section data, suggests that the union wage premium is on the order of 20% (Lewis (1986)). This large rent for union workers may seem implausibly large, and several economists have questioned whether cross-section studies estimate a pure union effect (see Lewis (1986) for a review). They argue that the natural employer response to higher union wages is to raise hiring standards.[1] If employers react in this manner, and if they observe more about workers than does the researcher, then union workers will have higher unmeasured (by the researcher) productivity attributes. The "union wage premium" contains a return on these unmeasured attributes and the estimated union wage effect is biased upwards.

Two approaches to this omitted-variables bias have appeared in the literature. The first accounts for the endogeneity of the union variable using either an instrumental variables technique or a selectivity adjustment (Heckman (1979)). This approach is intuitively appealing since it is based on the notion that an individual obtains a union job when a weighted sum of his observed and unobserved characteristics crosses a threshold. The main drawback is the need to make arbitrary distributional and/or exclusion assumptions.

The use of panel data allows one to avoid those assumptions. If the unobserved productivity differences are constant over time one can control for them by estimating a fixed-effects model. One can use standard specification tests (e.g. Hausman (1978)) to investigate whether previous studies, which do not control for unobserved productivity differences, have produced biased results.

1. See Pettengill (1980) and comments by Pencavel (1981) for a particularly careful development of this argument.

The use of panel data and fixed-effects models is an important advance in empirical economics. However, one weakness in current empirical practice is the fact that the fixed-effects model is usually the most general model considered. In fact, panel data contain more information than that required to identify a fixed-effects model. Thus, the appropriateness of the fixed-effects model itself can be investigated by testing the over-identifying restrictions it places on the reduced form. This is not commonly done in the empirical literature.

The purpose of this paper is two-fold. The first is to compare the estimates of the union wage premium when controlling for unmeasured productivity differences to those obtained when one does not control for such differences. As part of the comparison, the results of a formal test for the absence of person effects which are correlated with the union variable are presented.

The second goal of this paper is to test the appropriateness of the standard person-effect model. Four types of tests are considered. The first is an omnibus test based on the following idea (Chamberlain (1982)): Consider the wage equation from a cross-section model which has been augmented by a person-specific effect. If this person effect is correlated with union status as a point in time, then, in general, it will be correlated with union status at all points in time. Values of time-varying variables from other periods enter the equation for period *t only* through their correlation with the person effect, and enter the current period equation in a manner that is constant over time. This produces testable restrictions on an unrestricted reduced form that relates values of time-varying variables to the value of the wage in each period. Tests based on these restrictions are carried out both under the assumption of homoscedasticity and of arbitrary heteroscedasticity.

This omnibus test has the potential to detect misspecification in many directions. Its generality comes at the cost of potentially low power in detecting misspecification in particular directions. We also consider two narrower tests of the person-effect model. A person-specific wage model with time-constant coefficients implies a regression equation in differences. The difference equation implies restrictions on the coefficients relating the current wage to the lagged wage and to current and lagged values of the explanatory variables. Testing these restrictions in an instrumental variables framework leads to a narrower test of the person-effect model.

The second narrow test considers misspecification in directions not considered by the omnibus test. The test is obtained by noting that the difference equation implies that changes in the explanatory variables should have the same effect (in absolute value) on wage rates whether they are increases or decreases. The change in union status is decomposed into a variable denoting entering union status and one denoting leaving union status. If the standard person-effect model is correct, these two variables will have equal but opposite effects on the change in wage. This specification adds a cross-product term to the difference equation, and therefore is sensitive to misspecifications that will not be picked up by the omnibus test or the instrumental-variables approach. Both sets of narrow tests will be performed under both variance assumptions.

The last test considers a different type of misspecification. In the conventional model the wage effects of all other explanatory variables are the same for union and non-union workers. Here we test that hypothesis while allowing for a person effect which is correlated with union status. For numerical reasons (see below) this test is only carried out under the homoscedasticity assumption.

The outline of the paper is as follows: Estimation methods and testing procedures are presented in Section 2. The data are described in Section 3, and the empirical results are discussed in Section 4. The null hypothesis of no person effect correlated with the union variable is strongly rejected, Allowing for such a person effect lowers the estimate of the union wage premium from 20% to 5–8%. The standard person-effect model is not rejected by the omnibus test nor by the first narrow test. However, the second narrow test (decomposing the change in union status) does reject the model. The last test for interaction effects finds evidence for the hypothesis that the union wage effect is different for different workers. Non-white workers, younger workers, and workers with less schooling have larger wage premia. These results suggest the importance of using narrower, but potentially more powerful, tests as well as omnibus tests to assess model specification. Section 5 concludes the paper.

One final note of caution. This paper presents a battery of tests which are clearly not independent. Hence the nominal size of any particular test is not the true size. For purposes of exposition, we refer to a "rejection" when the nominal significance level is greater than 0·05. However, we would then expect 1 test in 20 to "reject" even if all the null hypotheses were correct. The reader is invited to combine his or her own priors with the sample evidence presented here. In particular, one should not overly focus attention on any particular "rejection".

2. MODEL TESTS

2.1. *Basic specification*

Consider estimating a standard human capital wage equation (Mincer (1974)) using panel data. Specifically, assume that N (large) individuals (indexed by i) are observed at T (small and fixed) time points (indexed by t). The equation for individual i's log wage in period t takes the form

$$y_{it} = \psi_t' f_i + \beta_t' x_{it} + \varepsilon_{it}, \qquad i = 1, \dots, N, \qquad t = 1, \dots, T. \tag{2.1}$$

The individual's characteristics in period t have been divided into a q-vector of observed characteristics f_i which are fixed over time (e.g. race) and a k-vector of time-varying characteristics x_{it}. For this study, the most important element of x_{it} is the union dummy variable which is coded one if the wage in period t is covered by a collective bargaining agreement and zero otherwise. Assume that the disturbance term ε_{it} takes the following form:

$$\varepsilon_{it} = \gamma_t c_i + u_{it}. \tag{2.2}$$

The general model is then

$$y_{it} = \psi_t' f_i + \beta_t' x_{it} + \gamma_t c_i + u_{it}. \tag{2.3}$$

We assume that u_{it} is uncorrelated with c_i, f_i, and $x_i = (x_{i1}, \dots, x_{iT})'$. The term c_i is the unobserved person effect (unmeasured productivity). We cannot assume that c_i is uncorrelated with f_i and x_{it}. In particular, if c_i contains productivity differences which are observed by employers (though not by the researcher), then one expects a positive covariance between c_i and the union dummy, as employers facing higher union wages respond by hiring more productive workers. The inability to control for c_i in a cross section leads to an upward bias in the cross-section estimate of β_t.

The conventional person-effect model in the literature imposes restrictions on (2.3). The γ_t's are assumed equal in all periods and the β_t's are assumed constant and equal to β. That model (normalizing the common γ to unity) is

$$y_{it} = \psi_t' f_i + \beta' x_{it} + c_i + u_{it}. \tag{2.4}$$

The common β is the "union effect" on wages.

Panel data may allow us to control for unmeasured productivity differences (c). For example, in the conventional model with two years of data, differencing the data (or equivalently, adding dummy variables for each person) allows consistent estimation of $(\psi_2 - \psi_1)$ and β (as $N \to \infty$ for fixed T).

The consistency of these estimates depends on the assumption that the true model is given by (2.4). Most previous work has treated (2.4) as the most general model considered, and has focussed on the bias (if any) which arises from ignoring unmeasured productivity differences. The focus here will be two-fold. In addition to asking what bias results from ignoring c, we will also be concerned with the appropriateness of the specification (2.4). That model places testable restrictions on the process generating wage rates which we investigate below.

We begin with an omnibus test in the next section, and then proceed to narrower, but potentially more powerful tests. In the empirical work we present two sets of results for each test. First, we treat the linear equations as conditional expectation functions, and use the conventional covariance matrix estimators as weighting matrices in estimation and testing. Second, we treat the linear equations as projections, on the grounds that the unknown conditional expectation functions may be nonlinear. (In particular, we know nothing of the form of $E(c|x)$.) If they are, the disturbances will be arbitrarily heteroscedastic, since the variance of the approximation error will depend on the values of the explanatory variables. In this case we use the methods of Chamberlain (1982) and White (1982) to construct covariance matrix estimators which allow for arbitrary heteroscedasticity. Lastly, we construct the test of the hypothesis that other variables have the same effects for union and nonunion workers.

2.2. *Omnibus test*

Assume for simplicity that, conditional on c_i, wages depend only on union status, so that x_{it} is a scalar and f_i drops out of (2.3). (This assumption is relaxed in the empirical work below.) Then (2.3) becomes

$$y_{it} = \beta_t x_{it} + \gamma_t c_i + u_{it}. \tag{2.5}$$

The bias arises because c_i is correlated with x_{it}. If c_i is correlated with x_{it}, in general it will be correlated with x_{is}, $s = 1, \ldots, T$. Formalize this notion as

$$c_i = \lambda_1 x_{i1} + \cdots + \lambda_T x_{iT} + \xi_i = \lambda' x_i + \xi_i, \tag{2.6}$$

where $\lambda = (\lambda_1, \ldots, \lambda_T)'$ is the vector of partial correlation coefficients and ξ_i is a disturbance which is orthogonal to x_i by construction. Substitute for c_i in (2.5) to obtain an estimating equation based on observables:

$$y_{it} = \beta_t x_{it} + \gamma_t \lambda' x_i + (\gamma_t \xi_i + u_{it}). \tag{2.7}$$

A convenient scale normalization is $\gamma_1 = 1$. For each period, (2.7) implies a projection of y_{it} onto all observed values x_i with restrictions on the coefficients over time. The unrestricted reduced form of the model is

$$y_i = \Pi x_i + e_i, \tag{2.8}$$

where $y_i = (y_{i1}, \ldots, y_{iT})'$. Π is the $T \times T$ matrix of projection coefficients, and e_i is the T-vector of disturbances. The model in (2.7) implies the nonlinear restrictions

$$\Pi = \text{diag}\{\beta_1, \ldots, \beta_T\} + \gamma\lambda', \tag{2.9}$$

where $\gamma = (\gamma_1, \ldots, \gamma_T)'$. That is, $\pi_{ts} = \beta_t + \gamma_t \lambda_t$ for $s = t$, and $\gamma_t \lambda_s$ for $s \neq t$.

Equation (2.9) suggests a method for estimating the parameters β, λ, and γ and testing the implied restrictions. First estimate the reduced form Π. Then use a method of moments estimator to obtain β, λ, and γ using (2.9). This amounts to restricted GLS. Finally, test the validity of the person effect model by testing the overidentifying restrictions. The test is an omnibus test in that rejection does not imply a specific alternative, since the test is against an unrestricted reduced form. The test of the null hypothesis that the unobserved person effect is uncorrelated with union status is a test of $\lambda = 0$.

Note that in the usual person effect model the restrictions are linear. There (2.4) implies that

$$\Pi = \beta I + l\lambda'. \tag{2.10}$$

where l is a T-vector of ones. In contrast, (2.9) allows departures in two economically interesting directions. If macroeconomic conditions affect the extent to which employers can select high productivity workers or the return to this productivity we would expect $\gamma_t \neq 1$. (Note that if $\gamma_t \neq 1$ the usual difference estimator is inconsistent.) Alternatively, if wage bargains are affected by the business cycle then β may vary over time.

2.3. *Instrumental variables test for misspecification in a particular direction*

The omnibus test above may not be very powerful, particularly if the Π matrix is imprecisely estimated. We now consider an alternative approach which has a natural solution via the use of instrumental variables. In essence, the test of whether the conventional person-effect model (2.4) is valid is a test of whether a differencing procedure is valid. This test has the advantage of providing linear, as opposed to nonlinear, restrictions and should be easier to implement.

To ease the exposition, retain the assumption that x_{it} is a scalar and there are no f_i terms. We suppress the person-subscript i for notational clarity. In equation (2.5) solve for c in the equation for y_{t-1} and substitute this expression into the equation for y_t to obtain

$$y_t = \beta_t x_t + (\gamma_t/\gamma_{t-1})y_{t-1} - (\beta_{t-1}\gamma_t/\gamma_{t-1})x_{t-1} + [u_t - (\gamma_t/\gamma_{t-1})u_{t-1}]. \tag{2.11}$$

To set scale let $\gamma_1 = 1$. This equation must be estimated using instrumental variables (or a similar technique) since y_{t-1} is correlated with u_{t-1}. Begin with an overparameterized version of (2.11) and estimate

$$y_t = \varphi_{1t}x_t + \varphi_{2t}x_{t-1} + \varphi_{3t}y_{t-1} + \eta_t,\ t = 2, \ldots, T, \tag{2.12}$$

where $\varphi_{1t} = \beta_t$, $\varphi_{2t} = -(\beta_{t-1}\gamma_t/\gamma_{t-1})$, and $\varphi_{3t} = (\gamma_t/\gamma_{t-1})$. Estimate this system using three-stage least squares ($3SLS$) where all values of x are used as instrumental variables for the lagged y term. At this point we test the over-identifying restrictions of the simultaneous equations model (i.e. the exclusion restrictions).

The next step is to test the γ's. If they are not all equal (to 1), then there is no clean interpretation of the regression which uses the change in y as the dependent variable. The test of whether the coefficients on the lagged y terms above are unity is equivalent to testing $\gamma_t = 1$ in the omnibus test framework.[2] While in the omnibus test framework

2. If the asymptotics involved T as well as N we would be testing a unit root, with the concomitant problems. Since the asymptotics here only involve N, there is no such problem.

we required nonlinear methods to estimate the γ_t's here we can use linear methods to estimate ratios of the γ_t's. The use of the change in y as the dependent variable is justified if we fail to reject this hypothesis.

The conventional person effect model (2.5) further implies that the coefficients on current and lagged x are equal in absolute value but opposite in sign,

$$y_t=\beta x_t-\beta x_{t-1}+y_{t-1}+[u_t-u_{t-1}]. \tag{2.13}$$

This is simply the difference equation described above. If the γ_t's are all unity but the β_t's vary over time, then the coefficient on lagged y will be unity, but the coefficients on current and lagged x will not be equal but opposite.

2.4. *A nonlinear specification: decomposing the change in x*

The third test changes the basic estimating equation to include cross-products in the union variables. If x_{it} never changes it is perfectly collinear with c_i and we cannot estimate β. The union variable is discrete and can change in only two ways. An uncovered worker might become covered by a collective bargaining agreement, or a covered worker may no longer be covered. We examine the possibility that the two events do not have the same impact on wage rates.

Decompose the change in x into the following:

$$\text{ENTER}_t=1 \text{ if } x_t=1 \text{ and } x_{t-1}=0;\ 0 \text{ otherwise.} \tag{2.14a}$$

$$\text{LEAVE}_t=1 \text{ if } x_t=0 \text{ and } x_{t-1}=1;\ 0 \text{ otherwise.} \tag{2.14b}$$

$$\text{STAY}_t=1 \text{ if } x_t=1 \text{ and } x_{t-1}=1;\ 0 \text{ otherwise.} \tag{2.14c}$$

The fourth possibility, that the individual was never covered by a union contract, is absorbed into the intercept. The equation of interest is then

$$\Delta y_t=\alpha_{1t}\,\text{ENTER}_t+\alpha_{2t}\,\text{LEAVE}_t+\alpha_{3t}\,\text{STAY}_t+\Delta\mu_t. \tag{2.15}$$

where $\Delta y_t=y_t-y_{t-1}$ and Δu_t is defined similarly. An equivalent specification is

$$\Delta y_t=\tau_1 x_{t-1}+\tau_2 x_t+\tau_3 x_t x_{t-1}+\Delta u_t, \tag{2.16}$$

where $\alpha_1=\tau_2$, $\alpha_2=\tau_1$, and $\alpha_3=\tau_1+\tau_2+\tau_3$. If the specification in (2.5) is correct (including the restriction that the coefficients are constant over time)., then the restrictions are

$$\alpha_{1t}=-\alpha_{2t}=\beta, \qquad t=2,\ldots,T. \tag{2.17a}$$

$$\alpha_{3t}=0, \qquad t=2,\ldots,T. \tag{2.17b}$$

Note that this test could be used with a continuous x variable as well by separating the change in x into increases and decreases. Then test whether the coefficient on the increase in x is equal in absolute value but opposite in sign to the coefficient on the decrease in x.[3]

2.5. *Do the effects of other regressors vary with union status?*

The last test is whether the effects of other regressors vary with union status. If c is correlated with union status, then it is also correlated with interactions of union status

3. In principle one could begin with an unrestricted reduced-form coefficient matrix Π, as in the omnibus test. This would entail entering all possible interactions of the five union variables freely into each of the five unrestricted cross-section equations, as opposed to just entering the levels and estimate 153 (31 interaction times 5 equations) free coefficients for the portion of the Π matrix corresponding to the union variables. This procedure is not feasible with the data used here. The empirical work below does not implement this test until after examining the omnibus test and the instrumental-varibles test. These tests suggest that the decomposition proposed is a natural direction in which to proceed.

and other regressors. We use the methods of sections 2·3 and 2·4 here, adding interaction terms to the model while also allowing them to be correlated with c.

3. DATA

The data are a sample of male heads of household drawn from the Panel Study of Income Dynamics (PSID) from the years 1976 though 1980. We included men who were part of the representative portion of the PSID, not disabled, between the ages of 20 and 60 in 1976, either black or white, and worked for money income in each of the years 1976 through 1980. We excluded those who were self-employed, had labour income from more than one source, or were paid by some method other than wage or salary, in order to construct a clean wage variable. These selection criteria produced a sample of 588 men. Twenty per cent of them experienced a change in union status over the sample period.

A full description of the data appears in an appendix (available on request). The variables used in the analysis are the following:

LW_t: logarithm of the hourly wage rate (in cents) in year t.
U_t: 1 if the wage in year t was set by collective bargaining; 0 otherwise.
SM_t: 1 if living in an SMSA in year t; 0 otherwise.
AGE: age in years in 1976.
SCHL: years of schooling.
RACE: 1 if black, 0 if white.
SOUTH1: 1 if living in the South in 1976; 0 otherwise.

Appendix Table A1 contains descriptive statistics.

4. EMPIRICAL RESULTS

4.1. *Simple cross section*

Table 1 displays the results treating each year of the panel as a separate cross-section and fitting the least-squares projection of LW_{it} onto f_i and x_{it}. These estimates provide the benchmark against which we compare the panel estimates below, and permit us to determine the extent of the bias in the cross-section estimate which ignore the person effect c_i.

TABLE 1

Simple cross-section OLS regressions of log wage on current union status
($N = 588$) (standard errors in parentheses)

	$U1$	$U2$	$U3$	$U4$	$U5$
$LW1$	0·163 (0·025)				
$LW2$		0·198 (0·024)			
$LW3$			0·177 (0·025)		
$LW4$				0·171 (0·027)	
$LW5$					0·184 (0·026)

Note: All equations also include age, age-squared, schooling, schooling-squared, age × schooling, race, South1, current SMSA, and a constant.

We display only the coefficients associated with the union variables in all tables. (Complete results are available on request.) The time notations one to five correspond to the years 1976 to 1980. The other variables in the equations are a full quadratic in age and schooling, race, South 1, SM_t, and a constant.[4]

The union coefficients range from 0·163 to 0·198, with a simple mean of 0·179. The cross section estimate of the union wage premium is 20% ($\exp\{0{\cdot}179\}-1=0{\cdot}196$), comparable to those of most cross section studies. If the sorting story were correct, unmeasured productivity is positively correlated with union status, and we expect the panel estimate to be smaller.

4.2. *Omnibus test: restricted GLS*

The first step is estimating the unrestricted reduced form by projecting each (log) wage on f and all leads and lags of x. Appendix Table A2 presents the portion of the unrestricted $\hat{\Pi}$ corresponding to the union variables. If leads and lags of union status are unimportant in wage determination the off-diagonal elements of $\hat{\Pi}$ should be zero.

The reduced form disturbances in (2.8) are likely to be serially correlated even if the u's are i.i.d. since $e_{it}=\gamma_t\zeta_i+u_{it}$. If the u's were i.i.d. one could impose the factor structure on the disturbance covariance matrix when estimating Π, yielding greater precision in the estimates. Alternatively, one could allow the u's to be freely correlated and therefore allow the e's to be freely correlated over time. This approach prevents misspecification of the disturbance covariance structure from generating inconsistencies in the slope coefficient estimates.

Our focus is the slope coefficients. Since the cross-section dimension (N) is large and the time-series dimension (T) is small, and since the asymptotics rely on large N for fixed T, the latter approach is safer, and is the one adopted in all the empirical work below. This approach is in the same spirit as allowing for arbitrary heteroscedasticity in the reduced-form disturbances.

Table 2 displays the results of imposing restrictions on $\hat{\Pi}$ using minimum-distance techniques. The first three panels of the table use the conventional (homoscedastic) covariance matrix of $\hat{\Pi}$ as the norm and the second three use the covariance-matrix estimator which allows for arbitrary heteroscedasticity. The first panel imposes the restrictions of the omnibus test for the presence of a person effect (2.9). This is the most general model considered. There is no evidence against the restrictions ($\chi^2(11)=9{\cdot}23$). The estimated union effects (β's) range from 0·065 to 0·093 and the $\hat{\gamma}$'s range from 0·852 to 1·474. Similar results obtain when we allow for arbitrary heteroscedasticity in the fourth panel. The $\hat{\beta}$'s range from 0·031 to 0·119 and the $\hat{\gamma}$'s range from 0·847 to 1·334. In both cases there is no evidence against the restrictions ($\chi^2(11)=9{\cdot}23$ under homoscedasticity and 11·57 with heteroscedasticity).

The second and fifth panels display the results for a standard person-effect model (2·10) in which the γ's are all unity and the β's are all equal. The estimated union effect is 0·084 (with a standard error of 0·015) under homoscedasticity, about half the average cross-section estimate from Table 1. With heteroscedasticity the estimate is somewhat smaller, 0·055 (0·019), about one fourth the average cross-section estimate. In both cases the models are consistent with the reduced form ($\chi^2(19)=15{\cdot}46$ under homoscedasticity and 20·12 with heteroscedasticity). The test statistic for the incremental restrictions is

4. If the region variable varies over time there is not enough variation to estimate the GLS model with heteroscedasticity. The homoscedastic results are not sensitive to the treatment of the region variable or the SMSA variable. In the empirical work the SMSA coefficients vary freely.

TABLE 2

Omnibus test for the presence of c based on the estimated $\hat{\Pi}$ from Table A2: restricted GLS
(standard errors in parentheses)

Conventional GLS: Homoscedasticity					*Extended GLS: Arbitrary Heteroscedasticity*				
2.1. Restrictions from (2.9): $\chi^2(11)=9\cdot23$					2.4. Restrictions from (2.9): $\chi^2(11)=11\cdot57$				
β_1	β_2	β_3	β_4	β_5	β_1	β_2	β_3	β_4	β_5
0·081	0·093	0·074	0·065	0·087	0·074	0·119	0·050	0·031	0·062
(0·028)	(0·028)	(0·033)	(0·021)	(0·035)	(0·031)	(0·031)	(0·040)	(0·022)	(0·027)
γ_1	γ_2	γ_3	γ_4	γ_5	γ_1	γ_2	γ_3	γ_4	γ_5
1·000	0·852	1·334	1·474	1·221	1·000	0·847	1·223	1·334	1·117
—	(0·210)	(0·252)	(0·357)	(0·191)	—	(0·200)	(0·192)	(0·298)	(0·187)
λ_1	λ_2	λ_3	λ_4	λ_5					
0·018	0·022	0·045	0·012	0·018	0·028	0·027	0·058	−0·010	0·043
(0·047)	(0·050)	(0·056)	(0·044)	(0·047)	(0·047)	(0·041)	(0·051)	(0·050)	(0·041)
2.2. Restrictions from (2.10): $\chi^2(19)=15\cdot46$					2.5. Restrictions from (2.10): $\chi^2(19)=20\cdot12$				
β					β				
0·084					0·055				
(0·015)					(0·019)				
λ_1	λ_2	λ_3	λ_4	λ_5	λ_1	λ_2	λ_3	λ_4	λ_5
0·016	0·024	0·045	0·011	0·019	0·026	0·028	0·052	−0·007	0·040
(0·049)	(0·054)	(0·054)	(0·049)	(0·49)	(0·047)	(0·044)	(0·047)	(0·045)	(0·042)
2.3. $\lambda=0$: $\chi^2(24)=30\cdot54$					2.6. $\lambda=0$: $\chi^2(24)=42\cdot58$				
β					β				
0·111					0·109				
(0·013)					(0·015)				

the difference between the χ^2 statistics, and shows no evidence against the restrictions $\beta_t=\beta$ and $\gamma_t=1$.

The third and sixth panels display the results for the conventional random-effects model (Balestra and Nerlove (1966), Maddala (1971)) which assumes c is uncorrelated with union status ($\lambda=0$). In this model the cross-section estimates in Table 1 are consistent though not efficient. We obtain virtually identical estimates in both cases: $\hat{\beta}=0\cdot111$ (0·013) under homoscedasticity and 0·109 (0·015) with heteroscedasticity. The estimated union effect is the optimal (matrix-) weighted average of the cross-section estimates under the null hypothesis $\lambda=0$, though it is considerably smaller in magnitude than the cross-section estimates.

There is strong evidence against the hypothesis $\lambda=0$. The incremental $\chi^2(5)$ statistics, against the model in (2.10), take the values 15·08 (homoscedastic) and 22·46 (heteroscedastic). A Hausman-type test of the null hypothesis that the $\hat{\beta}$'s are equal yields a $\chi^2(1)$ statistic of 13·02 (homoscedastic) and 21·44 (heteroscedastic).

4.3. *A test of differencing: instrumental variables*

We now implement the instrumental-variables procedure from Section 2.3 which provides both a test of the person-effect model as well as a clean estimate of the union effect. We use the equation for the previous year's wage to solve for c, and substitute into the equation for current wage to get an equation giving the current wage as a function of the lagged wage and current and lagged union status in equation (2.11). Consider the unrestricted version of this system in equation (2.12). If the coefficients are constant over time, and if the standard person-effect model is correct, then the coefficient on the lagged wage is unity and the coefficients on current and lagged union status are equal in absolute value but opposite in sign. This is the model of equation (2.13), which is essentially a difference equation. This specification is equivalent to the standard person-effect model of equation (2.5).

Estimation of (2.12) must account for the correlation between the lagged wage and the disturbance term. Three-stage least-squares (3*SLS*) procedures are used, treating the lagged wage as endogenous, and using the union status at other points in time as instrumental variables.[5] There are two versions of 3SLS, corresponding to the two versions of GLS used in the omnibus test. Conventional 3SLS ($\hat{\delta}_3$) assumes homoscedascitity in the disturbances. "Extended 3SLS" allows for arbitrary heteroscedasticity. There are two (asymptotically equivalent) computational methods for extended 3SLS. The first ($\hat{\delta}_{G3}$) uses the residuals from conventional two-stage least-squares (2SLS) in order to compute the weight matrix used in the minimization problem. The second ($\hat{\delta}^*_{G3}$) uses the residuals from heteroscedastic 2SLS to compute the weight matrix. (For details, see Chamberlain (1982).)

The unrestricted 3SLS estimates are contained in Appendix Table A3. They show no evidence against the 20 overidentifying restrictions. The $\chi^2(20)$ statistics take the values 16·98, 13·85, and 12·62 for $\hat{\delta}_3$, $\hat{\delta}_{G3}$, and $\hat{\delta}^*_{G3}$, respectively. There is general agreement among the three estimators on the signs and orders of magnitude of the estimated coefficients. Hence, in the rest of this section we will maintain the hypothesis that the overidentifying restrictions are correct. To test against the unrestricted reduced form one would add the chi-squares above to those of the incremental tests. In all cases below for which the restrictions are not rejected, the test against an unrestricted reduced form also does not reject.

If there is a time-invariant person effect in the wage equations, then the coefficient on the lagged wage should be unity in each of the four equations. Imposing only the restriction that $\varphi_{3t}(=\gamma_t/\gamma_{t-1})$ from equation (2.12) is unity for each t results in incremental $\chi^2(4)$ statistics of 4·86, 4·62, and 5·79 for $\hat{\delta}_3$, $\hat{\delta}_{G3}$, and $\hat{\delta}^*_{G3}$, respectively (table not shown). Therefore there is a clean interpretation to a regression with the wage change as the dependent variable.

We impose restrictions on the unrestricted 3SLS coefficients in a series of steps. These results appear in Table 3. Table 3.1 displays the results of imposing the restriction that the 3SLS coefficients are constant over time, that is, that φ_{1t}, φ_{2t}, and φ_{3t} in equation (2.12) are equal to φ_1, φ_2, and φ_3, respectively. There is no evidence against these restrictions. The incremental $\chi^2(9)$ statistics take the values 11·98, 12·15, and 13·17 for $\hat{\delta}_3$, $\hat{\delta}_{G3}$, and $\hat{\delta}^*_{G3}$, respectively. The coefficient on the lagged wage is approximately unity, and the coefficients on current and lagged union are close in absolute value.

Table 3.2 presents the results for the difference equation (2.13) which imposes these restrictions formally. The added restrictions here are that the coefficient on the lagged wage is unity and the coefficients on current and lagged union status are equal in magnitude

5. The varibles in the f vector are allowed to enter freely into each of the equations. The equations also contain current and lagged SMSA variables, and the SMSA variables from other points in time are used as instrumental variables. All results presented here and below are insensitive to the treatment of the SMSA variables.

TABLE 3

Restricted 3SLS estimates: restrict coefficients from Table A3
(standard errors in parentheses)

	3.1. Coefficients constant over time		
	$\hat{\delta}_3$	$\hat{\delta}_{G3}$	$\hat{\delta}_{G3}{}^*$
LW_{t-1}	1·100 (0·092)	1·053 (0·075)	1·058 (0·066)
U_t	0·077 (0·015)	0·049 (0·019)	0·044 (0·018)
U_{t-1}	−0·092 (0·019)	−0·056 (0·021)	−0·055 (0·021)
$\chi^2(9)$	11·98	12·15	13·17
	3.2. Change model		
	$\hat{\delta}_3$	$\hat{\delta}_{G3}$	$\hat{\delta}_{G3}{}^*$
U	0·081 (0·014)	0·050 (0·018)	0·046 (0·018)
$\chi^2(11)$	13·96	13·46	14·00

Note: Column headings: $\hat{\delta}_3$ = conventional 3SLS (homoscedasticity). $\hat{\delta}_{G3}$ = extended 3SLS (heteroscedasticity) with residuals from conventional 2SLS used as norm. $\hat{\delta}_{G3}{}^*$ = extended 3SLS with residuals from extended 2SLS as norm.

but opposite in sign. The test against the 3SLS model appears at the bottom of the table, so the incremental $\chi^2(2)$ statistics take the values 1·98, 1·31, and 0·83 for $\hat{\delta}_3$, $\hat{\delta}_{G3}$, and $\hat{\delta}^*_{G3}$, respectively. The estimated union coefficient is 0·081 (0·014) for the model which assumes homoscedasticity ($\hat{\delta}_3$) which is very similar to the GLS estimate in Table 2.2 of 0·084 (0·015). Allowing for arbitrary heteroscedasticity yields estimates of the union effect of 0·050 (0·018), and 0·046 (0·018) for $\hat{\delta}_{G3}$ and $\hat{\delta}^*_{G3}$, respectively. These are similar to the restricted GLS estimate in Table 2·5 of 0·055 (0·019).

These results suggest that the usual fixed-effects approach to this problem is valid. The fixed-effects estimator uses the deviations from individual-specific time-means, and regresses the deviations in the wage on the deviations in the union variable. For these data, this procedure results in an estimated union coefficient of 0·083, with a standard error of 0·020, which is similar to the others derived under the homoscedasticity assumption.[6]

4.4. *Entrants versus leavers: a nonlinear specification in x*

The results thus far indicate that the data are consistent with a model with an unobserved person-specific effect which is correlated with the union status variable. Further, there is no evidence against the standard person-effect model (equation (2.4)) in which a regression of the change in wage on the change in union status yields a clean estimate of the union effect, purged of the omitted variables bias which affects the cross-section estimate. This

6. These equations also take deviations of other time-varying variables. We imposed the restriction that the coefficients on the time-invariant explanatory variables were constant, so that they dropped out of the equation. The estimate shown is from an equation in which the SMSA variable was taken as deviations from time-means.

section presents the results of a narrower test of the specification, detailed above in Section 2.4, in which we decompose the change in union status into indicators for entering covered status (ENTER) and for leaving it (LEAVE), and ask whether their effects on the wage change are symmetric.

We employ the same general strategy as above. Appendix Table A4 displays the estimates of the wage change equations (2.15) for years 2 to 5. These equations allow current and lagged SMSA to enter freely into each change equation. (The results are not sensitive to the treatment of the SMSA variable.) The point estimates suggest a positive union wage premium. The coefficients on ENTER are positive, while those on LEAVE are negative. The coefficients on STAY are not significantly different from zero in three of the four equations.

Table 4 displays the results of imposing restrictions on the wage change coefficients. There are two columns. The first displays the results assuming homoscedasticity, while the second displays the results when we allow for arbitrary heteroscedasticity.

We impose the restriction that the wage change coefficients are constant over time in the first panel of the table. This is the restriction that α_{1t}, α_{2t}, and α_{3t} in equation (2.15) are equal to α_1, α_2, and α_3 respectively. There is no evidence against the restrictions. The $\chi^2(9)$ statistics take the values 13·00 and 10·00 for the conventional GLS and the extended GLS, respectively. The coefficient on STAY is not different from zero, either statistically or substantively, in either case. The second panel of the table constrains the coefficient on STAY (α_3) to zero. There is no evidence against the restriction, and the coefficients on ENTER and LEAVE do not change. Both conventional and extended GLS yield similar estimates of the coefficients on ENTER (α_1) and LEAVE (α_2). The

TABLE 4

Restricted wage change equations: impose restrictions on coefficients in Table A4
(standard errors in parentheses)

	Conventional GLS	*Extended* GLS
	4.1. Coefficients constants over time	
ENTER	0·117	0·107
	(0·107)	(0·029)
LEAVE	−0·037	−0·026
	(0·017)	(0·025)
STAY	0·001	0·001
	(0·005)	(0·005)
$\chi^2(9)$	13·00	10·00
	4.2. Add restriction that coefficient on STAY is 0	
ENTER	0·116	0·106
	(0·017)	(0·029)
LEAVE	−0·037	−0·027
	(0·017)	(0·025)
$\chi^2(10)$	13·02	10·07
	4.3. Add equal but opposite restriction	
UNION	0·076	0·060
	(0·013)	(0·020)
$x^2(11)$	27·74	14·87

ENTER coefficients are 0·116 (0·017) and 0·106 (0·029), respectively, while the LEAVE coefficients are −0·037 (0·017) and −0·027 (0·025), respectively.

The conventional person-effect models implicitly constrain the coefficients on ENTER and LEAVE to be equal in magnitude but opposite in sign. Table 4.3 presents the results of constraining $\alpha_1 = -\alpha_2$. Maintaining the hypothesis that the coefficients are constant over time and that $\alpha_3 = 0$, there is evidence against the equal but opposite restriction. The incremental $\chi^2(1)$ statistics take the values 14·72 and 4·80 for the conventional and the extended GLS, respectively. Maintaining the hypothesis that the restriction is correct, the estimated union coefficients are 0·076 (0·013) and 0·060 (0·020), respectively, which are very similar to the results from the omnibus test and the instrumental variables procedures.

There is some disagreement between the conventional and the extended GLS. The chi-square statistic at the bottom of Table 4.3 is a test of the restricted model against the unrestricted alternative in Appendix Table A4. The conventional GLS shows clear evidence against the model ($\chi^2(11) = 27{\cdot}74$), while the extended GLS does not ($\chi^2(11) = 14{\cdot}87$). The sum of the ENTER and LEAVE coefficients ($\alpha_1 + \alpha_2$) in the second panel of the table is 0·079 (0·021) for conventional GLS and 0·079 (0·036) for extended GLS. We conclude that the bulk of the evidence is against the restriction.

4.5. *Testing for interactions*

The final specification test asks whether the effects of the other regressors varies with union status, so that the appropriate specification would include interactions between union status and those variables. To be concrete, suppose that the effect of race varies with union status. The appropriate specification then includes union and union × race. If union is correlated with the unobserved c, so is union × race. We utilize both the GLS approach of Section 2.3 and the instrumental variables approach of Section 2.4 to address this question. We add interactions between union status at each point in time and the time-invariant regressors (age and its square, schooling and its square age × schooling, race and south) to the model. These models are only estimated under the homoscedasticity assumption since the covariance matrix under the heteroscedasticity assumption was numerically singular, ruling out minimum distance tests.

Table 5 displays the results of these experiments. The first two columns are GLS results using the method of Section 2.3. The unrestricted reduced form (coefficients not shown) contains interactions of all union variables with the time-invariant regressors in addition to all levels of the union and SMSA variables. In the first column we display the β coefficients from a model comparable to Table 2.2 in which all interaction terms are set to zero and the β, λ structure is imposed on the union coefficients. There is evidence against the model ($\chi^2(194) = 316{\cdot}5$) though $\hat{\beta}$ of 0·083 (0·013) is quite close to the results in Table 2.2 of 0·084 (0·015). In the second column we display the $\hat{\beta}$'s when we impose the β, λ structure on the interaction terms as well. There is evidence against the restrictions, as compared to the unrestriced reduced form ($\chi^2(152) = 244{\cdot}7$). The $\hat{\beta}$'s are estimated quite imprecisely, with the exception of the union × race interaction.

The third column displays the $\hat{\beta}$'s using the instrumental variables approach of Section 2.4. The exclusion restrictions from the "unrestricted" 3SLS model are consistent with the data ($\chi^2(92) = 111{\cdot}1$, table not shown). The incremental restrictions of the change model are not consistent with the data ($\chi^2(60) = 155{\cdot}5$), however. Similarly to the GLS results, the $\hat{\beta}$'s are estimated rather imprecisely.

TABLE 5

Interactions Between Union Status and Other Explanatory Variables
(standard errors in parentheses)

	(1)	(2)	(3)
U	0·083	0·277	−0·092
	(0·013)	(0·346)	(0·355)
$U\times$ age		−1·198	−0·765
		(1·132)	(1·150)
$U\times$ age^2		0·073	0·077
		(0·113)	(0·113)
$U\times$ school		0·184	0·663
		(0·361)	(0·367)
$U\times$ school^2		−0·169	−0·311
		(0·119)	(0·118)
$U\times$ age $\times$ school		0·299	−0·101
		(0·466)	(0·474)
$U\times$ race		(0·078	0·066
		(0·030)	(0·030)
$U\times$ south1		−0·004	0·021
		(0·003)	(0·032)
χ^2	316.5	244·7	155·5
df	194	152	60

Notes:
(1) GLS model; zero-out all interaction terms. β, λ on U.
(2) GLS model. β, λ structure on U and interaction terms.
(3) 3SLS model restricted to be a change model.
χ^2 is against an unrestricted reduced form for columns (1) and (2). χ^2 is against the "unrestricted" 3SLS model for column (3). The "unrestricted" 3SLS model had $\chi^2(92) = 111{\cdot}1$.

We calculate the implied union wage effect for five different data configurations below. In all five we set age and schooling to their mean values in the sample. In the first we set race and south to their sample means. In the second we set race and south to zero, and in the third and fourth we alternately set race and south to one, and in the fifth we set both to one. The implied union wage effects are:

Data configuration	GLS	IV
mean age, school, race, south.	0·075	0·074
mean age, school. race = 0. south = 0.	0·050	0·040
mean age, school. race = 0. south = 1.	0·046	0·061
mean age, school. race = 1. south = 0.	0·128	0·106
mean age, school. race = 1. south = 1.	0·124	0·127

The results in the first row are similar to the GLS and instrumental variables results (under homoscedasticity) in Tables 2 and 3. This is to be expected, since the single β in the models above refers to the union wage effect for a randomly chosen individual. We find that the union wage premium is higher for non-whites. At the mean age, the union effect is higher for those with lower levels of schooling. At the mean schooling level, the union effect is higher for younger workers. These are consistent with the literature (Lewis (1986)).

5. DISCUSSION

5.1. *Size of the union wage effect*

This paper has two goals. The first is to provide estimates of the union wage effect which are free of an omitted variables bias due to the presence of an unmeasured person-specific effect which is correlated with the union variable. That person effect may be thought of as unmeasured productivity characteristics which are observed by the employer but not by the researcher. A rational employer might respond to higher union wages by raising hiring standards, leading to a positive covariance between the unmeasured productivity characteristics and the union status variable. That covariance will impart an upward bias to cross section estimates of the union wage effect.[7]

Cross-section estimates of the union wage effect are on the order of 20%. When we allow for a person effect which is correlated with the union variable, the estimate drops to the 5–9% range. Table 6 presents a summary of the various estimates of the union wage effect. One-half to three-fourths of the union effect estimated in the cross section may be attributed to the existence of a person effect. There is evidence that the union effect varies among different types of workers, even after controlling for unobserved individual-specific effects. Younger workers, less educated workers, and non-whites gain more from union coverage, even after controlling for c.

TABLE 6

Summary of estimated union coefficients
(standard errors in parentheses)

	Homoscedastic		*Heteroscedastic*		
	OLS-GLS	$\hat{\delta}_3$	OLS-GLS	$\hat{\delta}_{G3}$	$\hat{\delta}_{G3}{}^*$
1. Simple cross-section[a]	0·179				
2. Fixed effects[b]	0·080				
	(0·020)				
3. Omnibus test[c]	0·084		0·055		
	(0·015)		(0·019)		
4. Instrumental variables[d]		0·081		0·050	0·046
		(0·014)		(0·018)	(0·018)
5. Wage change[e]	0·076		0·060		
	(0·013)		(0·020)		
6. Interactions at means[f]	0·075	0·074			

Notes: [a] Table 1. [b] From text. [c] Table 2. [d] Table 3. [e] Table 4. Wage change model is rejected by the data. [f] From text, derived from Table 5.

Both the point estimates of the union effect and the size of the reduction as compared to the cross-section estimate are similar to those found by Chamberlain (1982) using NLS data for young men. His sample contained a larger number of men, though only three

7. Note that this is not the only motivating story for the person effect. If more able workers choose union jobs, the empirical implications would be the same.

years of data each. The tests of the person-effect model become sharper with more years of data, since there are considerably more restrictions.[8] The results are also similar to those of Brown (1980) and others who have used these techniques (see Lewis).

5.2. *Appropriateness of the usual person-effect model*

The second goal of this paper is to test the appropriateness of the person-effect model most commonly employed in empirical economics. Four tests are suggested. The first is an omnibus test for the presence of a person effect which is based on restricting the way past and future union variables enter the equation for the current wage. The second is a narrower test which uses instrumental-variables techniques to overparameterize and then test a model of differencing. The third introduces a nonlinear specification of the union varibles, and decomposes the change in union status into two components. It then tests whether the two components have symmetric effects on the wage change. The fourth is a test of whether interaction effects belong in the model.

The first two tests provide no evidence against the usual person-effect model. The estimated coefficients are similar across the tests, and tests against unrestricted reduced forms fail to reject. When the nonlinearity in the explanatory variables is introduced, however, there is evidence against the usual model. There is also evidence in favour of the hypothesis that the effects of other regressors vary with union status. For these reasons, the estimated union effects should be interpreted cautiously.

5.3. *Comparison to conventional IV solutions*

The conventional solution in the case of a suspected endogenous explanatory variable is the use of instrumental variables. For purposes of comparison we estimated two sets of IV models, treating the union status variable as endogenous. In the first set we use a linear predictor for union and in the second we use the predicted probability from a probit model. The auxiliary equation (not shown) contains a third-order polynomial in age and schooling, all SMSA variables, race, south and interactions of age and schooling with race and south.

The results using a linear predictor appear in columns (1)-(3) of Table 7. In the first column we use single-equation methods, while in the second column we treat the wage equations as a system, allowing the union coefficients to vary over time. In the third column we constrain the union coefficients to be equal over time in the wage system. The estimated $\hat{\beta}$'s are significantly larger here than in the models above. The single equation results are larger than the cross-section estimates. When system methods are used the $\hat{\beta}$'s drop on the order of $\frac{1}{3}$, and when constrained to be equal the estimate is similar to the cross-section average.

The results are basically similar when we use a probit predictor of union status in columns (4)-(6). The single-equation estimates are larger than those with the linear predictor, while the system estimates are smaller. The constrained estimate in column (6) is smaller than that obtained with the linear predictor, but is still much closer to the cross-section estimate than to the panel-data estimates above.

8. Consider the omnibus tests. In testing (2.9) against an unrestricted reduced form, there are T^2-3T-1 restrictions. This test is not feasible when $T=3$. In testing (2.10) against an unrestricted reduced form, there are T^2-T-1 restrictions. This leads to 5 restrictions when $T=3$ as compared to 19 restrictions when $T=5$.

TABLE 7

Conventional Instrumental Variables Results Treating Union as Endogenous
(Standard errors in parentheses)

	(1)	(2)	(3)	(4)	(5)	(6)
Union			0·214 (0·089)			0·164 (0·078)
$U1$	0·328 (0·156)	0·238 (0·124)		0·376 (0·147)	0·208 (0·110)	
$U2$	0·315 (0·134)	0·186 (0·100)		0·343 (0·135)	0·160 (0·092)	
$U3$	0·358 (0·144)	0·243 (0·110)		0·392 (0·139)	0·190 (0·096)	
$U4$	0·290 (0·147)	0·188 (0·116)		0·327 (0·145)	0·147 (0·104)	
$U5$	0·281 (0·142)	0·246 (0·109)		0·273 (0·136)	0·142 (0·096)	

Notes: (1) Linear IV, single equation methods (2) Linear IV, system method. (3) Linear, IV, system method, coefficient constrained equal across years. (4) Probit IV, single equation methods. (5) Probit IV, system method. (6) Probit IV, system method, coefficient constrained equal across years.
Instrumental variables are a full third-order polynomial in age and schooling and interaction of age and schooling with race, region, and SMSA.

Why are these estimates so different from the panel-data estimates? In the panel models above we do not assume that the time-invariant variables, for example, age, are uncorrelated with the unobserved c. We simply cannot separately identify the "structural" effect of age and its correlation with c. If age is correlated with c, then the instrumental variables used here are not valid instruments, and the resulting parameter estimates are inconsistent. The difference between the conventional IV results and those of the panel models suggests that this is the case. In general, then, it will be difficult to obtain consistent estimates of the union wage effect using instrumental-variables methods (at least in the cross section).

5.4. *Caveats*

The panel-data methods employed here require that the sample contain individuals whose union status changes over time. There are two potential problems in basing the estimate of the union wage effect on changers. The first is measurement error, and the second is the implicit assumption that union status changes are random.

It has been argued (e.g. Mincer (1983), Freeman (1984), and Chowdhury and Nickell (1985)) that many of the "observed" union status changes are not true changes, but merely the result of measurement error. Mincer argues that observed changes in union status which occur without a job change are likely to be spurious.[9] Freeman uses outside

9. We attempted to address this problem with these data by constructing a dummy variable indicating a job change (JOBCHG) and redoing the analysis of Section 4.3 using ENTER, LEAVE, STAY, their interactions with JOBCHG and JOBCHG. The interactions of the status change variables with the job change dummy should yield better estimates of the union effect if this kind of measurement error were a problem. Unfortunately, the cell sizes were very small and the estimates unstable. The pooling hypothesis that the coefficients are constant over time was strongly rejected. We have little confidence in the results and do not display them here.

information (gathered apart from the household survey which generates the individual data) from the employer and concludes that there is measurement error in the union status variable. Estimates of the union wage effect using only the sample for which worker and firm responses agree are larger than the usual within-sample estimates. Chowdhury and Nickell parameterize both the measurement-error process and the process generating the true union variables. They use instrumental-variables procedures and undo the fixed-T bias in the resulting within estimator. They too find that allowing for measurement error leads to much larger estimates of the union wage effect.

In other work with these data (Jakubson (1986)) we examine the possibility that measurement error is driving these results. There a model is derived which nests both the measurement-error models of Freeman and of Chowdhury and Nickell as well as the person-effect model as special cases. That model allows one to determine the extent to which unobserved heterogeneity, as opposed to measurement error, is responsible for the difference between the panel and cross-section estimates. The results there suggest that while there is evidence of measurement error in the union status variable, adding measurement error to a model with person effects results in only a small increase in the estimate of β while adding a person effect to a model of measurement error results in a large decrease in the estimate of β. Hence most of the difference is ascribable to unobserved heterogeneity, which is the focus of this paper.

The second potential problem is the implicit assumption that union status changes are random. Changes in status generally require job changes, since certification and de-certification elections are infrequent events. If job changes depend on the wage, as in a matching model (Jovanovic (1979), Flinn (1982)), then the change in union status is endogenous and the estimates here are subject to the usual simultaneous-equations bias.

This argument suggests that the exogeneity of union status, conditional on c, may not hold. To address this point, we also implemented the instrumental-variables procedure in Section 2.3 using only past values as instruments. The results were quite similar to those presented above. The evidence, combined with the failure to reject the overidentifying restrictions of the 3SLS model suggests (Appendix Table A3) that forcing all the endogeneity to appear through c is not a bad approximation in these data.[10]

Finally, there is an issue of interpretation. According to the employer selection story, employers see a queue of applicants for union jobs, and pick those with high values of c (unmeasured productivity characteristics). If the union wage effect were the same for all people, then eliminating c from the wage equation would lead to a clean estimate of that effect.

However, if the union effect, say b, varies among people, then we would expect that only those people with high values of b would enter the queue for union jobs. The estimates of the union effect above, then, do not estimate $E(b)$, but rather $E(b \mid b > b^*)$, where b^* is the minimum value of b for which an individual joins the queue. The estimates at best refer only to those who would be better off in a union.

10. We also took another approach to this issue. To the extent that union status changes are upgrading, either because a low skill worker moves up into a union slot, or because a union worker is promoed to a supervisory position, we might expect more random changes among younger workers than among older workers. We re-estimated the models of Section 4.3 on the subsample of those 30 years of age or younger in 1976 ($N = 220$). The results were virtually identical to those of Section 4.3. This suggests either that non-random changes in union status are not a problem, or, more likely, that non-random changes are not confined to older workers.

APPENDIX

TABLE A1

Means and standard deviations

Variable	Mean	Standard deviation
$LW1$	6·235	0·356
$LW2$	6·334	0·351
$LW3$	6·435	0·363
$LW4$	6·516	0·374
$LW5$	6·627	0·370
AGE/100	0·364	0·112
AGESQ/1000	1·447	0·887
SCHL/10	1·150	0·282
SCHLSQ/100	1·403	0·625
AGE × SCHL/1000	0·408	0·142
RACE	0·352	0·478
SOUTH 1	0·464	0·499
$SM1$	0·675	0·469
$SM2$	0·672	0·470
$SM3$	0·673	0·469
$SM4$	0·682	0·466
$SM5$	0·687	0·464
$U1$	0·427	0·495
$U2$	0·432	0·496
$U3$	0·434	0·496
$U4$	0·427	0·495
$U5$	0·417	0·494

TABLE A2

Unrestricted cross-section GLS regressions of log wage on all values of union status, (standard errors in parentheses)[a]

	$U1$	$U2$	$U3$	$U4$	$U5$
$LW1$	0·090	−0·004	0·076	0·043	−0·022
	(0·055)	(0·060)	(0·060)	(0·055)	(0·054)
	(0·055)	(0·060)	(0·060)	(0·058)	(0·050)
$LW2$	0·020	0·125	0·049	0·017	0·005
	(0·052)	(0·057)	(0·057)	(0·052)	(0·052)
	(0·055)	(0·051)	(0·056)	(0·052)	(0·050)
$LW3$	0·025	0·055	0·080	−0·013	0·057
	(0·055)	(0·059)	(0·060)	(0·054)	(0·054)
	(0·051)	(0·053)	(0·058)	(0·054)	(0·050)
$LW4$	0·022	0·021	0·056	0·071	0·026
	(0·058)	(0·063)	(0·063)	(0·057)	(0·057)
	(0·051)	(0·054)	(0·056)	(0·054)	(0·052)
$LW5$	0·009	0·011	0·035	−0·005	0·142
	(0·056)	(0·061)	(0·062)	(0·056)	(0·055)
	(0·057)	(0·060)	(0·064)	(0·057)	(0·055)

Notes: All equations also include age, age-squared, schooling, schooling-squared, age × schooling, race, South1, all values of SMSA and a constant.

[a] The first standard error shown is calculated assuming homoscedasticity. The second allows for arbitrary heteroscedasticity.

TABLE A3

Unrestricted 3SLS: Current wage on lagged wage and current and lagged union status
(standard errors in parentheses)

	$\hat{\delta}_3$	$\hat{\delta}_{G3}$	$\hat{\delta}_{G3^*}$		$\hat{\delta}_3$	$\hat{\delta}_{G3}$	$\hat{\delta}_{G3^*}$
	Year 2: $t=2$				*Year* 3: $t=3$		
LW_{t-1}	0·832	0·822	0·845	LW_{t-1}	1·562	1·342	1·339
	(0·250)	(0·204)	(0·221)		(0·311)	(0·173)	(0·152)
U_t	0·122	0·122	0·119	U_t	0·024	0·016	0·019
	(0·027)	(0·033)	(0·037)		(0·035)	(0·035)	(0·032)
U_{t-1}	−0·061	−0·063	−0·064	U_{t-1}	−0·161	−0·108	−0·112
	(0·036)	(0·035)	(0·041)		(0·056)	(0·049)	(0·043)
	Year 4: $t=4$				*Year* 5: $t=5$		
LW_{t-1}	1.163	1.091	1.063	LW_{t-1}	1·041	1·037	1·038
	(0·198)	(0·148)	(0·139)		(0·189)	(0·186)	(0·176)
U_t	0·060	0·029	0·028	U_t	0·095	0·071	0·066
	(0·029)	(0·032)	(0·029)		(0·030)	(0·038)	(0·037)
U_{t-1}	−0·951	−0·049	−0·042	U_{t-1}	−0·101	−0·075	−0·071
	(0·038)	(0·034)	(0·031)		(0·038)	(0·038)	(0·037)
$\chi^2(19)$	16·98	13·85	12·62				

Notes: (1) All equations also include age, age-squared, schooling, schooling-squared, age × schooling, race, South1, current and lagged SMSA, and a constant. (2) Lagged wage endogenous. All values of union, SMSA, and f used as instruments. (3) Chi-square statistic is a test of the exclusion restrictions. (4) Column headings: $\hat{\delta}_3$ = conventional 3SLS (homoscedasticity). $\hat{\delta}_{G3}$ = extended 3SLS (heteroscedasticity), residuals from conventional 2SLS as norm. $\hat{\delta}_{G3^*}$ = extended 3SLS (heteroscedasticity), residuals from extended 2SLS as norm.

TABLE A4

Unrestricted wage change equations
(standard errors in parentheses)

	Dependent Variables $\Delta LW_t = LW_t - LW_{t-1}$			
	ΔLW_2	ΔLW_3	ΔLW_4	ΔLW_5
ENTER	0·111	0·092	0·096	0·177
	(0·036)	(0·032)	(0·035)	(0·039)
	(0·063)	(0·053)	(0·055)	(0·075)
LEAVE	−0·080	−0·013	−0·032	−0·036
	(0·038)	(0·032)	(0·032)	(0·036)
	(0·054)	(0·046)	(0·063)	(0·057)
STAY	0·035	−0·018	−0·001	0·001
	(0·015)	(0·014)	(0·018)	(0·018)
	(0·014)	(0·015)	(0·016)	(0·017)

Notes: (1) First standard error calculated under homoscedasticity. Second standard error calculated with arbitrary heteroscedasticity. (2) Equations also include age, age-squared, schooling, schooling-squared, age × schooling, race, South1, current and lagged SMSA, and a constant.

Acknowledgement. This work owes a great deal to advice and instruction from Gary Chamberlain, Glen Cain, and Arthur Goldberger. I have also benefited from comments from Richard Blundell and David Lillien, and from participants at workshops at Cornell University, Princeton University, SUNY-Binghamton, and the University of Western Ontario. Special thanks to John Ham for extensive comments on earlier drafts. The comments of Charles Bean and three anonymous referees have greatly improved the paper. I retain sole responsibility for any errors which remain. This work was partially funded by SSRC Grant SS-55-82-07 and by NSF Grant SES-8016383.

REFERENCES

BALESTRA, P. and NERLOVE, M. (1966), "Pooling Cross Section and Time Series Data in the Estimation of a Dynamic Model: The Demand for Natural Gas", *Econometrica*, **34**, 585-612.

BASMANN, R. (1965), "On the Applicability of the Identifiability Test Statistic and its Exact Finite Sample Distribution Function in Predictive Testing of Explanatory Economic Models" (mimeo).

BENTLER, P. M. (1983), "Simultaneous Equation Systems as Moment Structure Models", *Journal of Econometrics*, **22**, 13-42.

BROWN, C. (1980), "Equalizing Differences in the Labor Market", *Quarterly Journal of Economics*, **94**, 113-134.

CHAMBERLAIN, G. (1982), "Multivariate Regression Models for Panel Data", *Journal of Econometrics*, **18**, 1982, 5-46.

CHAMBERLAIN, G. (1984), "Panel Data", in Griliches, Z. and Intriligator, M. (eds.), *Handbook of Econometrics, Vol 2* (Amsterdam: North-Holland), 1247-1318.

CHOWDHURY, G. and NICKELL, S. (1985), "Individual Earnings in the US: Another Look at Unionization, Schooling, Sickness, and Unemployment Using Panel Data", *Journal of Labor Economics*, **3**, 38-69.

FLINN, C. J. (1982), "Wages and Labor Mobility of Young Workers" (University of Wisconsin Social Systems Research Institute Workshop Series No. 8231).

FREEMAN, R. B. (1984), "Longitudinal Analysis of the Effects of Trade Unions", *Journal of Labor Economics* **2**, 1-26.

HANSEN, L. P. (1982), "Large Sample Properties of Generalized Method of Moments Estimators", *Econometrica*, **50**, 1029-1054.

HAUSMAN, J. (1978), "Specification Tests in Econometrics", *Econometrica*, **46**, 1251-1272.

HAUSMAN, J. and TAYLOR, W. (1981), "Panel Data and Unobservable Individual Effects", *Econometrica*, **49**, 1377-1398.

HECKMAN, J. J. (1979), "Sample Selection Bias as a Specification Error", *Econometrica*, **47**, 153-161.

JAKUBSON, G. (1983) *Unobserved Heterogeneity in Labor Economics: Applications of Panel Data Techniques* (unpublished Ph.D. dissertation, University of Wisconsin).

JAKUBSON, G. (1986) "The Effects of Measurement Error in Binary Explanatory Variables in Panel Data Models: Why Do Cross Section and Panel Estimates of the Union Wage Effect Differ?" (Princeton University, Industrial Relations Section Working Paper No. 209).

JOVANOVIC, B. (1979), "Job Matching and the Theory of Turnover", *Journal of Political Economy*, **87**, 972-990.

LEWIS, H. G. (1986) *Union Relative Wage Effects: A Survey* (Chicago: University of Chicago Press).

MADDALA, G. S. (1971), "The Use of Variance-Components Models in Pooling Cross-Section and Time-Series Data", *Econometrica*, **39**, 341-358.

MELLOW, W. (1981), "Unionism and Wage Rates: A Longitudinal Analysis", *Review of Economics and Statistics*, **63**, 43-52.

MINCER, J. (1974) *Schooling Experience, and Earnings* (New York: National Bureau of Economic Research).

MINCER, J. (1983), "Union Effects: wages, Turnover, and Job Training", in Ehrenberg, R. (ed.), *Research in Labor Economics, Supplement 2*.

PARSLEY, C. J. (1980), "Labor Unions and Wages: A Survey", *Journal of Economic Literature*, **18**, 1-31.

PENCAVEL, J. (1981), "Review of 'Labor Unions and the Inequality of Earned Income'", *Journal of Economic Literature*, **19**, 1636-7.

PETTENGILL, J. (1980) *Labor Unions and the Inequality of Earned Income* (Amsterdam: North Holland).

WHITE, H. (1982), "Maximum Likelihood Estimation of Misspecified Models", *Econometrica*, **50**, 1-25.