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WHY ARE WAGES CYCLICAL IN THE 1970S?

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ABSTRACT

This paper investigates cyclicality in real wages between 1969 and 1982, using 14 years of data from the Panel Survey of Income Dynamics. First, it investigates the extent to which movements in and out of the labor market created apparent wage cyclicality. Second, it investigates whether cyclical movements of workers between heterogeneous wage sectors within the labor market created cyclicality. Little evidence of the first effect is found. The second effect is much more important, and cyclicality clearly occurs in the movement of workers between different labor market sectors. However, sector selection is not correlated with wage determination. Thus, individual wage change estimates of cyclicality need to control for sector location, but need not account for sector selection. The third conclusion of the paper is that cyclicality is present in real wages even within sectors over this time period, and is the result of both cyclicality in overall wage levels (cyclicality in the constant term in wage equations), as well as in the coefficients associated with particular worker characteristics.

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I. INTRODUCTION

The relationship between the business cycle and wages has been a much discussed topic. Keynes suggested that real wages should be countercyclical, since decreases in the real wage should induce increases in employment. However, early empirical evidence found that aggregate wages moved procyclically (Dunlop [1938]). More recent empirical work utilized time series analysis to suggest that aggregate real wages since the 1940s show little evidence of any cyclicality (Neftci [1978], Sargent [1978], Altonji and Ashenfelter [1980] or Geary and Kennan [1982]). However, the latest studies have indicated that, at least in the decade of the 1970s, aggregate wages showed a clear procyclical pattern (Bils [1985], Blank [1985], Coleman [1984], or Raisian [1983].) These later studies typically use broader wage definitions[1], which somewhat accounts for their divergent results. However, Coleman repeats several earlier studies on equivalent data from the 1970s and finds evidence of procyclical wage movements. These more recent studies also make a point of using micro data. They uniformly conclude that cyclical effects are apparent in the micro data as well as in the aggregate wage data.

Given that predictions regarding wage cyclicality emerge from a wide variety of economic models, it is important to understand the nature of the apparent wage cyclicality that has been observed in recent years. This paper further investigates cyclicality in real wages between 1969 and 1982, focussing on two issues. First, changes in the composition of the labor force over the cycle can create cyclical wage changes. This paper investigates cyclical changes in worker selection in and out of the labor market as well as in movements between heterogeneous labor market sectors. As we shall see below, if such selection issues are not explicitly addressed empirically, then even micro data estimates of wage changes may exhibit spurious wage cyclicality. While I find little evidence of significant selection in and out of the labor market (at least among white men), there is clear evidence that aggregate wage estimates are affected by cyclical worker movements between heterogeneous sectors; but because there is little correlation between sectoral choice and wage determination, micro data estimates are not affected by these movements.

Second, once compositional labor market changes are accounted for, there are two ways by which individual wage changes may be associated with changes in macroeconomic activity. There may be a direct relationship to overall wage levels, manifest by cyclicality in the constant of the wage equation over time, which can be measured by including a cyclical variable in a wage change equation. This is the approach taken by all existing research. Alternatively, this paper also explores the possibility that there may be cyclical changes in the entire wage/skill relationship (cyclicality in the coefficients determining the return to individual skill characteristics.) This paper finds significant evidence that both types of cyclicality have occured in recent years.

II. MODELLING THE CYCLICALITY IN AGGREGATE WAGES IN A HOMOGENEOUS LABOR MARKET

The basic labor market model used in this paper is the classic human capital wage equation for individual i in year t,

$$(1) \qquad w_{it} = \ln(W_{it}) = \tau_o + X_{it}\tau + u_{it} + \varepsilon_{it},$$

where W represents the wage rate, X is a vector of individual characteristics which affect productivity and hence determine wages, τ is a vector of related coefficients, which represents the weights these characteristics are given in the wage determination process, u is the cyclical effect on individual i's wage, and ε is a random error term. The X's often include additional variables which are institutionally important in the labor market, although they may or may not have direct productivity impacts (such as union status or region.)[2] Define the cyclical effect as

$$u_{it} = f(X_{it})u_t, \quad \text{where} \quad f(X_{it}) = \delta_o + X_{it}\delta.$$

u_t is the pure cyclical effect, while $f(X_{it})$ is the effect associated with the characteristics vector X. (1) can be rewritten as

$$(2) \qquad w_{it} = (\tau_o + \delta_o u_t) + X_{it}(\tau + \delta u_t) + \varepsilon_{it}$$
$$= \beta_{ot} + X_{it}\beta_t + \varepsilon_{it}.$$

If wages are determined homogeneously throughout the labor market, differing only across the variables included in the vector X, then equation (2) represents the wage determination process for any individual i.

Let w_t represent the mean wage in period t, calculated from among all labor force participants, with X_t being the vector of mean characteristics for these workers. The change in aggregate wages between periods is

$$(3) \quad (w_{t+1} - w_t) = (\beta_{ot+1} - \beta_{ot}) + (X_{t+1}\beta_{t+1} - X_t\beta_t)$$
$$= (\beta_{ot+1} - \beta_{ot}) + X_t(\beta_{t+1} - \beta_t) + (X_{t+1} - X_t)\beta_{t+1}$$

The three terms on the right hand side of equation (3) decompose the change in aggregate mean wages into three parts: a homogeneous time-varying effect which occurs for all demographic groups; changes in the wage coefficients which differ across demographic groups; and aggregation effects, resulting from changes in the means of the X's.

The third term will be nonzero when there is selectivity in the workers who move in and out of the labor force over the cycle. For instance, assume period t represents a recession period and period t+1 a boom period. If additional workers are attracted into the labor market in boom periods who have lower average skills than the mean worker in a recession period, then this implies that $X_{t+1} \leq X_t$ for all elements of the vector X.[3] In this case, the third term on the right hand side of (3) is clearly negative, and is a measure of the aggregation bias. If the ß's are procyclical ($\beta_{t+1} > \beta_t$), then measured cyclicality in aggregate wages will understate the true cyclicality in individual wages. In fact, depending on the relative size of these three terms, it is possible that aggregate wages could even appear to be countercyclical.

That research which investigates cyclicality in aggregate wage data obviously suffers from an inability to separate aggregation bias effects from true cyclical effects.

In contrast, the micro data research cited above typically estimates individual wage change equations, including changes in the unemployment rate as one of the independent variables. The sign and significance on the change in unemployment is taken as a measure of the cyclicality imbedded in wages. Note that there are two problems with this approach. First, these equations can typically be estimated only from data on those persons who are stably employed over several time periods. As Moffitt, Keane and Runkle [1987] note, focusing only on workers who do not leave the labor market does not guarantee unbiased estimates of wage cyclicality. Assume we can characterize the decision to participate in the labor market as

(4) $P^{*}_{it} = Z_{it}\pi_t + u_{it}$,

where P^* is a measure of the utility comparison between labor market participation and nonparticipation for individual i, Z is a vector of individual characteristics, π is a related coefficient vector, and u is a random error term. If the error term in (2) is correlated with u, the error in (4), then estimating (2) (or some transformation of it such as individual wage changes) will result in biased estimates of the ß's.[4] Thus, in order to accurately estimate the true ß's (and their underlying cyclicality), one must empirically account for labor market participation choices made by workers.

Second, the inclusion of a simple change in unemployment rates in an individual wage change equation essentially measures only the cyclicality in the first term of equation (3) (by parameterizing it as a change in unemployment rates), and ignores the second term, which allows for changes over time in the determinants of wages. There are good theoretical reasons to expect that macroeconomic cycles will have different impacts on workers with different labor market characteristics. In a world where both capital and labor are completely replicable in the short run and where there are no economies or diseconomies of scale in the production process, wage determination should remain unaffected by levels of production. If demand doubles, the firm can immediately duplicate its production process and double its output with no change in the nature of production. However, if these conditions are not met, then the nature of the production process itself will change as activity levels vary. This can readily affect the value of worker skills to the firm, changing the wage/skill relationship which human capital models describe.

If capital is not immediately replicable in the short run, any attempt to increase production in response to rising demand will require more intensive utilization of existing capital. Multiple shifts or speeded-up production lines are common in times of high economic growth. These changes might increase the value of coordinational activities within the firm, thus increasing the value of formal training and/or management experience. For workers on the production line, if the increase in production is accomplished by a greater division of labor, job de-skilling could occur as workers are given more limited tasks. Formal training, or job experience could become less important to the firm. Alternatively, if equivalent additional labor is not available to the firm, the value of experience and training could increase, as attempts are made to increase the productivity level of the existing work force.

Realize that this analysis assumes that wages reflect the current productive value of the worker to the firm. A variety of institutional arrangements might prevent changes in the value of the worker to the firm from being translated into immediate wage changes. The effect of worker/firm wage contracts -- both explicit and implicit -- has been much explored in the literature. There may clearly exist incentives for both workers and firms to provide "wage smoothing" of some nature, breaking the link between point-in-

-time wages and the marginal product of the worker. In this case, wage levels and their determinants will vary less over the cycle, although in many models the decrease in wage variation over the cycle is offset by an increase in employment variability. Thus, the greater the extent of wage smoothing in the labor market, the more one would expect to find aggregate wages affected primarily by changes in labor market participation and composition.[5]

However, if wage smoothing is not complete, or if it is not available in certain sectors of the labor market, one might find changes over the cycle in the estimated coefficients of the entire wage equation. This effect can be modelled by allowing the vector ß to vary over time.

III. EMPIRICAL EVIDENCE ON WAGE CYCLICALITY IN A HOMOGENEOUS LABOR MARKET

This section will present evidence on the components of aggregate wage cyclicality. I will also provide evidence on the extent to which accounting for labor market participation decisions changes estimates of wage cyclicality. Throughout this section, I assume that a single wage equation adequately characterizes the entire labor market, an assumption which will be dropped in the next section when I investigate the effect of sectoral heterogeneity on wage cyclicality.

SOME COMMENTS ON DATA

This study uses the Panel Survey of Income Dynamics (PSID) from the 14 years 1969 through 1982. In this initial set of results I do not make use of the longitudinal nature of this data set, but use it as a series of consecutive cross sections. While it might at first appear desirable to estimate cyclicality from individual wage change equations, this creates potential problems. I am interested in describing the sources of recent aggregate wage cyclicality. As noted above, individual wage change equations necessarily focus only on those individuals who remain in the labor market for several consecutive years. For persons who enter or leave the labor market, or who are unemployed for long periods of time, continuous wage observations are not available. Omitting these people from the sample may eliminate the most likely sources of aggregate cyclicality. Similarly, as we shall discuss below, workers who switch jobs between heterogeneous sectors may experience changes in their whole wage determination process, a difficult process to model at the individual level if there are different wage/skill regimes in different sectors. As a result of these problems, I take a different approach in the estimates below, which provides consistent estimation of the effects I seek to explore, but which may not always be fully efficient since it ignores some of the cross-time information available on those individuals who remain in the labor market for multiple periods.

I initially treat the PSID as a series of 14 sequential cross-sections. I utilize the data for all male household heads in each designated year between the ages of 20 and 65 who report labor market earnings. I use the entire PSID sample to create these yearly data sets, which is composed of a random sample and a low-income sample. (I make separate estimates for black and white men; without using the low-income sample, I would not have enough observations on black men to be able to investigate them separately.) As a result, sample weights must be used to weight my sample back to a random sample. These are provided within the PSID. All numbers and estimates reported here are based on weighted data. These weights change over time as the demographics of the PSID sample and the demographics of the country change.[6]

Wages are defined as average hourly earnings, calculated by dividing total labor market income over the year by total hours of work. As a result, they include overtime and second-job income.[7] All wage data is transformed to 1981 dollars. Note that by using a measure of wages based on annual earnings, I thus include in my sample of employed workers any individuals who had some labor income over the year. This should decrease the effect of changes in labor market participation on labor force composition.[8]

EMPIRICAL RESULTS

Using the 14 cross-sections described above, I estimate 14 separate OLS wage equations for white men and for black men. Columns 1 and 2 of Table 1 describe the data used in these estimations. At the top of Table 1 is summary information on the dependent variable, average hourly earnings. Row 1 shows the mean wage in 1981 dollars during these 14 years, calculated as the average of the 14 mean wage variables from each sample. For white men, the average wage level is \$10.70, with a mean annual change of \$.04/year.[9] To estimate aggregate wage cyclicality, I use the mean wage rates from each of the 14 years to estimate the 13-observation regression

(5) $\quad \text{Wage}_t - \text{Wage}_{t-1} = \alpha_o + \alpha_1((\text{GNP}_t - \text{GNP}_{t-1})/\text{GNP}_{t-1}) + \mu_t$

The coefficient α_1 indicates the change in wage rates induced by a 1% increase in GNP.[10] For both white and black men, significant evidence of cyclicality in aggregate wages is apparent: A 1% increase in GNP increases white men's wages by slightly more than \$.04/hour, and increases black men's wages by almost \$.06/hour.

The variables which compose the X vector in the estimated wage equations are also described in Table 1. For each variable, I indicate their mean level across all individuals and all years. I also estimate cyclicality in these means over the 14 years of data by running a regression similar to (5). Thus, for education, this is the regression

(6) $\quad \text{Educ}_t - \text{Educ}_{t-1} = \alpha_o + \alpha_1((\text{GNP}_t - \text{GNP}_{t-1})/\text{GNP}_{t-1}) + \mu_t.$

The resulting α_1 coefficients are reported below the means for each variable.

Within this aggregate data there is no evidence of cyclicality in any of the means of these variables, for either white or black men. Thus, there is little support for the hypothesis that much of the cyclicality in aggregate wages can be explained by workers with different skill characteristics moving in and out of the labor market. The results in Table 1 indicate that changes in mean worker characteristics show virtually no cyclicality over time.[11]

The coefficients resulting from the 14 OLS wage equations are presented in columns 1 and 2 of Table 2.[12] I have 14 estimates of each coefficient. The mean of these 14 estimates is presented first, followed by the mean of their standard errors. I also report the standard deviation of the coefficients over the 14 years, which provides a comparison of the average variation in the estimates across the years to the average within-year standard errors. There is clearly some significant variation in the coefficient estimates over the years -- the cross-year standard deviation is typically higher than the mean within-year standard error for all the coefficients.

The cyclical patterns in these coefficients are estimated by regressing the change in these coefficients against the percent change in GNP, similar to equations (5) and (6) above.[13] The estimated relationship between percent growth in GNP and the change in the coefficients over time is shown in the fourth row for each variable. The earlier discussion noted both the possibility of overall shifts in the wage level (cyclicality in the constant) as well as cyclicality in the other wage determinants. The results in Table 2 demonstrate both effects. While there is evidence of procyclicality in the constant for white men (a homogeneous upward shift in wage levels as the economy expands), there is also evidence that an increase in macroeconomic activity increases the effect of age and age squared (a proxy for experience) in determining wages. The coefficients on education and union status show little evidence of cyclicality. For black men only the education coefficient shows mildly procyclical effects.

The implication of these results is that most of the cyclicality in aggregate wages appears to be explained by shifts in the constant and the coefficients of the wage equation, with little effect of aggregation bias due to changes in the characteristics of workers over the cycle. To further test this proposition, I estimate a set of wage equations for each year with an additional term included to adjust for selectivity in and out of the labor force. This is a standard econometric technique, first developed by Heckman [1974]. Briefly, a probit equation (as specified in (4)), representing the probability of labor market participation is initially estimated using all data, from both workers and nonworkers. The results of this probit are used to calculate a selection correctivity term, λ_t, which is included in the wage equation, and corrects the error term for any correlation between the probability of participation and the wage level.[14] The means of the 14 coefficients which result from the selectivity-corrected wage estimates, and their mean standard errors, as well as the standard errors of the coefficients over the 14 years are given in columns 3 and 4 of Table 2. It is clear that the none of the coefficients for either white or black men change in any significant way as a result of this selectivity correction. The reason for this is apparent at the bottom of Table 2, where the coefficients on the selectivity terms are presented. In only two of the 14 regressions for white men is this coefficient significant. It is also clear that there is no significant cyclicality in the coefficient. Thus, for white males, there is no evidence in this data that cyclical movements in and out of the labor market affect aggregate wage cyclicality. This picture is slightly less clear for black men. In 6 of the 14 regressions, there is significance on the selectivity term. (The mean coefficient and mean standard error indicate insignificance, but the variance in the coefficients over the years is large.) This indicates that there is some effect on wages due to the selectivity of who moves in and out of the labor market among black men. However, the regression coefficient relating changes in GNP to changes in the estimated selectivity coefficients indicates that there is no cyclicality in these coefficients.

I am not the first to research this issue. Moffitt, Keane and Runkle [1987] investigate the effects of selectivity into the labor market, using several relatively complex models of individual wage changes, corrected for selectivity bias. In contrast to my results, they do find this correction makes a difference -- in fact, worker movements in and out of the labor market appear to increase the procyclicality in aggregate wage measures. There are at least two reasons why these results differ from mine. First, they use a different data set, with observations only on young men, a group which may be more prone to labor force participation changes. Second, they have point-in-time estimates of wages and labor market participation, rather than the annualized measure available in my data set.[15] As noted above, one would expect greater compositional changes with higher-frequency data. However, even after these selectivity effects are accounted for, they find evidence of further wage cyclicality, similar to the results presented here.

The conclusion is that there are no clear cyclical shifts in worker characteristics over time in this data, and thus little evidence of aggregation bias due to changes in the skill levels of labor market participants. Given no evidence of correlation between labor force participation and wages, especially for white men, micro data estimating procedures which ignore this issue should provide consistent estimates of wage cyclicality.

IV. HETEROGENEITY IN THE WAGE/SKILL RELATIONSHIP BETWEEN SECTORS

Although there is little evidence of aggregation bias in this data induced by labor market participation changes, there is another way in which labor market composition may change over the cycle. Until now I have assumed that the relationship between wages and worker skills is the same for all workers at a point in time. However, if wage determination is heterogeneous across different sectors of the labor market, and if workers move between these sectors in a cyclical manner, then apparent cyclicality in the determinants of wages may be due to changes in sectoral composition. To see this, assume that the labor market is composed of two types of jobs, each of which utilize worker skills differently. Call these manufacturing and non-manufacturing jobs. For any worker i in a manufacturing job in time t, the wage/skill relationship is

(7) $$w_{mit} = X_{mit}\beta_{mt} + \varepsilon_{mit},$$

while for any nonmanufacturing worker j the relationship is

(8) $$w_{njt} = X_{njt}\beta_{nt} + \varepsilon_{njt}.$$

Because of the difference in the nature of the jobs, one expects that mean worker characteristics will vary between these sectors as workers choose the sector which best repays their set of skills. What happens if this heterogeneity is ignored, and one estimates a single wage equation across all workers, calculating a single β_t? It can be shown that the resulting estimate of β_t from the combined sample is

(9) $$\beta_t = \theta_{mt}\beta_{mt} + \theta_{nt}\beta_{nt}$$

where $\theta_{mt} = (X_{mt}'X_{mt})/(X_{mt}'X_{mt} + X_{nt}'X_{nt})$

and $\theta_{nt} = (X_{nt}'X_{nt})/(X_{mt}'X_{mt} + X_{nt}'X_{nt})$

and X_{jt} represents the mean vector of characteristics in sector j at time t. That is, the β_t estimated from the combined sample is a weighted combination of the underlying "true" coefficients, where the weights are determined by the variance of the respective X's. In a similar manner,

(10) $$\beta_{t+1} = \theta_{mt+1}\beta_{mt+1} + \theta_{nt+1}\beta_{nt+1}.$$

Let $\delta_{mt} = n_{mt}/(n_{mt} + n_{nt})$ and $\delta_{nt} = n_{nt}/(n_{mt} + n_{nt}) = 1 - \delta_{mt}$ while $\delta_{mt+1} = n_{mt+1}/(n_{mt+1} + n_{nt+1})$ and $\delta_{nt+1} = 1 - \delta_{mt+1}$. The change in aggregate wages is now

(11) $$\begin{aligned}(w_{t+1} - w_t) &= (X_{t+1}\beta_{t+1} - X_t\beta_t) \\ &= (\delta_{mt+1}X_{mt+1} + \delta_{nt+1}X_{nt+1})(\theta_{mt+1}\beta_{mt+1} + \theta_{nt+1}\beta_{nt+1}) \\ &\quad - (\delta_{mt}X_{mt} + \delta_{nt}X_{nt})(\theta_{mt}\beta_{mt} + \theta_{nt}\beta_{nt}).\end{aligned}$$ [16]

In this situation changes in the aggregate ß's can no longer be interpreted as "pure" cyclical effects. β_{t+1} and β_t have become implicated in the aggregation bias. Part of their observed cyclicality may be due to cyclical changes in β_m and β_n, but part may also be due to cyclical changes in the weights, θ_m and θ_n. In fact, in the absence of any cyclicality in the underlying coefficients ($\beta_{mt} = \beta_{mt+1}$ and $\beta_{nt} = \beta_{nt+1}$), there may still be cyclicality in the aggregate coefficients, β_t and β_{t+1}, as θ_m and θ_n change over time. The primary implication of this section is that if there is heterogeneity in the wage/skill determination process across sectors and if the mix of workers between sectors changes over the cycle, it will be almost impossible to separate out the effects of aggregation bias from the effects of true cyclicality, unless one can clearly identify and estimate separate wage functions for each heterogeneous group. Even micro data studies which estimate individual wage change equations may be affected by this problem. If job shifts between sectors are not explicitly accounted for in the estimation, then cyclical variables (such as the unemployment rate) may pick up the effects of these omitted variables, reflecting cyclical shifts between wage regimes on the part of individual workers, rather than actual cyclicality in wage rates.

IV. EMPIRICAL EVIDENCE ON LABOR MARKET HETEROGENEITY AND CYCLICALITY

As an initial exploration of the possibility of sectoral heterogeneity in the labor market, I estimate OLS wage equations for three different categories of workers from each successive cross-section of workers. Because of my concern regarding aggregation of workers whose wage/skill relationship may vary I separate all professional, managerial, and administrative employees (hereafter referred to as PMA workers) and estimate a wage equation for them. With the remaining non-PMA workers, I create two groups, one composed of all workers in manufacturing industries, and the other composed of non-manufacturing employees.[17] Separate wage regressions provide 14 annual observations on each coefficient for each group. The means of the data (over all individuals and all years) in each of the groups are shown in Table 1, columns 3 through 5 for white men and columns 6 through 8 for black men.

As Table 1 indicates, PMA workers have much higher average hourly earnings, than do other workers, but there is no sign of cyclicality in their wages. However, both manufacturing and non-manufacturing wages show significant cyclicality among both white and black men. Although there is no cyclicality in their aggregate wages, PMA workers appear to have procyclical education levels and mild countercyclicality in unionization rates (which are low among these workers). Manufacturing workers show evidence of procyclicality in education levels, and non-manufacturing workers show evidence of procyclicality in age and age squared. Given previous evidence that significant shifts in and out of the labor force do not occur, these results are consistent with a story in which the manufacturing sector in boom times attracts and/or keeps workers with more education than the typical manufacturing worker, but less education than the average PMA worker, raising educational levels in both sectors. From the nonmanufacturing sector, manufacturing attracts and/or keeps workers who match the average age in that sector, but who in low-growth times move into the nonmanufacturing sector, lowering average age in that sector. Thus, while the aggregate measures of worker characteristics in columns 1 and 2 indicated little shift over time, disaggregation into sectors indicates that workers appear to be moving between sectors over the cycle in such a way that the characteristics of the mean worker in each sector changes with macroeconomic activity.

The coefficients from the wage regressions for each of these three groups are presented in Table 3. Table 3 is essentially the sector-specific analogue of Table 2, which estimated a single wage equation for all workers. As Table 3 indicates, there are significant differences in the wage/skill determination process among workers in each of these three labor market groups.[18] For instance, the return to education among black PMA workers is very high (perhaps indicating a scarcity of educated black men.) The return to experience (here proxied by age[19]) is highest in manufacturing for blacks and in PMA jobs for whites. Unionization clearly has the strongest impact on nonmanufacturing wages for both black and white workers.

Table 3 also investigates the cyclical pattern in these coefficients. Among white men, the coefficient on education shows procyclical effects (greater returns to education in boom times) in manufacturing. In nonmanufacturing, returns to age are procyclical and the union coefficient is countercyclical. Surprisingly, the constant is significantly countercyclical for both manufacturing and nonmanufacturing workers among whites. Thus, although aggregate wage patterns are procyclical, there is a countercyclical homogeneous effect on wages in these two sectors, which is then offset by other cyclical effects. Among black men, there is less evidence of cyclicality on these coefficients. In short, compared to Table 2, when wages are estimated separately by sector, many new cyclical patterns in the coefficients emerge.

The differences in wage coefficient estimates between the three labor market groups, the cyclicality in the means of worker characteristics within the manufacturing and non-manufacturing sectors, and the differences in the cyclical patterns of wage determinants between Tables 2 and 3 indicates there are changes in the sectoral composition of the labor force over the cycle. If wages are correlated with sectoral choice, estimating wage equations without accounting for the sectoral choice process may result in biased coefficient estimates, and apparent cyclicality in wage determinants may merely reflect cyclicality in sectoral movements as discussed above.

Of the studies cited earlier which present evidence of wage cyclicality over the 1970s, few deal with the problem of heterogeneous wage determination between sectors. Bils explicitly considers the role of job switches in wage changes and concludes that virtually all of the cyclicality in his estimates is coming from individuals who change jobs between time periods. Moffitt, Keane and Runkle estimate a limited selection model among manufacturing workers and find evidence of selectivity effects. To fully explore this issue, I implement a joint estimation procedure of a three-way sectoral choice model and three simultaneous sectoral wage equations.[20]

Assume that workers choose between three labor market possibilities: employment as a PMA worker, or work in the manufacturing or nonmanufacturing sector. Designate these three labor market groups as P, M, and N. Observing a worker in sector P is equivalent to knowing that sector P is preferred to M and that P is preferred to N. If wage levels are correlated with sectoral choice, then one wants to estimate wages for PMA workers jointly accounting for the two sectoral preferences they have demonstrated.

Let the utility gained by a worker in sector j be denoted U_j. Then preferences among three sectors can be completely characterized by three equations (it is assumed that these equations are for individual i at time t):

(12) $U^*_{PN} = U_P - U_N = Z\delta_1 + \mu_1$ (determines the selection of P over N);

(13) $U^*_{MN} = U_M - U_N = Z\delta_2 + \mu_2$ (determines the selection of M over N);

(14) $U^*_{PM} = U_P - U_M = Z\delta_3 + \mu_3$ (determines the selection of P over M).

Note that the third preference equation is completely determined by the first two. In other words, $U^*_{PM} = U^*_{PN} - U^*_{MN}$.[21] While we clearly do not observe the value of U^* in any situation, we do observe whether or not a particular sector has been chosen. Thus, choice of the sector P is assumed to imply that $U^*_{PN} > 0$ and $U^*_{PM} > 0$. Choice of sector M implies that $U^*_{MN} > 0$ and $U^*_{PM} \leq 0$. Choice of sector N implies that $U^*_{MN} \leq 0$ and $U^*_{PN} \leq 0$.

Because wage determination is assumed to differ between these labor market groups, there are three possible wage regimes an individual can enter:

(15) $W_P = X\beta_P + \varepsilon_P$

(16) $W_M = X\beta_M + \varepsilon_M$

(17) $W_N = X\beta_N + \varepsilon_N$.

If there is a correlation between sector selection and wage levels, then estimating equations (15) - (17) alone will produce biased estimates of the β coefficients, since the expected value of the ε's will be correlated with the μ's and hence will not equal zero. To correct for this intercorrelation, one must estimate the wage equations jointly with the sector selection equations.

For any individual i, the likelihood that he or she is observed in sector P earning W_{Pi}, can be written as

(18) $\Pr(\varepsilon_P = (W_{Pi} - X_i\beta_P)/\sigma_P \ , \ \mu_{1i} > -Z_i\delta_1, \ \mu_{3i} > -Z_i\delta_3 \ ).$

The likelihood of earning a wage in sector M is

(19) $\Pr(\varepsilon_M = (W_{Mi} - X_i\beta_M)/\sigma_M \ , \ \mu_{2i} > -Z_i\delta_2, \ \mu_{3i} \leq -Z_i\delta_3 \ ),$

while the likelihood of earning a wage in sector N is

(20) $\Pr(\varepsilon_N = (W_{Ni} - X_i\beta_N)/\sigma_N \ , \ \mu_{1i} \leq -Z_i\delta_1, \ \mu_{2i} \leq -Z_i\delta_2 \ ).$

Assuming that the ε's and μ's are jointly normally distributed, Appendix 1 provides the statistical details as to how these 3-element probability functions can be written in terms of univariate and bivariate conditional normal functions. Estimation of the resulting likelihood function across all individuals (equation A9 in Appendix 1) will provide estimates of the three vectors of wage coefficients (β_P, β_M, and β_N), the standard errors of these three wage equations (σ_P, σ_M, and σ_N), two vectors of sectoral choice coefficients (δ_1 and δ_2, from which δ_3 can be derived), and 5 correlation coefficients (Γ_{12}, the correlation between μ_1 and μ_2; $\Gamma_{1\varepsilon P}$, the correlation between μ_1 and ε_P; $\Gamma_{1}\varepsilon_N$, the correlation between μ_1 and ε_N; $\Gamma_{2\varepsilon M}$, the correlation between μ_2 and ε_M; and $\Gamma_{2\varepsilon N}$, the correlation between μ_2 and ε_N; from these $\Gamma_{3\varepsilon P}$ and $\Gamma_{3\varepsilon M}$ can be derived; $\Gamma_{1\varepsilon M} = \Gamma_{2\varepsilon P} = \Gamma_{3\varepsilon N} = 0$.) Significant parameter estimates of these correlation coefficients would indicate that the sectoral choice and sectoral wage equations are correlated and must be jointly estimated to produce unbiased estimates of the ß's.

The results of estimating this joint sectoral choice/wage model for white men on each of the 14 years are presented in Table 4. As before, I show the mean of the 14 estimated coeffients and their standard errors, as well as the standard deviation of the coefficients over the 14 years, and the regression coefficient that correlates changes in these coefficients to changes to GNP. The coefficients on the sectoral choice equations are consistent with what one might expect. Less educated and older men are more likely to be manufacturing workers than nonmanufacturing workers, and are also more likely to be non-manufacturing than PMA workers. Manufacturing jobs are less likely to be located in the south or the west.

There is little evidence of cyclicality in the determinants of choice between the PMA and manufacturing sectors. However, countercyclicality in both age coefficients in the choice of manufacturing over nonmanufacturing implies that more young workers move into or remain employed in manufacturing in boom times. Procyclicality in the constant in the choice manufacturing over nonmanufacturing and countercyclicality in the constant of PMA over manufacturing implies that the manufacturing sector draws workers away from both other sectors in boom times.

Comparing the wage coefficients in Table 4, with joint wage/sectoral choice estimation, to those in Table 3, where each sector's wage is independently estimated, there are few differences. Not only are estimated values similar, but so are the patterns of cyclicality. In nonmanufacturing, there is cyclicality in the coefficients on age, union status and the constant; in manufacturing there is mild cyclicality on the education coefficient, while PMA workers show little evidence of any cyclical effects.

The reason for this similarity is clear at the bottom of Table 4, where the mean estimates of the correlation coefficients resulting from this joint estimating procedure are presented. These are uniformly small and insignificant, and none of them demonstrate any cyclical effects. (In no equation for any year do any of the estimated correlation coefficients show significance.) This indicates that there is no correlation between the errors in the wage equations and the errors in the sectoral choice equations, which means that sectoral choice, although cyclically affected, need not be accounted for in order to derived unbiased estimates of the wage determinants in each sector. This implies that estimated cyclicality in the wage coefficients in manufacturing and nonmanufacturing shown in Table 3 reflect actual changes in the wage determination process over the cycle in these sectors, and are not contaminated by sector selection.

The results in Table 4 indicate that some sector-specific cyclicality occurs due to movements between sectors (as shown by cyclicality in worker characteristics in manufacturing and nonmanufacturing), while some of it occurs because of actual cyclical changes in the determinants of wages within each sector. To further explore the issue of movement between sectors, I investigate both the nature of cross-sectoral movements over these 14 years, as well as the extent to which wage cyclicality occurs among those who do not change sectors.

Using the longitudinal nature of the PSID, I construct 13 samples, each a two-year matched sample containing two years of information on all male household heads who participated in the labor market for both years. Thus the first sample contains all male heads who work in both 1969 and 1970, while the last sample is composed of all male heads who work in both 1981 and 1982. With these two-year samples I can compare wage changes and labor market movements across each two year period using data from the same individuals.

There are six possible inter-sectoral moves that a worker can make between years. These are listed at the top of Table 5. Using the two-year matched samples I derive 13 observations on the percent of workers who make each type of sectoral move in each two-year period. As Table 5 indicates, the largest flows are clearly in and out of the non-manufacturing sector -- on average 4.9% of all workers move into this sector each year (2.9% from PMA jobs and 2.1% from manufacturing jobs), and 5.6% of all workers leave it for work in another sector. The ratio of intersectoral movers to total workers in each two year period is regressed against the percent change in GNP over these years, and the results are shown in the second row of Table 5. Significant cyclicality is evident, as more workers leave nonmanufacturing and move into manufacturing when the economy expands, while fewer workers move into PMA jobs during an expansion, being more content to stay in manufacturing or in nonmanufacturing.

Yet, while movements between sectors are cyclical, there is little cyclicality in the number of people who remain in each sector over each two year period. The bottom of Table 5 uses the two-year matched samples to look at workers who stay in each sector for both years. On average, 30.2% of all workers stay in PMA jobs, 17.6% stay in manufacturing, while 40% remain in non-manufacturing. There is no cyclicality in these numbers. Although more people leave nonmanufacturing to move into manufacturing during boom times, fewer of them leave to move into PMA work, thus leaving about the same percentage of "stayers" in non-manufacturing. Examination of the other sectors reveals similar offsetting patterns. The cyclical movements between sectors does not change the percent remaining in a given sector.

Average wage changes over each two-year period for movers and stayers are also shown in Table 5. There is clearly a great deal of variation in the wage changes different individual experience as they move between sectors, as evidenced by the large average standard deviations. However, there is no evidence of cyclicality in these wage changes. In contrast, among the stayers in a sector, while PMA workers show no cyclicality in their wage changes across years, both manufacturing and non-manufacturing workers exhibit strong procyclicality in wages. Realize the implication of this result: individual wage changes among workers who remain stably employed within the manufacturing and nonmanufacturing sector show cyclical patterns. Since there can be no issue of aggregation bias or compositional change among these workers, this is perhaps the strongest possible evidence of "real" wage cyclicality over decade.

VI. SUMMARY

Aggregate wages are clearly cyclical during the 14 year period investigated in this study. Little of this cyclicality at the aggregate level appears to be related to selective movements of workers in and out of the labor market; in fact, there is no evidence here that any correlation between labor force participation and wage levels occurs for white men, once education, age and union status are accounted for. However, cyclicality in the determinants of wages is apparent; there is procyclicality in both the constant (a homogeneous shift in wages with business activity) and in the weighting on age, which means that older and more experienced workers have a wage advantage in boom times.

However, these aggregate estimates assume a homogeneous labor market. There is significant evidence that wages are separately determined for at least three groups: professional, managerial and administrative workers, and all other workers in manufacturing and in nonmanufacturing. Significant movement in the work force occurs between these sectors over the cycle. In particular, more workers either move into or stay in manufacturing, or stay in nonmanufacturing. This shift is strongest among younger workers, so that the average age of workers in manufacturing drops in boom times. However, there is no correlation between these sectoral movements and sector-specific wage levels, once a standard set of worker characteristics are accounted for. Thus, micro-data studies of wage changes should control for sector location, but can ignore sector selectivity and still produce unbiased estimates of cyclical effects.

In addition to cyclicality in cross-sector movements among workers with different skill characteristics, there is also cyclicality in wage determinants within sectors over these years. Both manufacturing and nonmanufacturing workers show homogeneous countercyclical changes in wage levels (countercyclicality in the constant.) This is offset by other procyclical effects. Manufacturing workers experience an increase in the coefficient on education over the cycle. Nonmanufacturing workers receive more repayment for experience in boom times, and less repayment to unionization. PMA workers experience no cyclicality in their aggregate wages, and this is reflected in a lack of cyclicality in any of their wage coefficients. This group is thus largely unaffected by business cycles. In short, both cyclical changes in the constant as well as changes in the weighting on skill characteristics occurs over the cycle, so that even workers who remain stably employed within a given sector evince wage cyclicality if they are not in PMA jobs.

The results of this study raise a variety of issues which deserve further investigation. First, given that aggregate wages prior to the 1970s showed little cyclicality, it would be interesting to compare the labor market in the 1970s to an earlier time period and investigate what has changed. Second, the nature and effect of individual job changes has been little studied in the literature. More careful micro-data analysis of this issue would add to our understanding of the sectoral labor market movements noted here. Third, while this paper provides evidence that the wage determination process changes over the cycle, a better understanding of how production and hiring processes actually vary over the cycle, would be useful to provide some causal understanding of the empirical results reported here.

1. Earlier studies looked only at manufacturing wages. More recent work uses aggregate wages from the entire labor market. In addition, wage definitions in these newer studies often include overtime pay, second job income, and other more cyclical components.

2. There are more complex (and probably more realistic) ways of modeling the relationship between wages and worker skills. See, for instance, Heckman and Sedlacek [1985]. Unfortunately, the data we typically have available contains only rather gross measures of worker skills, such as education level, age or experience. It is certainly possible to view the standard wage-estimating equation in (1) as a reduced form of a more complex relationship between worker skills, job requirements and wages. In this case, the τ's still provide a translation of worker skills into wage levels, but a causal interpretation of the process by which τ is determined may be less clear.

3. In this example I assume that it is less skilled workers who leave the labor market during recessions, but this is not clear a priori. More skilled workers may have higher reservation wages, or a higher value of non-market time, and thus may remain out of the labor market longer once unemployed.

4. This is a straightforward conclusion from the sample selectivity literature. See Heckman [1974].

5. See Abowd and Card [1987] for empirical evidence on the extent of wage smoothing.

6. The PSID follows everyone from the original sample and adds in all new individuals who join the households of an existing sample member. Thus, the size of the PSID is steadily increasing over time as new children and spouses appear. Existing PSID individuals also enter my cross-sections as they age and become household heads. The white male sample increases from 1657 to 2641 during these 14 years, and the black male sample increases from 694 to 1297.

7. As others have noted, this type of wage definition can be subject to serious errors. It would be preferable to have actual reported wage rates, but this is not available for all workers within the PSID. To the extent that errors in the average hourly earnings series are not correlated with business activity, this might create noise in my data, but should not bias my results.

8. If labor market participation is selectively chosen during the year, then the coefficient on any annual measure of economic growth will be downward biased. The preferred alternative is a measure of growth derived only during the period the worker is in the labor market. To the extent that I find significant cyclical effects, they are minimum estimates of the true effect.

9. The small real annual change in wages reflects the overall stagnant macro-economy during this time period. However, though real earnings grow very little during these 14 years, there is significant cyclical activity. In 5 of these years GNP growth is negative, in 5 years it exceeds 5%, and in the remaining 4 years it varies between 2.6% and 3.4%.

10. I choose to proxy the business cycle with changes in GNP. This is the variable which is used to officially define cyclical activity in the economy. I have duplicated all results reported here using changes in unemployment rates rather than changes in GNP. In no case do the results differ.

11. As noted above, this is at least partially due to the fact that I am using a measure of average hourly earnings based on annual income and hours. Those excluded from the sample of workers in any given year must be non-labor market participants over the entire year.

12. The wage equation estimated for each year uses ln(wage) as the dependent variable, and includes education, age, age squared, a dummy variable for unionization, and a constant.

13. I could regress individual wage changes against changes in GNP, rather than using just the mean wage change. This would mean using only individuals who are employed in two consecutive years; it would also involve an enormous number of observations over the 14 yeas. This would produce the same estimates as reported here since OLS fits through the means. The standard errors of the two techniques will differ. Under reasonable assumptions, the standard errors reported here are larger than those which would be produced if all the micro-data were utilized jointly. Further problems in the standard errors arise from the fact that the dependent variable itself is an estimate. While I could adjust the variance/covariance matrix for the standard deviations in the estimated ß's for each year, I have no idea how to calculate the covariance between the estimates of ß across the years. (The fact that the estimated regression is in first difference form only increases these problems.) Not adjusting for this should produce smaller standard errors than is accurate. _A priori_ I cannot tell which of these two effects would dominate. I have chosen to report the uncorrected standard errors.

14. This technique is quite common in the empirical literature, thus I do not repeat the econometric specification in great detail. In brief, the selectivity term is calculated as

$$\lambda_t = f(\delta Z_t)/(1 - F(\delta Z_t))$$

where δ is the vector of coefficients estimated from a probit equation on labor market participation. In my estimates, δ includes education, age, age squared, number of dependents, and dummy variables indicating marital status and residence in the northeast, northcentral or southern regions of the country.

15. Although the estimation procedures differ between the two papers, they both should provide consistent estimates of wage cyclicality. Moffitt, Keane and Runkle follow the approach of other papers and measure cyclicality by including a change in the unemployment rate in their individual wage change regressions.

16. Like equation (4), this too can be written in terms of the changes in the ß's and the changes in the X's. However, the mathematical expression is long and not at all revealing.

17. Heckman and Sedlacek as well as Moffitt, Keane and Runkle note differences between the manufacturing and nonmanufacturing sector. I experimented with a variety of different sectoral breakdowns. While the manufacturing distinction was important, it was also clear that white collar workers needed to be differentiated from other workers.

18. One can reject the hypothesis that the three subgroups are similar in their wage equations at the 1% level of significance for both black and white workers in each of the 14 years. (The mean coefficients over the 14 years look more similar than the estimated coefficients in any given year.)

19. Of course, I would much prefer to use a variable which measured actual years of work experience. The PSID provides this only after 1973. Since I need all the time observations I can get, this leaves me with no choice but to use the less accurate "age" variable in place of experience.

20. I report the results of this estimation only for white males for two reasons: First, white men's wages show no evidence of being affected by labor force participation movements, as noted above, so ignoring the participation selectivity issue should not effect these results. (It would be very difficult to estimate a model in which both labor market participation and choice between three sectors occurs simultaneously.) Second, because of the small number of black men in the PSID sample, estimating sectoral choices and separate wage equations for each of the three sectors in a complex econometric model can be difficult. This is particularly a problem for the PMA group of workers; in the early years of the PSID, less than 50 black men are in this group.

21. For a more detailed presentation and an empirical example of the use of this type of a three-way choice model, see Blank [1985].

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Table 1

MEAN LEVELS AND CYCLICAL PATTERNS IN WORKER CHARACTERISTICS - 1969-1982

	All Workers		Sectoral Groups[1]					
			White Men			Black Men		
	White Men	Black Men	PMA	Mfg.	Non-Mfg.	PMA	Mfg.	Non-Mfg.
Dependent Variable: Average Hourly Earnings ($81)								
Mean Level[2]	10.70	8.67	13.72	9.79	8.89	15.14	8.12	7.25
Avg. Annual Change	.04	.09	-.02	.04	-.01	-.10	.08	.06
Cyclical Coefficient[3]	.0412*	.0599*	-.0029	.0566*	.0791*	-.0066	.0507*	.0462*
	(.0220)	(.0272)	(.0413)	(.0198)	(.0267)	(.1413)	(.0235)	(.0236)
Independent Variables: Education (years)								
Mean Level	12.66	10.70	14.67	11.03	11.92	14.06	10.09	10.12
Cyclical Coefficient	-.0001	-.0157	.0143*	.0150*	-.0024	-.0722	-.0224*	-.0143
	(.0023)	(.0133)	(.0103)	(.0096)	(.0058)	(.0731)	(.0164)	(.0188)
Age								
Mean Level	40.16	39.89	40.31	41.08	39.54	41.17	38.51	40.11
Cyclical Coefficient	.0052	.0402	-.0648	-.0150	.0546*	.0902	-.0509	.0933
	(.0250)	(.0615)	(.0519)	(.0441)	(.0245)	(.1716)	(.0888)	(.0865)
Age Squared								
Mean Level	1765.29	1743.43	1754.20	1847.22	1729.25	1817.48	1625.52	1771.79
Cyclical Clefficient	.5651	3.9015	-4.8732	-.7513	4.0088*	6.6278	-3.8002	8.9401
	(2.0530)	(5.1600)	(4.4026)	(3.6048)	(1.8074)	(14.6390)	(6.9582)	(7.2261)
Union (1 = Union Member)								
Mean Level	.250	.297	.107	.496	.240	.106	.418	.268
Cyclical Coefficient	-.0003	.0005	-.0026*	-.0010	-.00001	.0009	.00007	.0001
	(.0010)	(.0013)	(.0016)	(.0027)	(.0014)	(.0060)	(.0017)	(.0018)

*Significant at 10% level.

[1] Sectoral Groups: PMA = All Professional, Managerial and Administrative workers;
Mfg. = All Non-PMA workers in manufacturing industries;
Non-Mfg. = All Non-PMA workers in nonmanufacturing industries.

[2] Represents the mean (over 14 years) of each annual mean variable.

[3] Represents the coefficient α_1 from the 13-observation regression $(X_{t+1} - X_t) = \alpha_0 + \alpha_1((GNP_{t+1} - GNP_t)/GNP_t) + e$, where X_t is the mean in year t.

Table 2

MEAN LEVELS, VARIANCE AND CYCLICAL PATTERNS IN COEFFICIENTS

FROM OLS WAGE REGRESSIONS - 1969-1982

	Simple OLS		OLS with Selectivity Term	
	White Men	Black Men	White Men	Black Men
Education				
Mean Coefficient[1/]	.0689	.0584	.0661	.0606
Mean Std Error[1/]	.0039	.0044	.0038	.0046
Std Dev of Coefficients[2/]	.0063	.0118	.0051	.0155
Cyclical Coefficient[3/]	-.0006	.0018*	-.0005	.0020*
	(.0006)	(.0012)	(.0005)	(.0014)
Age				
Mean Coefficient	.0635	.0638	.0637	.0630
Mean Std Error	.0032	.0035	.0032	.0036
Std Dev of Coefficients	.0081	.0130	.0070	.0143
Cyclical Coefficient	.0008*	-.0013	.0006*	-.0010
	(.0004)	(.0014)	(.0003)	(.0014)
Age Squared				
Mean Coefficient	-.0006	-.0006	-.0006	-.0006
Mean Std Error	.00004	.00005	.00005	.00006
Std Dev of Coefficients	.0001	.0002	.0001	.0002
Cyclical Coefficient	-.00001*	.00002	.000008*	.00001
	(.000005)	(.00002)	(.000003)	(.00002)
Union (1 = Union Member)				
Mean Coefficient	.2667	.3416	.2496	.3322
Mean Std Error	.0295	.0659	.0286	.0653
Std Dev of Coefficients	.0342	.0801	.0315	.0720
Cyclical Coefficient	-.0018	.0038	-.0016	.0027
	(.0022)	(.0094)	(.0022)	(.0086)
Constant				
Mean Coefficient	-.1810	-.2093	-.1569	-.2018
Mean Std Error	.0327	.0403	.0328	.0402
Std Dev of Coefficients	.0681	.0215	.0648	.0287
Cyclical Coefficient	.0154*	.0013	.0116*	-.0005
	(.0099)	(.0027)	(.0087)	(.0040)
Selectivity Correction				
Mean Coefficient	---	---	-.2686	.0290
Mean Std Error			.1528	.1204
Std Dev of Coefficients			.1407	.4640
Cyclical Coefficient			-.0113	.0832
			(.0208)	(.0658)

*Significant at 10% level.

[1/] Represents the mean of 14 coefficient estimates (1969-1983).

[2/] Represents the mean of 14 coefficient standard errors (1969-1983).

[3/] Represents the standard deviation of the coefficients over the 14 years.

[4/] Represents the coefficient α_1 from the 13-observation regression

$(X_{t+1} - X_t) = \alpha_0 + \alpha_1((GNP_{t+1} - GNP_t)/GNP_t) + e$, where X_t is the estimated coefficient in year t .

Table 3

MEAN LEVELS, VARIANCE, AND CYCLICAL PATTERNS IN COEFFICIENTS

FROM SECTORAL OLS WAGE REGRESSIONS[1/] - 1969-1982

	White Men			Black Men		
	PMA	Mfg.	Non-Mfg.	PMA	Mfg.	Non-Mfg.
Education						
Mean Coefficient[2/]	.0517	.0515	.0500	.0688	.0310	.0403
Mean Std Error[2/]	.0073	.0071	.0064	.0169	.0091	.0058
Std Dev of Coefficients[3/]	.0077	.0149	.0105	.0227	.0183	.0196
Cyclical Coefficient[4/]	-.0007	.0022*	-.0006	.0025	.0011	.0028
	(.0008)	(.0014)	(.0016)	(.0027)	(.0030)	(.0024)
Age						
Mean Coefficient	.0767	.0729	.0709	.0641	.0845	.0691
Mean Std Error	.0060	.0052	.0050	.0153	.0067	.0044
Std Dev of Coefficients	.0087	.0142	.0075	.0251	.0140	.0177
Cyclical Coefficient	.0004	-.0002	.0019*	.0005	-.0013	-.0029*
	(.0005)	(.0011)	(.0011)	(.0029)	(.0023)	(.0021)
Age Squared						
Mean Coefficient	-.0007	-.0007	-.0008	-.0006	-.0009	-.0007
Mean Std Error	.0001	.0001	.0001	.0002	.0001	.0001
Std Dev of Coefficients	.0001	.0002	.0001	.0004	.0002	.0003
Cyclical Coefficient	.000006	-.00001	-.00002	-.00003	.00002	.00005*
	(.000007)	(.00001)	(.00002)	(.00005)	(.00003)	(.00003)
Union (1 = Union Member)						
Mean Coefficient	.0531	.1862	.4545	.0436	.3187	.5132
Mean Std Error	.0641	.0408	.0465	.3498	.0808	.0833
Std Dev of Coefficients	.0292	.0595	.0490	.1608	.0710	.1104
Cyclical Coefficient	.0007	.0058	-.0098*	.0049	.0095*	-.0054
	(.0037)	(.0049)	(.0050)	(.0198)	(.0058)	(.0120)
Constant						
Mean Coefficient	-.1231	-.1174	-.1818	-.1029	-.2768	-.1998
Mean Std Error	.0568	.0525	.0490	.1388	.0564	.0478
Std Dev of Coefficients	.0628	.0826	.0718	.0654	.0465	.0469
Cyclical Coefficient	.0040	-.0088*	-.0058*	-.0042	.0003	.0116*
	(.0031)	(.0063)	(.0043)	(.0088)	(.0062)	(.0047)

*Significant at 10% level.

[1/] Sectoral Groups: PMA = All Professional, Managerial and Administrative workers;
Mfg. = All Non-PMA workers in manufacturing industries;
Non-Mfg. = All Non-PMA workers in nonmanufacturing industries.

[2/] Represents the mean of 14 coefficient estimates (1969-83).

[3/] Represents the mean of 14 coefficient standard errors (1969-1983).

[4/] Represents the coefficient α_1 from the 13-observation regression

$(X_{t+1} - X_t) = \alpha_0 + \alpha_1((GNP_{t+1} - GNP_t)/GNP_t) + e$, where X_t is the estimated coefficient in year t .

Table 4

MAXIMUM LIKELIHOOD ESTIMATES FROM JOINT SECTORAL CHOICE/SECTORAL WAGE ESTIMATION[1/]

White Males - 1969-1982

	Sector Selection Equations			Wage Equations		
	Pr(choose PMA over NonMfg.) (1)	Pr(choose Mfg over NonMfg.) (2)	Pr(Choose PMA over NonMfg.)[2/] (3)	PMA (4)	Mfg. (5)	NonMfg. (6)
Education						
Mean Coefficient	.1727	-.0495	.2222	.0505	.0530	.0493
Mean Std Error	.0202	.0256	.0425	.0287	.0143	.0196
Std Dev of Coefficients	.0223	.0092	.0162	.0071	.0124	.0093
Cyclical Coefficient	.0007	.0010	-.0003	-.0006	.0015*	-.0007
	(.0011)	(.0008)	(.0014)	(.0007)	(.0010)	(.0014)
Age						
Mean Coefficient	-.0964	.0262	-.1226	.0774	.0717	.0715
Mean Std Error	.0121	.0162	.0248	.0167	.0080	.0111
Std Dev of Coefficients	.0163	.0117	.0081	.0083	.0012	.0065
Cyclical Coefficient	-.0006	-.0012*	.0006	.0004	-.0001	.0012*
	(.0008)	(.0006)	(.0009)	(.0005)	(.0007)	(.0009)
Age Squared						
Mean Coefficient	.0012	-.0003	.0014	-.0007	-.0007	-.0008
Mean Std Error	.0002	.0002	.0003	.0002	.0001	.0001
Std Dev of Coefficients	.0002	.0002	.0001	.0001	.0002	.0001
Cyclical Coefficient	.00001	.000014*	-.00001	-.0001	-.000002	-.00001
	(.00001)	(.000009)	(.00001)	(.0001)	(.000010)	(.00001)
Region South						
Mean Coefficient	-.1655	-.2090	.0435	---	---	---
Mean Std Error	.0814	.0844	.0878			
Std Dev of Coefficients	.0808	.0326	.0707			
Cyclical Coefficient	.0023	.0004	.0019			
	(.0057)	(.0049)	(.0056)			
Region West						
Mean Coefficient	-.0994	-.3393	.2399	---	---	---
Mean Std Error	.1023	.0928	.1124			
Std Dev of Coefficients	.1150	.0480	.1006			
Cyclical Coefficient	-.0053	.0055	-.0108			
	(.0081)	(.0064)	(.0095)			
Union						
Mean Coefficient	---	---	---	.0524	.1840	.4386
Mean Std Error				.0746	.0440	.0570
Std Dev of Coefficients				.0306	.0550	.0440
Cyclical Coefficient				.0003	.0048	-.0099*
				(.0038)	(.0044)	(.0043)

(continued)

Table 4 - continued

	Sector Selection Equations			Wage Equations		
	Pr(choose PMA over NonMfg.) (1)	Pr(choose Mfg over NonMfg.) (2)	Pr(Choose PMA over NonMfg.)[2/] (3)	PMA (4)	Mfg. (5)	NonMfg. (6)
Constant						
Mean Coefficient	-.5905	-.3084	-.2820	-.1254	-.1072	-.1694
Mean Std Error	.3376	.2979	.1184	.3084	.2075	.1528
Std Dev of Coefficients	.1084	.1007	.1050	.0650	.0665	.0705
Cyclical Coefficient	.0006	.0165*	-.0159*	.0042	-.0046	-.0058*
	(.0116)	(.0099)	(.0087)	(.0035)	(.0050)	(.0034)
Standard Error						
Mean Coefficient	---	---	---	.5321	.4117	.5985
Mean Std Error				.0086	.0094	.0097
Std Dev of Coefficients				.0620	.0438	.0296
Cyclical Coefficient				-.0009	.0010	-.0019
				(.0022)	(.0027)	(.0020)

Correlation Coefficients[3/]	$r_{1\epsilon P}$	$r_{1\epsilon N}$	$r_{2\epsilon M}$	$r_{2\epsilon N}$	$r_{3\epsilon P}$	$r_{3\epsilon M}$
Mean Coefficient	.0087	-.0083	.0082	-.0271	.0088	-.0082
Mean Std Error	.3928	.2585	.3549	.5380	.3945	.3554
Std Dev of Coefficients	.0095	.0188	.0144	.0159	.0097	.0143
Cyclical Coefficient	.0010	.0032	.0015	.0009	.0010	-.0015
	(.0008)	(.0026)	(.0017)	(.0021)	(.0008)	(.0017)

		r_{12}	r_{13}	r_{23}		
Mean Coefficient		.5035	.4982	-.4982		
Mean Std Error		.7066	.7487	.7487		
Std Dev of Coefficients		.0139	.0070	.0070		
Cyclical Coefficient		.0004	-.0002	.0002		
		.0021)	(.0010)	(.0010)		

*Significant at 10% level.

[1/] See footnotes to Table 3 for sectoral definitions and further explanation of row categories.

[2/] Coefficients in column (3) are calculated for the coefficient estimation in columns (1) and (2). See Appendix.

[3/] See Appendix for definition of correlation coefficients.

Table 5

A. MOVERS BETWEEN SECTORS[1/]

White Men -1969-1982

	PMA-Mfg.	PMA-Nonmfg.	Mfg.-PMA	Mfg.+ Nonmfg.	Nonmfg.-PMA	Nonmfg.-Mfg.
Mean Percent of Workers[1/] Who Move per Year	.71	2.86	.94	2.14	3.51	2.06
Cyclicality Coefficient[2/] on Percent of Movers	-.0001 (.0003)	.0004 (.0010)	-.0005* (.0003)	.0002 (.0008)	-.0017* (.0008)	.0018* (.0007)
Average Wage Change[3/] (average std dev)	.18 (3.37)	-.39 (1.43)	1.65 (2.80)	-.23 (.70)	.40 (1.06)	-.14 (1.03)
Cyclicality Coefficient[4/] on Wage Change	.2173 (.3545)	.0419 (.1525)	-.2125 (.2922)	-.0402 (.0740)	.0664 (.1120)	.0076 (.1100)

B. STAYERS WITHIN SECTORS

	PMA	Mfg.	Nonmfg.
Mean Percent of Workers[1/] Who Stay for 2 Years	30.19	17.57	40.03
Cyclicality Coefficient[2/] on Percent of Stayers	-.0020 (.0029)	.0010 (.0014)	.0009 (.0031)
Average Wage Change[3/] (average std dev)	.30 (.41)	.22 (.31)	.20 (.26)
Cyclicality Coefficient[4/] on Wage Change	.0315 (.0429)	.0860* (.0208)	.0427* (.0246)

*Significant at 10% level.

For definition of Sectoral groups, see Foonote 1, Table 3.

[1/]Represents mean (over 13 two-year periods) of the percent of workers who move from 1st to 2nd sector in these two years.

[2/]Represents the coefficient α_1 from the regression $\#movers_{(t/t+1)}/\#workers_t = \alpha_0 + \alpha_1((GNP_{t+1} - GNP_t)/GNP_t) + e$, estimated over 13 observations.

[3/]Represents mean wage change over 13 two-year periods.

[4/]Represents the coefficient α_1 from the regression $Wage_{t+1} - Wage_t = \alpha_0 + \alpha_1((GNP_{t+1} - GNP_t)/GNP_t) + e$.

APPENDIX

ESTIMATING A JOINT SECTOR SELECTION/WAGE MODEL

A worker is choosing one sector out of three (P, M, or N), each of which have their own separate wage determination process. Let the utility available in each sector to worker i be characterized by the equations

(A1) $U_P = S\alpha_P + v_P$

$U_M = S\alpha_M + v_M$

and $U_N = S\alpha_N + v_N$

Choice of one sector over another is based on a utility comparison between the sectors, which leads to the three equations ((12) - (14) in the text):

(A2) $U^*_{PN} = U_P - U_N = Z\delta_1 + \mu_1$, where $\delta_1 = \alpha_P - \alpha_N$, $\mu_1 = v_P - v_N$;

$U^*_{MN} = U_M - U_N = Z\delta_2 + \mu_2$, where $\delta_2 = \alpha_M - \alpha_N$, $\mu_2 = v_M - v_N$;

and $U^*_{PM} = U_P - U_M = Z\delta_3 + \mu_3$, where $\delta_3 = \alpha_P - \alpha_M$, $\mu_3 = v_P - v_M$.

It is straightforward to see that $U^*_{PM} = U^*_{PN} - U^*_{MN}$, $\delta_3 = \delta_1 - \delta_2$, and $\mu_3 = \mu_1 - \mu_2$. Thus, we need only estimate the determinants of the two comparisons U^*_{PN} and U^*_{MN}, from which we can derive the determinants of the third choice, U^*_{PN}.

As indicated in the text, the wage equations for each sector are

(A3) $W_P = X\beta_P + \varepsilon_P$

$W_M = X\beta_M + \varepsilon_M$

and $W_N = X\beta_N + \varepsilon_N$.

The correlation matrix between the errors in the equations in (A2) and (A3) is

$$\Omega = \begin{array}{cccccc} 1 & & & & & \\ r_{12} & 1 & & & & \\ r_{13} & r_{23} & 1 & & & \\ r_{1\varepsilon P} & 0 & r_{3\varepsilon P} & \sigma_P & & \\ 0 & r_{2\varepsilon M} & r_{3\varepsilon M} & 0 & \sigma_M & \\ r_{1\varepsilon N} & r_{2\varepsilon N} & 0 & 0 & 0 & \sigma_N \end{array}$$

where $\Gamma_{3\varepsilon P} = \Gamma_{1\varepsilon P}/\surd 2(1 - \Gamma_{12})$, $\Gamma_{3\varepsilon M} = -\Gamma_{2\varepsilon M}/\surd 2(1 - \Gamma_{12})$, $\Gamma_{13} = \surd(1 - \Gamma_{12})/\surd 2$, and $\Gamma_{23} = -\surd(1 - \Gamma_{12})/\surd 2$. Thus, jointly estimating a full sectoral choice/wage model requires estimating three variances and five correlation coefficients.

The likelihood that worker i is observed in sector P, with wages W_P is

(A5) $L_{Pi} = \Pr(\ \varepsilon_P = (W_{Pi} - X_i\beta_P)/\sigma_P\ ,\ \mu_{1i} > -Z\delta_1\ ,\ \mu_{3i} > -Z\delta_3\ )$.

This can be written as the product of a univariate and a conditional bivariate distribution function:

(A5') $L_{Pi} = \phi(\varepsilon_P)\ \Phi'(\ \mu_{1i}, \mu_{2i} \mid \varepsilon_P)$,

where ϕ is a univarity normal density function, and Φ' is a conditional bivariate normal distribution. Φ' can be rewritten as a unconditional bivariate normal distribution Φ using straightforward statistical techniques, which results in the likelihood

(A5'') $L_{Pi} = \phi(\varepsilon_P)\ \Phi\left(\dfrac{-Z\delta_1 + \Gamma_{1\varepsilon P}\varepsilon_P}{\surd(1-\Gamma_{1\varepsilon P})}\ ,\ \dfrac{-Z\delta_3 + \Gamma_{3\varepsilon P}\varepsilon_P}{\surd(1-\Gamma_{3\varepsilon P})}\ ,\ \Gamma_{13} - \Gamma_{1\varepsilon P}\Gamma_{3\varepsilon P}\right)$

In a similar manner, the likelihood that individual i is paid in sector M is

(A6) $L_{Mi} = \phi(\varepsilon_M)\ \Phi\left(\dfrac{-Z\delta_2 + \Gamma_{2\varepsilon M}\varepsilon_M}{\surd(1-\Gamma_{2\varepsilon M})}\ ,\ \dfrac{Z\delta_3 - \Gamma_{3\varepsilon M}\varepsilon_M}{\surd(1-\Gamma_{3\varepsilon M})}\ ,\ \Gamma_{23} - \Gamma_{2\varepsilon M}\Gamma_{3\varepsilon M}\right)$

while the likelihood that individual i is paid in sector N is

(A7) $L_{Ni} = \phi(\varepsilon_N)\ \Phi\left(\dfrac{Z\delta_1 - \Gamma_{1\varepsilon N}\varepsilon_N}{\surd(1-\Gamma_{1\varepsilon N})}\ ,\ \dfrac{Z\delta_2 - \Gamma_{2\varepsilon N}\varepsilon_N}{\surd(1-\Gamma_{2\varepsilon N})}\ ,\ \Gamma_{12} - \Gamma_{1\varepsilon N}\Gamma_{2\varepsilon N}\right)$.

The overall likelihood function for an individual i is

(A8) $L_i = S_{Pi}L_{Pi} + S_{Mi}L_{Mi} + (1-S_{Pi})(1-S_{Mi})L_{Ni}$

where $S_{Pi} = 1$ if individual i is in sector P, 0 otherwise; and $S_{Mi} = 1$ if individual i is in sector M, 0 otherwise. The estimated likelihood function for the entire sample of n individuals is

(A9) $\sum_{i=1}^{n} L_i$.