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THE RELATION BETWEEN SKILL LEVELS AND THE CYCLICAL VARIABILITY OF EMPLOYMENT, HOURS, AND WAGES

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This paper uses micro data to examine differences in the cyclical variability of employment, hours, and wages for skilled and unskilled workers. Contrary to conventional wisdom, we find that, at the aggregate level, skilled and unskilled workers are subject to essentially the same degree of cyclical variation in wages. That is, relative offer wage differentials between skilled and unskilled workers are acyclical. However, we do find important differences in the patterns of employment and hours variation for skilled vs. unskilled workers when a college degree is used as a proxy for skill. Workers with a college degree have little cyclical variation in employment or weekly hours, while uneducated workers have highly procyclical employment and hours. Thus, we find that the quality of labor input per manhour rises in recessions, thereby inducing a countercyclical bias in aggregate wage measures. We find substantial differences across industries in the cyclical variation of employment, hours, and wage differentials. We interpret these results as indicative of important inter-industry differences in labor contracting.

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1. INTRODUCTION

While it has long been recognized that skilled workers face substantially lower cyclical variation in employment than unskilled workers, little evidence is available on the relative variation of their real wages over the cycle. Based largely on the work of Reder (1955, 1962), it has been widely accepted that wage differentials across skill levels are countercyclical. More precisely, the relative wage differentials between skilled and unskilled workers are believed to widen in recessions and narrow in booms. For instance, Azariadis (1976) brings this stylized fact to bear on his discussion of implicit contracts in the labor market, while Kydland (1984) discusses it in the context of his heterogeneous-agent business cycle model.

Most previous studies of wage differentials have used data that are aggregated based on some specific criterion of skill. For example, Reder (1955) divided the workforce into skilled, semi-skilled and unskilled categories using job classifications and proceeded to look at average wage measures for each category. The use of such aggregate data may obscure the effect of substantial compositional changes in the workforce over the cycle. In particular, systematic cyclical changes in the quality of the employed workforce within specific job classifications may bias Reder's aggregate measurement of the cyclicality of wage differentials between skilled and unskilled workers.

Raisian (1983) was among the first to study the cyclicality of wage differentials using micro panel data to control for compositional changes reflected in observed characteristics of workers and some unobserved measures of ability. He found that workers with more work experience and longer tenure on the current job exhibit significantly greater procyclical variability in wages and weekly hours worked but less cyclical variability in annual weeks worked. Contrary to Reder's findings, he concluded that relative wage differentials between skilled and unskilled workers are procyclical.

In this paper, we present new evidence on the cyclicality of wage differentials using micro panel data from the National Longitudinal Survey of Young Men, a panel containing twelve surveys over a period of sixteen years. The long panel enables us to obtain efficient estimates of the interaction between skill levels and the cyclical behavior of real wages. Our estimates control for aggregation bias on the basis of observed worker characteristics and also for unobserved individual fixed effects. Another potentially important source of bias, referred to as selection bias, arises from the fact that wages are observed in any period only for workers who are employed in that period. By choosing only those person-year observations where a wage is observed, estimated coefficients may pick up the effect of some unobserved component of ability that has a systematic effect on employment probabilities as well as on wages. We implement a maximum likelihood version of Heckman's (1974) selection model to correct for such selection bias. This source of bias has not been dealt with in earlier studies of wage differentials.[1]

By controlling for observed worker characteristics and unobserved fixed effects and correcting for selection bias, we are able to provide consistent estimates of the cyclical properties of offer wage differentials. The offer wage for workers of a particular skill level is defined as the wage offered to a 'representative' worker of that skill level, after controlling for heterogeneity within that skill category. Our results demonstrate that the two quantities discussed above, mean offer wages and average observed wages, have considerably different cyclical properties. This implies that changes in the average wage of employed workers are biased measures of changes in the mean of the offer wage distribution, both at the aggregate level and within specific skill categories.

In our empirical work, we do not attempt to develop a single measure of skill level but, instead, examine a variety of plausible proxies for human capital. In particular, we

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[1] The magnitude of this bias in measuring the cyclicality of the average real wage may be substantial, as shown by Keane, Moffitt and Runkle (1988).

focus on education levels, total labor market experience and tenure on the current job. These variables arguably proxy for different facets of human capital. Since Becker's (1962) seminal paper, it has been recognized that a careful distinction needs to be made between general human capital and firm-specific or industry-specific human capital. This distinction has implications for the effects of various facets of skills on employment, hours and wage variability. Indeed, we find that our proxies for skills differ considerably in their effects on cyclical fluctuations in employment, hours and wages.

We also provide results broken down by industry, in order to closely examine inter-industry differences in the cyclical behavior of the wage premium for skills. In addition, we separately measure the cyclicality of employment and weekly hours worked. This enables us to provide estimates of the relative magnitude of employment and hours variation in accounting for cyclical labor input variation in different industries.[2]

A key finding of the paper is that, at the aggregate level, skilled and unskilled workers face almost the same degree of relative cyclical variation in wages. In other words, offer wage differentials between skilled and unskilled workers are essentially acyclical. However, after controlling for other characteristics, older workers are estimated to have more procyclical wages.

Although their patterns of wage variation are similar, workers with a college degree have little cyclical variation in employment probabilities or weekly hours, while, for workers without a degree, employment probabilities as well as hours are procyclical. The greater procyclical variation in employment and hours for workers without a degree implies that the average quality of labor input per manhour rises in a recession. It follows that a substantial countercyclical bias may exist in measures of the real wage that simply divide

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[2] The standard measure of labor input is aggregate hours worked, which is the product of the number of persons employed and the average weekly hours worked (or whatever the appropriate frequency).

aggregate compensation by total manhours. Bernanke (1986) has earlier pointed out that greater cyclical variation in hours for unskilled workers may induce such a countercyclical bias in aggregate measures of wage cyclicality. Likewise, using data from the Michigan Panel Study of Income Dynamics, Kydland and Prescott (1988) have also found that the quality of the labor force rises in a recession.

At the industry level, we find that the wage premium for skills is strongly procyclical in durable and nondurable manufacturing and is countercyclical in retail trade and services. In durable manufacturing, workers with a college degree have much more procyclical variation in wages than other workers. Educated workers in durable manufacturing have relatively less procyclical variation in employment probabilities and are actually found to have countercyclical variation in weekly hours.

Variation in average weekly hours accounts for only about thirty percent of the variation in total hours worked (number of persons employed × average weekly hours) in the economy. However, in certain industries such as nondurable manufacturing, variation in average weekly hours accounts for a substantial portion of the variation in total hours. These and other industry results indicate substantial inter-sectoral differences in labor contracting.

It is useful to discuss the relation between skill levels and employment, hours and wage variability in the context of labor market contracting models. Accordingly, section 2 surveys some theoretical models of labor market contracting and compares their implications. This provides a framework for analyzing and interpreting our empirical results. Section 3 contains a description of the econometric techniques used in the paper. Section 4 describes the data set used in the estimation. Section 5 contains the main results. Section 6 summarizes our results and concludes the paper.

2. Conceptual Framework

The concept of a 'skilled worker' is rather nebulous since the term 'skill level' is often used as a portmanteau to refer to various aspects of human capital. The literature on human capital theory makes an important analytical distinction between general and firm-specific (or industry-specific) human capital (see Becker (1962)).[3] General human capital increases the productivity of a worker in any firm. Such capital is assumed not to depreciate when a worker switches from one firm (or industry) to another. Firm-specific capital is, by definition, not transferable across firms. There is an element of risk to investment in such capital since a separation between a worker and a firm leads to the loss (or significant depreciation) of such capital. The real resource costs of investment in specific capital include training costs and foregone output from time spent on training rather than on directly productive activities.[4] Workers may bear a portion of these costs by accepting a wage below their marginal product when they join the firm. This joint investment provides an incentive for both the firm and the worker to avoid a separation.

Specific human capital is a key ingredient in many models of labor market contracting that have direct implications regarding differences in the cyclical behavior of employment, hours and wages for workers of different skill levels. These models may be classified into two broad categories. The implicit contract models of Azariadis (1975, 1976), Baily (1974) and Gordon (1974), imply the existence of wage-smoothing arrangements provided by firms for

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[3] Notice that firm-specific and industry-specific capital are not necessarily identical. However, when issues of labor reallocation and wage dispersion etc. are examined in the context of business cycles, the typical unit of analysis is the industry (for example, see Lilien (1982)). This is partly driven by the fact that industry level data contain less measurement error. Also, the concept of a 'firm' is much less well defined than that of an industry. Given these facts and the constraints of our dataset, we will refer to industry-specific and firm-specific capital interchangeably. Alternatively, we could use the notion of a representative firm in each industry as the unit of our analysis.

[4] Oi (1962) uses a similar notion of fixed hiring costs to model skilled labor as a quasi-fixed factor input.

their workers. The implicit contract models of Hashimoto (1981) and Raisian (1983), on the other hand, imply the existence of labor contracts with more procyclical compensation for workers with higher skill levels. The main differences between these two sets of models arise from their differing assumptions regarding the rules that determine how the costs of investment in specific capital and the returns from it are shared by firms and workers.

The Azariadis-Baily-Gordon class of models postulates that risk-neutral firms may implicitly offer insurance to risk-averse workers by guaranteeing them relatively stable employment and wages when faced with uncertain demand for the firm's product. In it's basic form, this theory suggests that all workers receive some form of employment and/or wage insurance, reflected in the weak response of employment and wage measures to demand shocks or other real shocks.

By incorporating firm-specific human capital, this theory can be extended to the case of risk-averse firms and heterogeneous workers. Risk-averse firms would, in general, not be willing to take on the risks posed by fluctuations in demand or productivity. However, if firms bear the cost of investment in specific human capital, they might be reluctant to lose such specific capital embodied in their workers. When faced with adverse demand or productivity shocks that they perceived to be transitory, firms would have an incentive to retain workers with high specific skill levels. Thus, skilled workers may be offered contracts that, at business cycle frequencies, provide them with smoother wages and more stable employment patterns than unskilled workers.[5] Unskilled workers would simply be paid their marginal product in every period and their employment would depend solely on current period demand conditions. Hence, their employment and wages would tend to be strongly

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[5] Further, if a firm received the entire return from a worker's specific capital, it would be even more willing to assure him or her a relatively smooth wage in order to prevent a separation and the consequent loss of such specific capital. The precise extent of wage and employment smoothing would depend on the degree of the firm's risk-aversion, the cost of specific capital investment, the persistence of the shock etc.

procyclical.

The Hashimoto-Raisian type of models have markedly different implications. The key underlying notion in this set of models is that specific capital involves a joint investment by the firm and the worker. Further, the returns from this form of human capital are assumed to be shared by the two parties. This gives both parties, the worker and the firm, an incentive to avoid a separation that would cause specific capital to be lost. Workers with more firm-specific human capital would, thus, face a tradeoff between employment and wage variability. Since such skilled workers typically have higher incomes than unskilled workers, they are likely to have better access to asset markets where they could insure against income fluctuations. Consequently, skilled workers would be willing to accept more procyclical variation in wages than unskilled workers, in return for a greater degree of employment stability.

It follows from the above argument that, the larger their share in the returns from specific capital, the more would employment stability be valued by skilled workers (i.e. the more the variability in wages they would accept in return for not being laid off).[6] However, it is likely that skilled workers face a greater degree of adjustment at the intensive margin (i.e. weekly hours worked). That is, firms may respond to downturns by laying off unskilled workers and reducing the hours worked by skilled workers. This implication follows from the assumption that specific human capital is unaffected by hours variation but depreciates if a firm and a worker are separated for one or more periods.

However, the Hashimoto-Raisian model could also be consistent with countercyclical hours variation for skilled workers. Since highly skilled workers in many industries

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[6] This argument implicitly assumes that temporary and permanent separations between a firm and a worker are equivalent in that they cause specific capital to depreciate fully. This is the limiting case of a more general argument that would go through if there was a sufficiently large depreciation in specific capital resulting from a temporary separation.

typically earn salaries rather than hourly wages, working longer hours in a downturn may be a means of taking a temporary cut in hourly wages.

Thus, the Azariadis-Baily-Gordon and Hashimoto-Raisian models have similar predictions about employment variability, that skilled workers should face less cyclical variation in employment. Neither set of models has a definitive implication regarding relative cyclical variability of hours for workers of different skill levels, although, in its simplest form, the Hashimoto-Raisian model implies that skilled workers face more procyclical variation at the intensive margin (i.e. hours worked).

The predictions regarding differences in wage variability across skilled and unskilled workers are diametrically opposed in these two sets of models. The Azariadis-Baily-Gordon class of models posits the existence of contracts that assure skilled workers of smoother wages and employment, thereby implying a countercyclical wage premium for skilled labor. This is consistent with the findings of Reder (1955, 1962), who uses aggregate data to show that skilled-unskilled wage differentials narrow in booms and widen in recessions. The Hashimoto-Raisian model, on the other hand, implies that workers with more specific capital face more variable wages. That is, skilled workers may have more stable employment but are subject to a greater degree of wage variability than unskilled workers. This implies procyclical wage differentials between skilled and unskilled workers. Raisian (1983) provides evidence in support of this view.

We attempt to provide an empirical resolution of this issue using a detailed set of micro survey data to correct for various potential sources of bias. In our empirical work, we use different proxies for skills in order to disentangle the effects of various facets of human capital on wage and employment variability. The primary determinant of general human capital is education. The costs of investment in such human capital are usually considered to be borne entirely by the worker, as are the returns accruing from it. It is also likely that measures of general human capital, such as education, are highly positively correlated with levels of specific human capital. For instance, workers with a college degree presumably have attributes which make them more efficient at acquiring specific capital. Thus, education levels are a good measure of general as well as specific human capital.

A more direct proxy for specific human capital is tenure on the current job (see Altonji and Shakotko (1987)). On-the-job training and learning-by-doing are likely to enhance skills that are of particular value to a specific firm or industry. Further, longer tenure arguably indicates the existence of specific capital which the firm and/or the worker are reluctant to lose.[7] Another useful proxy for human capital is total labor market experience, although it is not obvious what aspect of human capital this best measures. We use all three variables described above as proxies for skills and estimate a series of models that independently analyze their effects on wage and employment variability.

3. Econometric Framework

The basic regression model is as follows:

$$\ln W_{it} = X_{it}\beta + U_t\alpha + \mu_i + \varepsilon_{it} \qquad \forall \;\; i = 1,2,..,N \; ; \; t = 1,2,..,T \tag{1}$$

The real hourly wage rate of individual i at time t is represented by W_{it}. X_{it} is a vector of observed individual-specific variables that affect this wage rate, with associated coefficient vector β. U_t represents an indicator of the business cycle. In our application, we use the aggregate unemployment rate in the economy as an indicator of the cycle.[8] The

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[7] Length of tenure is also a good measure of the quality of the match between a worker and a firm. Given the uncertainty inherent in job-matching, workers and firms would both be reluctant to terminate a good match when faced with a temporary decline in demand or productivity. For our purposes, the quality of a job match may be considered as part of a worker's specific capital.

[8] Our results were not significantly affected by the choice of the business cycle indicator. See the discussion in the next section.

coefficient α indicates the relation between the real wage and the business cycle. For instance, a negative estimate of α would imply that the average real wage declines when the aggregate unemployment rate rises (i.e. that the average real wage is procyclical). μ_i stands for a vector of unobserved individual-specific characteristics that are fixed over time. The elements of μ_i may be correlated with X_{it}. The regression error ε_{it} is assumed to be i.i.d..

We are interested in estimating the effects of observed measures of skill level on the cyclicality of a worker's real wage. This is accomplished by including an appropriate interaction term as follows:

(2) $$\ln W_{it} = X_{it}\beta + U_t\alpha + U_tE_{it}\gamma + \mu_i + \varepsilon_{it} \qquad \forall \quad i = 1,2,..,N \;;\; t = 1,2,..,T$$

The variable E_{it} is a measure of skill level (it should also be included in X_{it}). The coefficient γ on the interaction term U_tE_{it} captures differences in the cyclicality of wages for workers with different skill levels. A positive estimate of γ would indicate a countercyclical wage premium for skills i.e. the skill premium increases when the unemployment rate rises. Conversely, a negative γ would indicate a procyclical skill premium.

Estimating (2) by ordinary least squares (OLS), with $\mu_i + \varepsilon_{it}$ being the composite error term, would yield biased estimates of β and γ unless the variables in μ_i were uncorrelated with the regressors. This is not likely to be true in general. Workers with a high (unobserved) value of μ_i are high ability workers. If high ability workers were less likely to be laid off in a recession than were low ability workers, the mean level of μ_i among employed workers would covary positively with the aggregate unemployment rate. The correlation between such unobserved individual fixed effects and the unemployment rate would induce an upward (countercyclical) bias in the estimated unemployment rate coefficient. Similarly, if an unobserved component of ability was positively correlated with, say, the observed level of education, the estimated coefficient on the education variable would be biased upward.

The interaction coefficient γ is subject to similar bias. For instance, if an increase in the aggregate unemployment rate caused the average unobserved ability of workers within lower skill categories (i.e. those with lower values of E_{it}) to rise relative to the average unobserved ability of workers in higher skill categories, γ would be biased downward. This procyclical bias in the estimated cyclical variation of the skill premium would spuriously indicate a narrowing (or understate the increase) of the skill premium in a recession.

To deal with such unobserved individual fixed effects, we employ a fixed effects in levels estimator by using OLS to estimate the following transformed equation:

$$(3) \qquad \ln \tilde{W}_{it} = \tilde{X}_{it}\beta + \tilde{U}_t\alpha + \widetilde{U_t E_{it}}\gamma + \tilde{\varepsilon}_{it}$$

where $\ln \tilde{W}_{it} = \ln W_{it} - \frac{1}{T}\sum_{t=1}^{T} \ln W_{it}$

$$\tilde{X}_{it} = X_{it} - \frac{1}{T}\sum_{t=1}^{T} X_{it}$$

$$\tilde{U}_t = U_t - \frac{1}{T}\sum_{t=1}^{T} U_t$$

$$\widetilde{U_t E_{it}} = U_t E_{it} - \frac{1}{T}\sum_{t=1}^{T} U_t E_{it}$$

$$\tilde{\varepsilon}_{it} = (\varepsilon_{it} + \mu_i) - \frac{1}{T}\sum_{t=1}^{T}(\varepsilon_{it} + \mu_i) = \varepsilon_{it} - \frac{1}{T}\sum_{t=1}^{T}\varepsilon_{it}$$

This transformation subtracts out individual means over time for each variable, causing the individual fixed effects to drop out. The error term $\tilde{\varepsilon}_{it}$ is i.i.d. and is uncorrelated with the regressors. Note that, to implement the fixed effects model, we need to leave out control variables that are constant over time or collinear with the time trend.

To estimate the cyclical behavior of wages and skill premia at the industry level, we may include interactions of U_t and U_tE_{it} with industry dummies. Specifically, the following counterpart to the OLS model (2) may be employed:

$$(4) \qquad \ln W_{it} = X_{it}\beta + \sum_{j=1}^{J} I_{ijt}U_t\alpha_j + \sum_{j=1}^{J} I_{ijt}U_tE_{it}\gamma_j + \mu_i + \varepsilon_{it}$$

I_{ijt} is a binary indicator variable that takes the value one if worker i locates in industry j at time t. Otherwise, I_{ijt} equals zero. The coefficients α and γ are now indexed by industry. For instance, γ_j is an estimate of the cyclical variation in the skill premium in industry j. With appropriate transformations of the variables as described in (3), a similar pooled regression could be used to estimate the fixed effects model at the industry level:

$$(5) \qquad \ln \tilde{W}_{it} = \tilde{X}_{it}\beta + \sum_{j=1}^{J} I_{ijt}\tilde{U}_t\alpha_j + \sum_{j=1}^{J} I_{ijt}\widetilde{U_tE}_{it}\gamma_j + \tilde{\varepsilon}_{it}$$

A potential problem with the specification (5) is that it restricts individual fixed effects to be the same across all industries. This would bias the coefficients of industry-level estimates if there were industry-specific unobserved fixed effects that were correlated with any of the regressors.[9] Further, both (4) and (5) restrict the coefficient vector β to be the same across industries. This implies the strong assumption that the returns to observed worker characteristics are the same in all industries.

Apart from unobserved individual fixed effects and industry-specific effects, there remains another potential source of bias. All of the above discussion assumed that the mean

[9] Industry-specific fixed effects are a potential problem only in the case of workers switching industries over the sample period. Workers who stay in one industry over the entire sample period would have their industry-specific fixed effects eliminated by the transformation described in (3).

of $\tilde{\varepsilon}_{it}$ conditional on individual i being employed in period t was zero. But notice that wages are observed only for those individuals who are employed in a given period. If an unobserved component of ability that affected the wage rate for an individual was correlated with the unobserved component that affected that individual's probability of employment, we would be faced with a typical selection bias problem.[10] For instance, changes in U_t may cause workers with systematically high or low values of the time varying unobserved productivity component (reflected in high or low values of $\tilde{\varepsilon}_{it}$) to enter or leave employment in an industry. The effect of changes in average labor force quality resulting from the inflow or outflow of high or low productivity workers would then bias the unemployment rate coefficient. If, in addition, the magnitude of this effect differed by skill levels, a fixed effects estimate of γ_j would be a biased estimate of the change in the mean offer wage differential in industry j.

To eliminate the effect of cyclical changes in the composition of the workforce induced by such systematic selection, we estimate the variability of mean industry offer wages for different classes of workers using a maximum likelihood version of Heckman's (1974) self-selection model. This model estimates a wage equation for each industry jointly with a probit choice equation that determines whether a worker locates in that industry. The model is written as follows:

$$(6) \qquad \ln W_{ijt} = X_{it}\beta_j + U_t\alpha_j + U_tE_{it}\gamma_j + \mu_{ij} + \varepsilon_{ijt}$$

$$\text{observed iff } I_{ijt} = 1$$

[10] It might appear, from the specification in (2), that individual fixed effects could be eliminated by first-differencing the data. However, such a procedure may exacerbate this selectivity bias if there were any missing data, except under a set of restrictive conditions. This is because differencing would require selecting only those pairwise adjacent periods for both of which an individual has an observed wage. See Keane et al. (1988) pp. 1238-44 for a detailed discussion.

where $I^*_{ijt} = Z_{it}\theta_j + U_t\delta_j + U_tE_{it}\eta_j + \psi_{ij} + \omega_{ijt}$

$$I_{ijt} = \begin{cases} 1 \text{ if } I^*_{ijt} \geq 0 \\ 0 \text{ if } I^*_{ijt} < 0 \end{cases}$$

Here I^*_{ijt} is the latent index of a probit employment equation that determines whether worker i is employed in industry j at time t. Z_{it} is a vector of individual-specific regressors that affect the probability of employment in industry j at time t. The corresponding coefficient vector is denoted by θ_j. Typically, Z_{it} contains elements that enter into X_{it} as well as some additional variables that may affect labor supply propensity but not worker productivity. Since our data set does not contain any variables that clearly fall into this category, we include the same set of controls in the wage and employment choice equations. Further, our results were not sensitive to the overidentifying restrictions of omitting variables from X_{it}. Individual fixed effects in the employment choice equation are represented by ψ_{ij}.

We estimate binomial selection models separately for each industry. This allows fixed effects to vary across industries and, thus, obviates the potential bias from restricting the fixed effects for any given individual to be the same across all industries. Further, this also allows the coefficient vector β to vary across industries.[11]

The error terms ε_{ijt} and ω_{ijt} are assumed to have a bivariate normal distribution with correlation ρ_j and respective standard deviations σ_{ε_j} and 1. The latter variance is normalized to one for identification of the probit choice equation. The parameter ρ_j,

[11] Estimating a single, multinomial model with selection corrections would require sector-specific regressors in order to identify cross-correlations among the error terms in the choice equations. We do not have such regressors in our data set. See Keane (1990) on this.

estimated from the cross-equation correlation between wage equation residuals and the residuals from the employment equation, is crucial for correcting the selection bias. The sign of this correlation coefficient is informative. A negative estimate of ρ_j, for instance, indicates that workers with a high transitory wage component are more likely to be laid off in a downturn. This would, if a selection correction was not employed, bias the estimated effect of the cycle on the real wage and the skill premium.[12]

The source of selection bias can now be demonstrated fairly easily. For instance, consider the coefficient α_j in the above wage equation. Under the distributional assumptions made above (and ignoring fixed effects for the moment), we have

$$\frac{\partial E\left(\ln W_{ijt} \mid I_{ijt}=1\right)}{\partial U_t} = \alpha_j - \rho_j \sigma_{\varepsilon_j} m_{ijt} \delta_j$$

where $m_{ijt} = \lambda_{ijt} \cdot (\lambda_{ijt} + Z_{it}\theta_j + U_t\delta_j)$ and λ_{ijt} is the Mill's ratio.. It can be shown that $m_{ijt}>0$. Hence, the estimate of α_j is biased downward if ρ_j and δ_j have the same sign and is biased upward if they have opposite signs. The other coefficients in the wage equation are also affected by selection bias.

The selection corrected fixed effects estimator in this paper is implemented by full-information maximum likelihood.[13]

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[12] In the fixed effects selection model, estimates of the choice equation fixed effects are inconsistent for small T. Monte-Carlo experiments by Heckman (1981) show that this inconsistency is small for T>8. In our data set, T is on average 6 (with a maximum value of 12), indicating that inconsistency is a potential problem. However, the estimated ρ in the model with fixed effects in both the wage and employment equations always went to 1 or -1. Hence, the results we will report are from a model with fixed effects in the wage equation alone. This obviates the problem of inconsistency of the estimated fixed effects in the choice equation. Besides, consistent estimation of the choice equation parameters is not important for our main results. Further, in our estimates reported below, we obtain values of ρ close to zero. Hence, any transfer of inconsistency from the choice equation to the wage equation would be negligible.

[13] An alternative two-stage procedure developed by Heckman (1979) yields estimates that are

4. Data

The data set used in this paper is the National Longitudinal Survey of Young Men (NLS), comprising a nationally representative sample of 5,225 young males. They were between 14 and 24 years of age in 1966 and were interviewed in 12 of the 16 years from 1966 to 1981. Data were collected on their employment status, wage rates and sociodemographic characteristics. The sample was screened to include only those persons who, as of the interview date, were at least 21 years of age, had completed their schooling and military service and had available data for all variables used in our analysis. The final sample contained 4,439 males and a total of 23,927 person-year observations. This includes years when the person being interviewed was unemployed. The employment status dummy was non-zero in 21,203 of these person-year observations. Table A1 in the appendix reports sample means for the individual specific variables used in the estimation. Workers were classified into eleven broadly defined industries on the basis of the 3-digit census industrial classification (CIC) codes. The list of industries, their CIC codes and the sample size for each industry are reported in the appendix in Table A2.

The wage measure we use is the hourly straight time earnings reported by workers for the survey week. This measure was deflated by the Consumer Price Index (CPI) to provide a real wage measure normalized in terms of 1967 CPI dollars. It is important to note that this is a point-in-time wage measure taken as of the date of the interview. This obviates the recall bias that may contaminate annual measures that are obtained by dividing annual earnings by annual hours worked.[14] The NLS does not include data on overtime earnings in all of the interview years. Hence, we restrict ourselves to using a straight-time wage measure rather

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consistent but not efficient. This motivates our use of full-information maximum likelihood.

[14] Keane et al (1988) pp. 1245-46 discuss the other sorts of bias that may result from using annual survey data on wage income rather than the point-in-time measure used here.

than attempting to impute overtime earnings for years in which it was not available. To adjust for nonwage compensation, such as variation in fringe benefits across industries, the hourly wage rate for each worker was multiplied by the ratio of total labor costs to wages in the corresponding industry. Data on total labor costs were obtained from the National Income and Product Accounts. The log of this adjusted real wage measure, denoted by WCPI, is used in all of our analysis. This variable has a sample mean of 1.065 in 1967 CPI dollars.

The HOURS variable we use in this study is a measure of the weekly hours worked reported by the worker for the survey week. In four of the survey years, this variable was unavailable and we used the 'usual weekly hours worked' instead.[15] The three variables used as proxies for human capital are DEGREE, EXPERIENCE and TENURE. DEGREE is a dummy variable that takes th value one if the worker has a college degree and zero otherwise. EXPERIENCE is defined as the total number of years of labor market experience. It was calculated as the interview date minus the completion date of a worker's schooling or military service, whichever was later. It is important to note that the EXPERIENCE variable is a measure of labor force participation rather than of actual work experience. TENURE is defined as the length of uninterrupted tenure (in years) on the current job.

We use the aggregate civilian unemployment rate in the economy as an indicator for the business cycle. To be precise, the variable URATE is the seasonally adjusted monthly unemployment rate for all civilian workers aged 16 years and older. We also experimented with other indicators of the business cycle such as real GNP. Our main conclusions did not appear very sensitive to the particular choice of the business cycle indicator. In the next section, we report only the results using the aggregate unemployment rate.

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[15] For the survey years in which both of these hours variables were available, the correlation between them was about 0.6. About 45 percent of the observations for the HOURS variable used in this study lie in the range of thirty seven to forty hours a week.

5. Empirical Results

Employment Variability

Table 1 contains estimates from a set of linear employment probability models. The first panel reports results from a regression with the URATE*DEGREE interaction term.[16] The second panel contains results from a similar regression but with the URATE*EXPERIENCE term. In this table, the estimated coefficients on the interaction terms measure the differential impact of the cycle on employment probabilities for skilled and unskilled workers.[17] In the top row of panel 1, the significant positive coefficient on URATE*DEGREE for all workers (.0161, with a standard error of .0035) implies that workers with higher levels of education have less procyclical employment probabilities. In fact, the sum of the coefficients on URATE and URATE*DEGREE (-.0164 + .0161) is close to zero indicating that workers with a college degree have essentially acyclical employment patterns. EXPERIENCE, on the other hand, does not seem to affect employment probabilities over the cycle as the interaction term URATE*EXPERIENCE for all workers has a coefficient (-.0005, s.e. .0003) that is not significantly different from zero.

The remaining rows of the table break down the sample by industry. In our sample, durable manufacturing accounts for the bulk of the aggregate cyclical variation in employment. In this industry, workers with a college degree face little cyclical variation in employment probabilities. The employment probabilities of workers with a degree are

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[16] In this and all the tables that follow, we run separate regressions for each of the interaction terms. We do this to compare the effects of different proxies for human capital. Further, it is instructive (and much less tedious) to examine and interpret the magnitude of fixed effects and selection corrections for each of the human capital variables separately.

[17] TENURE was not used as a regressor in the employment choice equations in table 1. The estimated equations in that table are essentially reduced form equations for employment choice and, obviously, TENURE would be endogenous in the choice equation.

procyclical in services and F.I.R.E. (finance, insurance and real estate) and countercyclical in construction and retail trade. For workers without a degree, employment probabilities are highly procyclical in durable manufacturing and acyclical in all other industries.

Moving to panel 2, increased experience seems to lead to less procyclical employment in durable manufacturing. However, in retail trade and government, the URATE*EXPERIENCE coefficient is significantly negative, indicating that workers with more experience are more likely to be laid off in a recession. Experience does not have a significant effect in the remaining industries, where the weak employment effect may be due to substitution of younger workers for older workers in a recession. Given the young age of our sample, this may offset the overall negative employment effect in those industries during a recession.

On the whole, table 1 indicates that having a college degree significantly reduces the cyclical variation in a worker's employment probability. On the other hand, the total labor force experience possessed by a worker does not have a similar effect on the cyclicality of his employment probability except in durable manufacturing, where increased experience significantly reduces procyclical variation in employment.

Variation in Weekly Hours

Table 2 provides estimates of the cyclical variability of weekly hours worked. The estimation framework is identical to that for real wages, as discussed in section 3. As in the case of wages, unobserved individual fixed effects could potentially bias measures of cyclical variation in weekly hours worked. For instance, it is likely that low ability workers on average work fewer hours and are also more likely to get laid off in a recession. This compositional change over the cycle might induce an upward bias on the URATE coefficient and indicate countercyclicality in weekly hours worked. However, OLS estimates for virtually all of the coefficients of interest were of the same sign and were generally close in magnitude to the fixed effects (FE) estimates. Hence, we report only FE estimates in table 2.

Panel 1 of table 2 contains results from regressions with the URATE*DEGREE interaction term. In the top row, the coefficient on URATE for all workers is -.0061 (s.e. .0014) and the coefficient on URATE*DEGREE is .0082 (s.e. .0022).[18] Since the sum of these coefficients is near zero (.0082 - .0061 = .0021), weekly hours are essentially acyclical for workers with a degree. On average, however, weekly hours worked are estimated to decline by 0.42 percent for every one percentage point increase in the unemployment rate.[19] At the industry level, the results in panel 1 corroborate the aggregate finding that educated workers face little cyclical variation in weekly hours. In fact, weekly hours for educated workers appear to be weakly countercyclical in durable manufacturing, F.I.R.E. and services. On average, hours are procyclical in durable and nondurable manufacturing, transportation and utilities, retail trade and agriculture.

The fact that, for workers with a degree, weekly hours are much less cyclical at the aggregate level and are even countercyclical in industries such as durable manufacturing, is an important result. Since educated workers typically earn higher wages than other workers, our findings imply a substantial countercyclical bias in measures of hourly wages that simply divide the aggregate wage bill by aggregate hours in an industry.[20]

Turning to panel 2, it is clear that tenure has virtually no effect on weekly hours either at the aggregate level or in any of the industries. In panel 3, the coefficient on

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[18] The URATE coefficient is an estimate of the percentage change in weekly hours for workers without a degree, associated with a one percentage point rise in the unemployment rate. For workers with a degree, this is given by the sum of the coefficients on URATE and URATE*DEGREE.

[19] The mean value of the DEGREE variable in our sample is 0.23. Multiplying this by the coefficient on URATE*DEGREE and adding the product to the URATE coefficient yields an estimate of the percentage change in average weekly hours associated with a one percentage point increase in the unemployment rate (.23*.0082 - .0061 = -.0042).

[20] For the average wage measure from aggregate data to be countercyclically biased, it is sufficient that the interaction coefficient in the hours regression be significantly positive.

URATE*EXPERIENCE is significantly negative for all workers and in virtually every industry. This indicates that older workers are more likely to work reduced hours in a recession.

While table 2 shows that average weekly hours worked are clearly procyclical, the magnitude of the variation in weekly hours appears to be much less important than employment variation in accounting for cyclical fluctuations in aggregate hours. The aggregate results from all three panels indicate that weekly hours decline by about 0.4 percent when the unemployment rate goes up by one percent. In other words, variation in average weekly hours accounts for about 30 percent of the total variation in aggregate hours.[21] This echoes the findings of Hansen (1985) and others that a substantial fraction of the variation in aggregate hours in the postwar U.S. economy is explained by employment variation rather than weekly hours variation.[22]

However, in a few industries which exhibit weak employment responses to the cycle (cf. table 1), it appears that procyclical hours variation may account for a relatively larger share of the variation in total labor input. Nondurable manufacturing, transportation and utilities, retail trade and agriculture fall into this category.

Wage Variability

Table 3 presents results from a series of estimated wage equations that incorporate the

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[21] When unemployment goes up by one percentage point and hours fall by 0.4 percent, the reduction in total hours is roughly 1.4 percent. Hence, it can be inferred that the decline in hours accounts for about 30 percent (0.4/1.4) of the fall in total hours.

[22] Using postwar quarterly data for the U.S., Hansen (1985) examined the following decomposition:

$$\mathrm{var}(\log H_t) = \mathrm{var}(\log h_t) + \mathrm{var}(\log N_t) + 2\mathrm{cov}(\log h_t, \log N_t)$$

where H_t is aggregate hours worked, h_t is average hours worked and N_t is the number of persons employed, with all variables expressed as deviations from trend. He found that 55% of the variance in H_t was due to variance in N_t and only 20% was attributable to variation in h_t, with the remainder due to the covariance term.

URATE*DEGREE interaction term. The first two columns contain results from OLS regressions (specification (4) in section 3). The next two columns contain results from a fixed effects in levels estimator (specification (5)). The last two columns report results from a selection corrected fixed effects model (specification (6)).[23]

In the first panel of table 3, the estimated OLS coefficient on URATE*DEGREE for all workers is -.0294 (s.e. .0041) indicating that, at the aggregate level, workers with a college degree face relatively more procyclical real wages.[24] A similar pattern holds at the industry level. The coefficients on the interaction terms URATE*DEGREE are significantly negative in a majority of the industries. Thus, the OLS estimates imply that, in a downturn, skilled workers find their wages falling relative to the wages of unskilled workers. Recall that tables 1 and 2 showed that workers with a degree are protected from cyclical variation in employment and hours. In conjunction, these results suggest that skilled workers accept steeper wage cuts in a downturn but have more stable employment and hours than unskilled workers. This accords with the predictions of the Hashimoto-Raisian model.

We turn next to the fixed effects (FE) estimates in the second panel of table 3. The

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[23] Panels containing selection corrected fixed effects estimates do not report estimates from the probit employment choice equations that were estimated jointly with the wage equations. The full effect of changes in the aggregate unemployment rate on unemployment probabilities must be read off from the OLS employment probability models in table 1.

[24] The coefficient on URATE measures the percentage change in the average real wage, for workers without a degree, associated with a one percentage point rise in the aggregate unemployment rate. For example, a coefficient of -.0050 implies that a one percentage point increase in the aggregate unemployment rate causes a 0.5 percent decline in the real wage for unskilled workers (in the aggregate or in a particular industry, as the case may be). A positive coefficient on URATE, on the other hand, implies a countercyclical unskilled wage i.e. an increase in the unskilled wage when the unemployment rate rises.

The interaction term URATE*DEGREE indicates how the cyclicality of the real wage faced by workers with a college degree differs from that of workers without a degree. A coefficient of +.0100, for instance, indicates that, when the aggregate unemployment rate goes up by one percentage point, workers with a degree face a one percent increase in their real wage relative to that of unskilled workers (though the absolute real wage may decline for both types of workers). The sum of the coefficients on URATE and URATE*DEGREE measures the full effect of the cycle on the wage of workers with a degree.

change in the estimated coefficients relative to the OLS estimates is substantial, with some of the coefficients even reversing signs. Controlling for unobserved individual fixed effects changes the URATE coefficient for all workers from .0031 (s.e. .0024) to -.0062 (s.e. .0017). This indicates that, among workers without a college degree, low ability workers are more likely to be laid off in a downturn, thereby increasing labor force quality. This induces a positive (i.e. countercyclical) bias in the OLS URATE coefficient.

On the other hand, the coefficient on URATE*DEGREE changes from -.0294 (s.e. .0041) to .0013 (s.e. .0026), indicating that the OLS estimate of the interaction coefficient is procyclically biased.[25] The FE estimate implies that the skilled wage falls at about the same percentage rate as the unskilled wage. In other words, after the fixed effects correction, the skilled-unskilled relative wage differential appears to be essentially acyclical.[26]

At the industry level, the URATE*DEGREE coefficient is insignificant for most industries except wholesale trade, F.I.R.E. and services. In these three industries, the interaction coefficient becomes positive and significant, indicating a countercyclical skill differential (i.e. the relative wage of skilled workers rises in a downturn). In most industries, however, the fixed effects estimates do show that, after controlling for unobserved time-invariant measures of ability, the relative wages of skilled and unskilled workers remain essentially unchanged over the cycle.

The last panel of table 3 contains selection corrected fixed effects (SCFE) estimates. The estimated parameter ρ (not reported here) was small and insignificantly different from

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[25] The bias in the OLS URATE and URATE*DEGREE coefficients offset each other to some extent. At the mean of the data, the OLS estimate of overall wage cyclicality is weakly countercyclically biased.

[26] The variable URATE trends upward over our sample period. Hence, workers who take longer to get a degree and enter our sample towards the end have larger mean URATE*DEGREE values. Such workers also tend to have lower wages. This leads to a downward bias in the OLS interaction coefficient. The fixed effects estimates obviate this problem by considering only the effects of deviations of variables from their individual means.

zero in the aggregate and also for all industries. This indicates that the correlation between the transitory components of workers' wages and their employment probabilities is small, once fixed effects are accounted for. It appears that most of the compositional changes over the cycle can be measured by the combination of observed characteristics of workers and unobserved individual fixed effects. Thus, the selection correction has little impact on the estimates. For all workers, the coefficient on URATE goes from -.0062 (s.e. .0017) in the FE estimates to -.0057 (s.e. .0019) in the SCFE estimates while the URATE*DEGREE coefficient remains insignificantly different from zero. This confirms the result that, at the aggregate level, the relative offer wage differential between skilled and unskilled workers is essentially acyclical.[27]

At the industry level, the coefficients for most industries change from the FE estimates. Since the estimated ρ is insignificant for all industries, this change is attributable to the potential bias in the FE estimates resulting from restricting the fixed effects and the returns to observed characteristics (i.e. the coefficient vector β) to be the same across all industries.[28] The selection models are estimated separately for each industry, thereby controlling for general as well as industry-specific individual fixed effects. The industry estimates in the selection models also allow the returns to observed worker characteristics to vary across industries.[29]

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27 This implies that the absolute offer wage differential is, in fact, procyclical. We focus on relative wage differentials since the emphasis of this paper is on the relative variability of wages across skill levels.

28 Industry-specific individual fixed effects are a potential source of bias only if (i) they are correlated with the regressors in the model and (ii) individuals in the sample switch industries. Employing the same dataset as in this paper, Jovanovic and Moffitt (1990) find that gross flows across sectors average as much as 17.2 percent of the sample between two-year survey waves. Moreover, their three-sector classification probably understates the gross flows relative to the finer industry classification used in this paper. Such high mobility is partly attributable to the young age of the sample.

29 Fixed effects models estimated separately for each industry yielded point estimates close to the SCFE industry estimates. Rather than present yet another set of estimates, we chose

In durable and nondurable manufacturing and in mining, the coefficient on URATE*DEGREE turns significantly negative. This means that, in a recession, workers with a degree who are located in those industries face a larger decline in offer wages than workers without a degree. The difference between the FE and SCFE results may arise because skilled workers who leave manufacturing and mining in a recession have a lower level of industry-specific individual fixed effects (i.e. unobserved quality rises) than those who remain. Alternatively, this difference may arise because the returns to observable quality are higher in manufacturing and mining than on average and high (observed) quality workers move into these industries during a recession. In any case, these three industries provide strong support for the Hashimoto-Raisian hypothesis that skilled workers take larger wage cuts in a downturn than unskilled workers. On the other hand, in retail trade and services, the interaction term is positive and significant. In those industries, workers with a degree do better, in relative terms, when the aggregate unemployment rate in the economy goes up.

Next, we look at the effect of another human capital variable, TENURE. Table 4 contains OLS and fixed effects estimates of wage equations that include the URATE*TENURE interaction term.[30] The coefficient on URATE*TENURE for all workers is close to zero in both the the OLS and FE estimates. This seems to indicate that specific human capital levels, as measured by tenure on the current job, have virtually no effect on relative wage variability.

At the industry level, TENURE has little effect on the cyclicality of wages in a majority of the industries. In construction, agriculture and mining, workers with longer tenure have marginally more procyclical wages as the URATE*TENURE coefficients are negative but not very large in magnitude.

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to report only the SCFE industry estimates since they correct for all the sources of bias that we discussed earlier.

[30] As noted earlier, TENURE would be endogenous in the employment choice equation. Hence, we are unable to estimate the selection corrected fixed effects model using this variable.

We conclude from table 4 that workers with different amounts of tenure face essentially the same degree of cyclical variation in real wages. Interpreting specific capital levels as a measure of skills, this bolsters the conclusion drawn from the previous table that, at the aggregate level, the relative wage differential between skilled workers and unskilled workers is acyclical.

Finally, we examine the effect of total labor market experience on the cyclicality of wages. The first panel of table 5 contains OLS estimates of the wage equation with the URATE*EXPERIENCE interaction term. For all workers, the coefficient on URATE*EXPERIENCE is -.0010 (s.e. .0004), implying a tenth of a percent increase in the cyclical sensitivity of wages for every added year of experience.

A similar pattern holds at the industry level. The coefficients on the interaction terms URATE*EXPERIENCE are significantly negative in a majority of the industries. In industries where the average real wage is highly procyclical, experience doesn't have much effect. This includes construction, retail trade and F.I.R.E.. On the other hand, the coefficient on URATE is significantly positive in nondurable manufacturing, transportation and utilities, government and agriculture, indicating a countercyclical average real wage for new entrants in those industries. The URATE*EXPERIENCE coefficient is negative and significant in each of those four industries, implying that added experience reduces the countercyclicality of a worker's real wage.[31]

The fixed effects estimates in the second panel reinforce this picture. The coefficient on URATE becomes significantly positive in the aggregate and also for virtually all industries. The coefficient on URATE*EXPERIENCE for all workers goes from -.0010 (s.e. .0004)

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[31] The cyclicality of the average real wage is given by the sum of (i) the coefficient on URATE and (ii) the URATE*EXPERIENCE coefficient multiplied by the mean level of EXPERIENCE in the sample (7.9 for all workers). In the four industries mentioned here, the URATE coefficient is positive and more than 12 times the magnitude of the respective URATE*EXPERIENCE coefficient (which is negative in all four cases).

in the OLS estimates to -.0026 (s.e. .0003) in the fixed effects estimates. The URATE*EXPERIENCE coefficient is negative and significant in all industries. The estimated interaction coefficients at the industry level cluster around -.0026. That is, the procyclicality of wages increases by about a quarter of a percent for every added year of labor market experience. Thus, both the OLS and FE estimates show that, in a downturn, workers with more labor market experience find their wages falling relative to the wages of workers with little or no experience.

The selection corrected fixed effects estimates in the third panel show that the selection correction has virtually no effect on the results for all workers. The coefficients on URATE (.0122, s.e. .0018) and URATE*EXPERIENCE (-.0026, s.e. .0002) are almost identical to the FE estimates.[32] This is as expected since the parameter ρ was estimated to be close to zero in the aggregate and for all industries. At the industry level, many of the point estimates change from the FE estimates, again indicating the bias in the industry-level FE estimates resulting from restricting individual fixed effects and returns to observed ability to be the same across all industries.

Despite the change in the point estimates, most of the interaction coefficients at the industry level remain significantly negative. Thus, workers with higher levels of labor market experience face relatively greater procyclical variation in wages than recent entrants into the labor force. Since the EXPERIENCE variable is defined as current age minus age at entry into the labor force, it is possible that the above results are dominated by age effects rather than any aspects of human capital.

An important point to note about the aggregate and industry-level estimates in table 5 is that they clearly show that older workers (i.e. workers with more labor market

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[32] These estimates indicate that the average offer wage in our sample is weakly procyclical (.0122 - .0026*7.9 = -.0083).

experience), have more procyclical wages. Since our sample contains only young men, this implies that our estimates of the procyclicality of wages may significantly understate the true degree of procyclical variation in average wages in the U.S. economy.[33]

Interpretation of Findings

The results from the selection models at the aggregate level do not support the notion that skilled workers enter (implicitly or explicitly) into contracts with procyclical wages in order to secure more stable employment and thereby protect their investment in specific human capital. Workers with a college degree have much less employment variation at business cycle frequencies. But this is not explained in terms of a tradeoff between wage and employment stability since college educated workers are not subject to a larger degree of procyclical variation in offer wages than is the general workforce. Neither is it the case that skilled workers face more procyclical variation in weekly hours worked. In fact, workers with a degree appear to have very little cyclical variation in hours.

The industry-level estimates reveal that the aggregate results obscure considerable differences among industries in the nature of labor contracting. In durable and nondurable manufacturing, workers with a degree have more procyclical wages than other workers. In durable manufacturing, average employment probabilities are highly procyclical but workers with a degree are relatively protected from substantial employment variation. In nondurable manufacturing, most of the cyclical variation in labor input comes from variation in weekly hours, but hours are almost acyclical for workers with a degree. The employment and hours results together indicate that annual hours worked are essentially acyclical for college-educated workers in both industries. Thus, in the manufacturing sector, as suggested

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[33] For instance, using data from the Panel Study of Income Dynamics, Kydland and Prescott (1988) estimate average real wages to be strongly procyclical after adjusting for observed measures of worker quality.

by the Hashimoto-Raisian model, the relative wage premium for skills is procyclical and skilled workers do indeed seem to accept greater wage variation in return for employment stability.

Two industries, retail trade and services, are estimated to have countercyclical variation in the wage premium for skills. In retail trade, wages and employment probabilities are marginally countercyclical and weekly hours are acyclical for workers with a degree. In this industry, skilled workers appear to have labor contracts of the type suggested by Azariadis-Baily-Gordon. In services, average wages are highly procyclical but, for workers with a degree, wages are almost acyclical. However, educated workers in services also have strongly procyclical employment probabilities and countercyclical hours.

Workers with longer tenure on the current job face the same degree of cyclicality in wages as workers with little or no tenure, both at the aggregate and industry levels. In addition, length of tenure has little effect on employment or hours variability. The fact that we get such strong results with the degree variable but not with the tenure variable is, at first, rather puzzling. We surmise that the degree variable might proxy for the distinction between white-collar and blue-collar workers. These two classes of workers appear to have substantially different labor contracts, while the level of specific capital, as measured by tenure, is much less important in determining the precise nature of these labor contracts.

Workers with more labor market experience seem to have more procyclical variation in wages and hours worked than recent entrants into the labor force, but experience has no effect on employment variation.[34] However, this variable is probably the least reliable of the three proxies for human capital as it is simply a measure of labor force participation (or

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[34] In this context, it would also be of interest to examine the role of noncompetitive factors such as union membership. Unfortunately, except in a couple of years, our data set does not have a variable that would enable us to distinguish between union and nonunion workers.

age) rather than of actual employment patterns. In fact, the age effect appears to dominate the results of regressions with the URATE*EXPERIENCE interaction terms.

While older workers may have more specific capital than younger workers in a given firm, a firm has less incentive to retain older workers since the returns from their specific capital, if at all they accrue to the firm, are available for a much shorter time horizon than for younger workers. Since older workers do not experience more employment variation but have more procyclical wage and hours variation than younger workers, they appear to be protecting their specific capital by taking wage and hours cuts to avoid job separation.

6. Summary and Conclusion

The results of this paper indicate that, at the aggregate level, offer wage differentials between skilled and unskilled workers are essentially acyclical. Using education and tenure as proxies for skill levels, we find no evidence to support the view that relative wage differentials between skilled and unskilled workers are countercyclical, a view that has long been accepted as a stylized fact. Our OLS estimates, in fact, suggest that relative wage differentials may actually be procyclical (i.e. the difference between skilled and unskilled workers' wages widens in booms and narrows in recessions).

However, the OLS estimates turn out to be subject to bias resulting from systematic compositional changes that are not captured by observed worker characteristics. To provide correct measures of the cyclicality of wage differentials, we estimated a series of models that controlled for unobserved individual fixed effects as well as selectivity bias. The magnitude of the selectivity bias turns out not to be very significant in our sample, but unobserved fixed effects are found to severely bias the OLS coefficients. Correcting for observed and unobserved worker heterogeneity, we conclude that, at the aggregate level, correctly measured relative offer wage differentials do not have any consistent procyclical or countercyclical tendencies. However, after controlling for other characteristics, older workers do appear to have more procyclical wages than younger workers.

Variation in employment appears to be more important quantitatively than variation in weekly hours worked in explaining cyclical fluctuations in total labor input. On average, weekly hours worked are procyclical, with an average decline of about 0.4 percent for every percentage point increase in the aggregate unemployment rate. Variation in weekly hours per worker accounts for about thirty percent of the variation in total hours.

We find that workers with a college degree have acyclical employment probabilities and weekly hours, while uneducated workers have highly procyclical variation in employment and hours. These results imply that the average quality (in terms of skill level) of labor input per manhour rises in recessions and falls in booms. This suggests that measures of the real wage that simply divide the total wage bill by total manhours are likely to be substantially countercyclically biased. Furthermore, this bias may exist even in measures of the real wage that account for cyclical compositional changes in the workforce in terms of employment but not in terms of hours.

Our industry-level estimates reveal striking differences across industries in the cyclical variation of employment, hours and wages. For example, in our sample, durable manufacturing displays the strongest procyclical employment variation, although workers with a college degree face much less relative variation in employment in that sector. In both durable and nondurable manufacturing, workers with a degree have weakly countercyclical hours, but face much more procyclical variation in wages than other workers. Thus, the results for manufacturing support the Hashimoto-Raisian hypothesis that skilled workers accept more wage variation in return for employment stability, thereby also implying procyclical wage differentials between skilled and unskilled workers.

On the other hand, retail trade and services reveal a different pattern. In retail trade, workers with a degree have countercyclical wages while, for workers without a degree, wages are procyclical. In services, uneducated workers have strongly procyclical wages while workers with a degree have acyclical wages. Thus, for this measure of skill level, the relative skilled-unskilled wage differential is estimated to be countercyclical in these two industries.

In some industries such as nondurable manufacturing and retail trade, a large fraction of the variation in total hours worked appears to be accounted for by variation in average weekly hours rather than in the number of persons employed. In most other industries, as in the aggregate, employment variation seems more important than hours variation in accounting for cyclical fluctuations in total hours.

Our disaggregated results indicate that worker heterogeneity and sectoral differences interact in crucial ways over the business cycle.[35] Analyzing this issue is beyond the scope of this paper, but our results suggest that both these kinds of heterogeneity and the interactions between them are likely to play an important role in modeling and understanding business cycle fluctuations.

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[35] In a related paper (Keane and Prasad (1991)), we study the aggregate and sectoral effects of oil price shocks on wages and employment.

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Table 1

Estimated Correlations of Business Cycle With Employment Probabilities

	Panel 1		Panel 2	
INDUSTRY	U-RATE	U-RATE* DEGREE	U-RATE	U-RATE* EXPERIENCE
All Workers	-.0164** (.0020)	.0161** (.0035)	-.0099** (.0028)	-.0005 (.0003)
Durable Manufacturing	-.0137** (.0025)	.0109** (.0044)	-.0170** (.0035)	.0008** (.0004)
Nondurable Manufacturing	-.0003 (.0020)	-.0017 (.0034)	.0015 (.0028)	-.0003 (.0003)
Construction	-.0029 (.0018)	.0075** (.0032)	-.0003 (.0026)	-.0001 (.0003)
Transportation and Utilities	-.0015 (.0017)	.0046 (.0030)	.0001 (.0024)	-.0001 (.0003)
Wholesale Trade	-.0006 (.0013)	-.0028 (.0033)	-.0012 (.0018)	.0000 (.0002)
Retail Trade	.0022 (.0019)	.0079** (.0033)	.0088** (.0027)	-.0007** (.0003)
F.I.R.E.	.0012 (.0012)	-.0043** (.0020)	.0001 (.0016)	.0000 (.0002)
Services	.0017 (.0020)	-.0137** (.0035)	-.0026 (.0028)	.0002 (.0003)
Government	-.0016 (.0015)	.0049* (.0026)	.0029 (.0021)	-.0005** (.0002)
Agriculture	.0002 (.0009)	-.0000 (.0016)	.0005 (.0013)	-.0001 (.0001)
Mining	.0001 (.0007)	.0011 (.0013)	.0007 (.0010)	-.0001 (.0001)

NOTE: Standard errors are in parenthesis. ** indicates significant at 5% level. A * indicates the 10% level. Sample size = 23,927. Controls are a time trend, education, experience, and its square, four dummies for types of college degrees, five dummies for fields of degree, an SMSA dummy, a south dummy, a race dummy, a marriage dummy, number of children, and interactions of experience with education, a college degree dummy and a race dummy.

Table 2

Estimated Correlation of Business Cycle With Weekly Hours Worked
Fixed Effects Estimates
Dependent Variable - Log Weekly Hours

INDUSTRY	Panel 1		Panel 2		Panel 3	
	U-RATE	U-RATE* DEGREE	U-RATE	U-RATE* TENURE	U-RATE	U-RATE* EXPER.
All Workers	-.0061** (.0014)	.0082** (.0022)	-.0049** (.0018)	.0002 (.0003)	.0006 (.0023)	-.0007** (.0003)
Durable Manufacturing	-.0077** (.0023)	.0131** (.0029)	-.0057* (.0029)	.0003 (.0004)	.0020 (.0036)	-.0009** (.0003)
Nondurable Manufacturing	-.0098** (.0029)	.0088** (.0034)	-.0058* (.0036)	-.0000 (.0004)	-.0035 (.0042)	-.0007** (.0003)
Construction	-.0035 (.0032)	.0019 (.0039)	-.0063* (.0036)	.0004 (.0004)	.0003 (.0047)	-.0006* (.0003)
Transportation & Utilities	-.0076** (.0035)	.0097** (.0039)	-.0083* (.0044)	.0004 (.0004)	-.0029 (.0050)	-.0006* (.0003)
Wholesale Trade	-.0048 (.0045)	.0050 (.0035)	-.0028 (.0051)	-.0002 (.0004)	.0027 (.0057)	-.0009** (.0004)
Retail Trade	-.0058* (.0030)	.0048 (.0033)	-.0066* (.0035)	.0003 (.0004)	.0008 (.0043)	-.0008** (.0003)
F.I.R.E.	-.0043 (.0056)	.0091** (.0039)	-.0020 (.0059)	.0002 (.0005)	.0083 (.0071)	-.0011** (.0004)
Services	-.0047 (.0031)	.0082** (.0027)	-.0036 (.0032)	.0004 (.0004)	-.0039 (.0037)	-.0002 (.0003)
Government	-.0037 (.0044)	.0062* (.0035)	.0001 (.0052)	.0000 (.0004)	.0090* (.0055)	-.0011** (.0004)
Agriculture	-.0127** (.0061)	.0082 (.0084)	-.0146** (.0072)	.0005 (.0006)	.0062 (.0089)	-.0014** (.0004)
Mining	.0059 (.0079)	.0137* (.0083)	-.0031 (.0090)	.0006 (.0006)	.0225** (.0106)	-.0013** (.0005)

NOTE: Standard errors are in parenthesis. ** indicates significant at 5% level. * indicates the 10% level. Sample size = 21,004. For panel 2, sample size = 20,309 since the tenure variable is not available for all employed workers. Same set of controls as in Table 1, except that in Panel 2 tenure is added an additional control.

Table 3
Estimated Correlation of Business Cycle with Real Wages
Dependent Variable - Log Real Wage

INDUSTRY	OLS Estimates		Fixed Effects Estimates		Selection Corrected Fixed Effects	
	U-RATE	U-RATE* DEGREE	U-RATE	U-RATE* DEGREE	U-RATE	U-RATE* DEGREE
All Workers	.0031 (.0024)	-.0294** (.0041)	-.0062** (.0017)	.0013 (.0026)	-.0057** (.0019)	.0012 (.0013)
Durable Manufacturing	.0073** (.0036)	-.0348** (.0048)	-.0033 (.0026)	-.0028 (.0034)	-.0049* (.0030)	-.0059* (.0026)
Nondurable Manufacturing	.0082* (.0046)	-.0231** (.0051)	-.0044 (.0034)	-.0004 (.0039)	-.0029 (.0033)	-.0170** (.0030)
Construction	-.0118** (.0049)	-.0468** (.0056)	-.0112** (.0037)	-.0015 (.0046)	-.0135** (.0040)	.0010 (.0045)
Transportation & Utilities	.0222** (.0055)	-.0393** (.0053)	.0060 (.0041)	-.0057 (.0045)	.0037 (.0043)	.0067 (.0049)
Wholesale Trade	-.0005 (.0007)	-.0091 (.0057)	.0007 (.0052)	.0104** (.0041)	-.0020 (.0051)	.0046 (.0038)
Retail Trade	-.0079* (.0047)	-.0253** (.0052)	-.0065* (.0035)	.0055 (.0038)	-.0057 (.0036)	.0136** (.0041)
F.I.R.E.	-.0070 (.0086)	-.0181** (.0057)	-.0087 (.0065)	.0113** (.0046)	-.0111* (.0061)	-.0044 (.0043)
Services	-.0039 (.0049)	-.0245** (.0048)	-.0214** (.0036)	.0079** (.0031)	-.0161** (.0044)	.0152** (.0030)
Government	.0176** (.0067)	-.0300** (.0051)	-.0004 (.0051)	.0027 (.0041)	.0028 (.0049)	.0004 (.0030)
Agriculture	.0102 (.0092)	-.0132 (.0080)	.0117* (.0071)	-.0019 (.0097)	.0168* (.0101)	-.0130 (.0167)
Mining	-.0061 (.0118)	-.0387** (.0094)	-.0156* (.0092)	-.0022 (.0096)	.0021 (.0100)	-.0673** (.0080)

NOTE: Standard errors are in parenthesis. ** indicates significant at 5% level. * indicates the 10% level. Sample size = 21,004. Controls are a time trend, education, experience and its square, four dummies for types of college degrees, five dummies for fields of degree, four dummies for occupation, an SMSA dummy, a south dummy, a race dummy, a marriage dummy, number of children, and interactions of experience with education, a college degree dummy and a race dummy. Estimates for the selection models use the full sample of 23,927 person-year observations. The probit employment choice equation estimates from the selection models are not reported here.

Table 4

Estimated Correlation of Business Cycle with Real Wages
Dependent Variable - Log Real Wage

INDUSTRY	OLS Estimates		Fixed Effects	
	U-RATE	U-RATE* TENURE	U-RATE	U-RATE* TENURE
All Workers	-.0036 (.0027)	-.0001 (.0005)	-.0052** (.0021)	-.0004 (.0004)
Durable Manufacturing	-.0029 (.0041)	-.0002 (.0005)	-.0019 (.0043)	-.0002 (.0005)
Nondurable Manufacturing	.0030 (.0051)	-.0003 (.0005)	.0032 (.0053)	-.0003 (.0006)
Construction	-.0053 (.0050)	-.0024** (.0006)	-.0042 (.0053)	-.0025** (.0006)
Transportation and Utilities	.0071 (.0059)	-.0003 (.0005)	.0092 (.0062)	-.0002 (.0006)
Wholesale Trade	.0081 (.0072)	-.0002 (.0006)	.0054 (.0076)	.0003 (.0006)
Retail Trade	-.0093** (.0050)	.0003 (.0005)	-.0127** (.0052)	.0003 (.0006)
F.I.R.E.	-.0159* (.0082)	.0008 (.0007)	-.0171** (.0086)	.0008 (.0007)
Services	-.0103** (.0045)	-.0004 (.0005)	-.0125** (.0047)	-.0005 (.0005)
Government	-.0039 (.0069)	.0001 (.0006)	-.0011 (.0073)	.0002 (.0006)
Agriculture	.0367** (.0096)	-.0040** (.0007)	.0355** (.0101)	-.0042** (.0008)
Mining	.0025 (.0121)	-.0020** (.0006)	.0007 (.0127)	-.0021** (.0009)

NOTE: Standard errors are in parenthesis. ** indicates significant at the 5% level. * indicates the 10% level. Sample size is 20,309. Same controls as in Table 3, except that tenure is added as an additional control variable.

Table 5
Estimated Correlation of Business Cycle with Real Wages
Dependent Variable--Log Real Wage

INDUSTRY	OLS Estimates		Fixed Effects Estimates		Selection Corrected Fixed Effects	
	U-RATE	U-RATE* EXPER.	U-RATE	U-RATE* EXPER.	U-RATE	U-RATE* EXPER.
All Workers	.0033 (.0034)	-.0010** (.0004)	.0121** (.0017)	-.0026** (.0003)	.0122** (.0018)	-.0026** (.0002)
Durable Manufacturing	.0067 (.0048)	-.0009** (.0004)	.0145** (.0041)	-.0026** (.0003)	.0076* (.0046)	-.0017** (.0004)
Nondurable Manufacturing	.0206** (.0058)	-.0017** (.0005)	.0194** (.0049)	-.0030** (.0004)	.0056 (.0045)	-.0015** (.0004)
Construction	-.0174** (.0064)	-.0006 (.0005)	-.0036 (.0055)	-.0019** (.0004)	-.0006 (.0062)	-.0015** (.0006)
Transportation & Utilities	.0233** (.0068)	-.0012** (.0005)	.0195** (.0058)	-.0024** (.0004)	.0326** (.0061)	-.0039** (.0006)
Wholesale Trade	.0067 (.0084)	-.0009* (.0005)	.0193** (.0066)	-.0024** (.0004)	.0056 (.0069)	-.0010 (.0008)
Retail Trade	-.0136** (.0060)	-.0002 (.0004)	.0119** (.0049)	-.0025** (.0004)	.0268** (.0048)	-.0042** (.0005)
F.I.R.E.	-.0221** (.0097)	.0003 (.0006)	.0064 (.0082)	-.0021** (.0005)	.0183** (.0077)	-.0055** (.0010)
Services	-.0044 (.0051)	-.0015** (.0004)	.0060 (.0043)	-.0032** (.0003)	.0187** (.0034)	-.0047** (.0005)
Government	.0198** (.0075)	-.0016** (.0005)	.0159** (.0064)	-.0026** (.0004)	.0301** (.0056)	-.0047** (.0007)
Agriculture	.0251** (.0014)	-.0015** (.0006)	.0307** (.0104)	-.0026** (.0005)	.0032 (.0156)	.0013 (.0014)
Mining	.0074 (.0140)	-.0019** (.0007)	.0111 (.0122)	-.0031** (.0006)	.0284** (.0137)	-.0037** (.0012)

NOTE: Standard errors are in parenthesis. ** indicates significant at the 5% level. * indicates the 10% level. Sample size is 21,004. See note for Table 3 for list of controls.

APPENDIX

Table A1

Means of Variables in NLS Analysis Samples

Variable	Mean
Log Real Wage - WCPI	1.065
Real Price of Refined Petroleum - OIL	1.53
Unemployment Rate - U-RATE	6.38
Education (years) - EDUC	12.57
Experience on Current Job (years) - Tenure	4.00
Labor Market Experience (years) - EXPER	7.90
Experience Squared - $EXPER^2$	87.05
White Rate Dummy - WHITE	.74
Wife Present Dummy - WIFE	.69
SMSA Resident Dummy - SMSA	.70
South Resident Dummy - SOUTH	.41
Children in Household - KIDS	1.30
College Degree Dummy - DEG	.23
Employed Dummy	.89
OCCUPATIONAL DUMMIES:	
Professional and Technical Workers (0-370)	.31
Craftsmen and Foremen (401-545)	.19
Salesmen (380-395)	.05
Services (801-890)	.05
Operatives, Laborers, Farmers (200-222, 601-775, 901-985)	.29

NOTE: Census 3-digit occupation codes are used.

APPENDIX

Table A2

Sample Size by Industry

Industry	CIC Codes	Person-Year Observations
Durable Manufacturing	206-296	4,693
Nondurable Manufacturing	306-459	2,580
Construction	196	2,217
Transportation and Utilities	506-579	1,852
Wholesale Trade	606-629	1,039
Retail Trade	636-696	2,343
Finance, Insurance, Real Estate	706-736	833
Services	806-898	3,252
Government	906-998	1,389
Agriculture	16-18	535
Mining	126-156	327
Unemployed	---	2,724
Employed with Industry n/a	---	143

NOTE: Person-year observations for employed workers total 21,203. For 143 of these, the industry or occupation code is not available. This leaves 21,004 observations for employed workers that were used in analysis.