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EFFICIENCY WAGES AND THE INTER-INDUSTRY WAGE STRUCTURE

BY ALAN B. KRUEGER AND LAWRENCE H. SUMMERS[1]

This paper empirically tests and rejects classical competitive theories of wage determination by examining differences in wages for equally skilled workers across industries. Human capital earnings functions are estimated using cross-sectional and longitudinal data from the CPS and QES. The major finding is that the dispersion in wages across industries as measured by the standard deviation in industry wage differentials is substantial. Furthermore, F tests of the joint significance of industry dummy variables are decisively rejected. These differences are very difficult to link to unobserved differences in ability or to compensating differentials for working conditions.

Fixed effects models are estimated using two longitudinal data sets to control for constant, unmeasured worker characteristics that might bias cross-sectional estimates. Because measurement error is a serious problem in looking at workers who report changing industries, we use estimates of industry classification error rates to adjust the longitudinal results. In the fixed effects analysis, the industry wage differentials are sizable and are very similar to the cross-sectional estimates. In addition, the fixed effects estimates are robust under a variety of assumptions about classification errors and are similar using both data sets. These findings cast doubt on explanations of industry wage differentials based on unmeasured ability.

Additional analysis finds that the industry wage structure is highly correlated for workers in small and large firms, in different regions of the U.S., and with varying job tenures. Finally, evidence is presented demonstrating that turnover has a negative relationship with industry wage differentials. These findings suggest that workers in high wage industries receive noncompetitive rents.

KEYWORDS: Industry wage structure, efficiency wages, rent sharing, fixed effects, measurement error, labor turnover.

THE ESSENTIAL FEATURE of a perfectly competitive labor market is that workers who accept jobs can expect to receive compensation equal to their opportunity cost. Firms pay a wage that is just sufficient to attract workers of the quality they desire and no higher. Competitive theory makes a strong prediction about the structure of wages. Job attributes which do not directly affect the utility of workers should have no effect on the level of wages. Alternative theories such as the efficiency wage formulations surveyed by Stiglitz (1986) suggest that job attributes having nothing to do with the utility workers receive on the job should have systematic effects on wages because they influence the optimal wage for firms to choose. As Stiglitz (1986), Bulow and Summers (1986), and many other authors have argued, efficiency wage theories have positive and normative implications very different from those of more standard competitive models.

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This paper examines the magnitude of wage differentials for equally skilled workers. We focus on the role of industry affiliation in explaining relative wages. Our findings suggest that a worker's industry exerts a substantial impact on his wage even after controlling for human capital variables and a variety of job characteristics. We are led to conclude that there are important variations in wages which cannot be explained by standard competitive theories. These findings complement demonstrations of important relationships between firm size and wages (e.g. Brown and Medoff (1985)) and of large intra-industry wage differences (e.g. Dunlop (1957) and Groshen (1986)) in suggesting the importance of developing and testing alternative models of wage determination even in nonunion settings.

We focus on efficiency wage theories as an explanation for the setting of wages. Any economic theory that explains why wages deviate from their standard competitive level must in a tautologous sense explain why firms find it profitable to pay noncompetitive wages. In this sense, any explanation of noncompetitive wages must have an efficiency wage element. That is, it must postulate that over some range profits are an increasing function of the wage rate offered. In some cases, the efficiency wage theory is a triviality. For example, firms may find it unprofitable to violate minimum wage laws because of the fines that will be imposed. Or it may be necessary to pay supra-competitive wages to unionized workers in order to avoid strikes. Our principal interest is however in "pure" efficiency wage models in which firms can find it profitable to raise wages even when they will not be punished by some outside party for failing to do so. The limited evidence that is available suggests that high paying industries may benefit by reducing turnover as suggested by efficiency wage theories.

The paper is organized as follows. Section 1 briefly discusses the possible role of efficiency wage theories in explaining wage differentials. Section 2 presents our basic econometric results using data from the Current Population Survey (CPS) and documents the existence of substantial inter-industry variations in wages. Section 3 considers labor quality differences as an explanation of the industry wage structure. By providing fixed effects estimates we cast serious doubt on "unmeasured labor quality" explanations for inter-industry wage differences. Section 4 considers and rejects a number of other possible reconciliations of the results with competitive theory. We present evidence suggesting that wage differentials cannot be attributed to union effects, the short run immobility of labor, or compensating differentials. Section 5 provides some evidence that high wages are efficacious in reducing turnover and thus provides some additional evidence that workers in high wage industries receive rents. Section 6 concludes the paper by reviewing some broader evidence on the importance of industry wage differentials, and by reviewing evidence on the importance of these differentials for economic theory and policy.

1. EFFICIENCY WAGE THEORIES

Economists have a clear understanding of how perfectly competitive labor markets without any information or contracting problems would function. Equally productive workers would receive compensation packages that provide equal levels of utility. Wages would depend only on workers' abilities and not on characteristics of their employers that do not influence other nonpecuniary benefits of employment. Falsification of this prediction would force consideration of alternative theories that predict linkages between job characteristics and wages. Any such theory has the property that at least some employers must be paying more than the going wage for workers of the type they attract. This behavior can be rationalized only by assuming that some firms do not profit maximize, or that some firms find that increasing wages above the going rate is profitable. The latter possibility is the defining characteristic of efficiency wage theories.

At least four conceptually distinct efficiency wage theories may be adduced as possible rationales for the payment of noncompetitive wages. Our goal in this paper is to demonstrate the potential importance of efficiency wages, not to distinguish among alternative motives for paying them. We therefore describe these motives only briefly. For formal presentations of the relevant models, and references to the relevant literature, see Stiglitz (1984) and Katz (1986). The profitability of raising wages at least in some circumstances has been asserted by many authors including Adam Smith, Karl Marx, Alfred Marshall, Henry Ford, and Max Weber.

A first model of efficiency wages postulates that they are paid in order to minimize turnover costs. If firms must bear part of the costs of turnover, and if turnover is a decreasing function of the wages firms pay, there may be an incentive to raise wages in order to minimize turnover costs.

A second possibility is that increasing wages raises workers' effort level. Workers who are paid only their opportunity costs have little incentive to perform well since losing their jobs would not be costly. By raising wages, firms may make the cost of job loss larger and thereby encourage good performance.

Alternatively, a third model postulates that workers' feelings of loyalty to their firm increase with the extent to which the firm shares its profits with them. These feelings of loyalty may have a direct effect on productivity. As expounded by Akerlof (1984) such a model relies on notions about gift relationships that are not well captured by traditional utility functions.

A final model is based on selection rather than incentive efforts. Firms which pay higher wages will find that they attract a higher quality pool of applicants. If quality is not directly observable, this will be desirable.

If all firms were identical, one would not expect to see different firms paying different wages even if efficiency wage considerations were important. But when there are differences in their ability to bear the costs of turnover, to supervise and monitor their workers, or to measure labor quality, either because of differences in management capacity, or because of differences in the technology of production, then the optimal wage to pay will vary. Thus efficiency wage models unlike standard competitive formulations can explain why characteristics of firms that do not directly affect workers' utility can affect wage rates.

It should be clear that demonstrations that similar workers can over long periods of time be paid different wages in different industries makes plausible the idea that some workers are involuntarily unemployed, for involuntary unemployment can simply be thought of as confinement to a low wage home production industry.

Previous Studies

Previous studies have examined the effect an employee's industry has on wages to test segmented labor market theories that are closely related to the efficiency wage models considered here. Sumner Slichter (1950) was among the first economists to study the industry wage structure. After examining the average hourly wage rate of skilled and unskilled male workers in manufacturing industries between 1923 and 1946, Slichter was struck by the magnitude of industry wage differences for comparable workers.

Slichter found several "regularities" in the wage structure. First, he found the average unskilled wage rate in an industry to vary positively with the average hourly earnings of semi-skilled and skilled workers in the industry. Second, he found that industry wages are positively correlated with value added per worker in the industry, positively correlated with profit margins, and negatively correlated with the payroll to income ratio. And lastly, he found that "the wage structure changes over time, but the changes are fairly slow and the wage structure between industries within a period of twenty or thirty years exhibits only moderate changes." Slichter theorized that these facts were evidence that "managerial policy" is important in wage setting.

Thurow (1976) phrases the question as follows: "Earnings data and earnings equations are often corrected for both industry and geographic location, but should they be? Wage payments in a marginal-productivity world are supposed to be made on the basis of the skills supplied and not dependent upon the industry or region of use." The answer he finds is that "industry and geographic variables are significant in individual earnings functions.... This significance, itself, constitutes a deviation from the norms of a competitive market."

Using regression analysis, Wachtel and Betsey (1972) analyze the impact of one digit industries and three occupation groups on the residual of wages after controlling for education, experience and demographic factors. Like Thurow they conclude that "there is a substantial portion of the variance in wage earnings that can be explained by industry structure after the effects of personal characteristics have been eliminated." They further find that an employee's industry and occupation pair is more "important" in explaining wages than other "structural characteristics," such as union status and geographic location.

After carefully reviewing the empirical studies on dual labor market theory, Cain (1976) concludes that the importance of industry affiliation in determining wages is the most convincing evidence in support of dual labor markets.[2]

[2] Recently, Dickens and Lang (1985) examine the returns to education and experience across sectors. Their estimating technique allows for the simultaneous determination of the worker's sector and the characteristics of the sectors. As a result they can test whether primary sector jobs are rationed. They conclude that returns to experience and education differ across sectors, and that some workers are involuntarily confined to secondary sector jobs.

However, Cain aptly cautions that the industry effects on wages "may represent transitory demand factors, compensating nonpecuniary effects, or unmeasured human capital variables." These possibilities have not been adequately addressed in the existing empirical studies purporting to establish the importance of labor market segmentation. The empirical work reported below takes up Cain's challenge and examines possible competitive explanations for inter-industry wage differences.

2. DATA, METHODOLOGY, AND BASIC RESULTS

In textbook neoclassical labor economics an employee is compensated according to his or her opportunity cost, which is determined by accumulated human capital and the employer's work environment. If an employee's industry is a significant factor in determining wages after controlling for labor quality and working conditions we must look beyond the standard competitive theory and ask why firms choose to pay workers more than their alternative wage.

Our initial empirical analysis of industry wage differentials is based on cross-sectional data on individuals collected by the Bureau of the Census for the May 1974, 1979, and 1984 Current Population Surveys. The May CPS contains labor force data for members of the sampled households who are 14 years old or older. In May 1979 the Bureau of the Census asked additional questions on tenure, firm size, plant size, and fringe benefits of a randomly selected sample of households for its Pension Supplement. All of our results for 1979 are based on the Pension Supplement.[3] The samples we analyze contain full and part-time private non-agricultural employees 16 years old or older. The earnings variable is usual weekly earnings divided by usual weekly hours. We considered employees who reported earning less that $1.00 an hour or greater than $250.00 an hour to be outliers and eliminated them from the sample.

We estimate several standard cross-section wage equations in order to examine the importance of industry affiliation in explaining relative wages. Our strategy is to control for human capital, demographic background, and working conditions as well as possible, and then analyze the effect of industry dummy variables on relative wages. We normalize the estimated industry wage differentials as deviations from the (weighted) mean differential.[4]

Table I presents results of separate cross-section regressions of log wage on one digit census industries (CIC) with human capital and demographic controls for 1974, 1979, and 1984. The human capital and demographic controls are 9 occupation dummy variables, education, age, sex, race, union status, a central

[3] Results are qualitatively the same when the full 1979 sample is used.

[4] Since the wage regressions include a constant, we treated the omitted industry variable as having a zero effect on wages, calculate the employment-weighted average of wage differentials for all industries, and report the difference between the industry differentials and the weighted average. The resulting statistics are the proportionate difference in wages between an employee in a given industry and the average employee. The standard errors we report, however, are the unadjusted OLS standard errors.

TABLE I

ESTIMATED WAGE DIFFERENTIALS FOR ONE-DIGIT INDUSTRIES—MAY CPS[a]
(Standard Errors in Parentheses)

Industry	(1) 1974	(2) 1979	(3) 1984	(4) 1984 Total Compensation
Construction	.195	.126	.108	.091
	(.021)	(.031)	(.034)	(.035)
Manufacturing	.055	.044	.091	.131
	(.020)	(.029)	(.032)	(.032)
Transportation & Public Utilities	.111	.081	.145	.203
	(.021)	(.031)	(.034)	(.034)
Wholesale & Retail Trade	−.128	−.082	−.111	−.136
	(.020)	(.030)	(.033)	(.033)
Finance, Insurance and Real Estate	.047	−.010	.055	.069
	(.022)	(.035)	(.034)	(.034)
Services	−.070	−.055	−.078	−.111
	(.021)	(.030)	(.032)	(.032)
Mining	.179	.229	.222	.231
	(.035)	(.058)	(.075)	(.075)
Weighted Adjusted Standard Deviation of Differentials[b]	.097**	.069**	.094**	.126**
Sample Size	29,945	8,978	11,512	11,512

[a] Other explanatory variables are education and its square, 6 age dummies, 8 occupation dummies, 3 region dummies, sex dummy, race dummy, central city dummy, union member dummy, ever married dummy, veteran status, marriage × sex interaction, education × sex interaction, education squared × sex interaction, 6 age × sex interactions, and a constant. Each column was estimated from a separate cross-sectional regression.

[b] Weights are employment shares for each year.

** F test that industry wage differentials jointly equal 0 rejects at the .000001 level.

city dummy, marital status, veteran status, and several interaction terms.[5] Table II presents comparable results for two-digit CIC industries and Appendix Table A1 contains comparable results for 1984 for three digit CIC industries. The industry dummy variables are jointly statistically significant and they are generally statistically significant individually as well. The results are qualitatively the same when the samples are restricted to nonunion workers.

Furthermore, the industry variables have a sizable impact on relative wages. The coefficient for mining in Table II for 1984, for instance, implies that the average employee in the mining industry earns wages that are 24 per cent higher than the average employee in all industries, after controlling for human capital and demographic background. In 1984 the industry differentials ranged from a high of 37 per cent above the mean in the petroleum industry to a low of 37 per cent below the mean in private household services. These large wage differentials suggest that other factors besides opportunity costs are important in explaining wages.

The industry variables are very important in explaining variations in log earnings. As an indication of their importance, the standard error of the regression falls by 4.3 percentage points once industry controls are added to a

[5] We return to the effects of unions in Section 4.

TABLE II
ESTIMATED WAGE DIFFERENTIALS FOR TWO-DIGIT INDUSTRIES—MAY CPS
(Standard Errors in Parentheses)

Industry	(1) 1974	(2) 1979	(3) 1984	(4) 1984 Total Compensation
Mining	.203	.263	.241	.253
	(.022)	(.031)	(.033)	(.033)
Construction	.228	.137	.126	.112
	(.011)	(.016)	(.020)	(.020)
Ordnance	.202	.091	NA	NA
	(.040)	(.067)	NA	NA
Lumber	.003	−.035	.001	.038
	(.021)	(.037)	(.037)	(.037)
Furniture	−.059	−.120	−.006	.014
	(.025)	(.036)	(.048)	(.048)
Stone, Clay & Glass	.032	.052	.085	.137
	(.022)	(.034)	(.044)	(.044)
Primary Metals	.082	.114	.162	.262
	(.016)	(.026)	(.037)	(.037)
Fabricated Metals	.057	.039	.071	.132
	(.015)	(.026)	(.033)	(.033)
Machinery, Excl. Elec.	.083	.092	.185	.221
	(.013)	(.022)	(.024)	(.024)
Electrical Machinery	.055	.045	.107	.135
	(.013)	(.021)	(.025)	(.025)
Transport Equipment	.120	.156	.191	.267
	(.014)	(.021)	(.025)	(.025)
Instruments	.086	.137	.139	.167
	(.025)	(.040)	(.041)	(.041)
Misc. Manufacturing	−.116	−.110	.014	.034
	(.024)	(.042)	(.053)	(.053)
Food	.010	.019	.057	.109
	(.015)	(.026)	(.027)	(.027)
Tobacco	−.007	−.040	.340	.527
	(.063)	(.156)	(.129)	(.129)
Textiles	−.010	−.034	.011	.023
	(.019)	(.034)	(.039)	(.039)
Apparel	−.087	−.132	−.127	−.123
	(.016)	(.030)	(.032)	(.032)
Paper	.057	.088	.141	.178
	(.020)	(.033)	(.039)	(.039)
Printing	.052	.039	.092	.095
	(.017)	(.028)	(.028)	(.028)
Chemical	.157	.148	.221	.266
	(.018)	(.029)	(.033)	(.033)
Petroleum	.238	.278	.371	.619
	(.036)	(.062)	(.073)	(.073)
Rubber	.007	.023	.054	.098
	(.021)	(.036)	(.041)	(.041)
Leather	−.097	−.233	−.082	−.062
	(.034)	(.051)	(.060)	(.060)
Railroad	.200	.120	NA	NA
	(.023)	(.037)	NA	NA
Other Transport	.090	.120	.132	.160
	(.014)	(.022)	(.022)	(.022)
Communications	.159	.064	.171	.293
	(.016)	(.027)	(.029)	(.029)
Public Utilities	.138	.068	.259	.336
	(.021)	(.028)	(.032)	(.032)

TABLE II (*Continued*)

Industry	(1) 1974	(2) 1979	(3) 1984	(4) 1984 Total Compensation
Wholesale Trade	.035	−.015	.047	.025
	(.012)	(.020)	(.020)	(.020)
Eating & Drinking	−.267	−.125	−.189	−.219
	(.012)	(.020)	(.021)	(.021)
Other Retail	−.141	−.093	−.155	−.186
	(.030)	(.050)	(.067)	(.067)
Banking	.081	−.063	.064	.092
	(.014)	(.031)	(.022)	(.022)
Insurance	.048	.022	.071	.075
	(.013)	(.027)	(.021)	(.021)
Private Household	−.151	−.259	−.366	−.517
	(.019)	(.034)	(.033)	(.033)
Business Services	−.053	−.067	.000	−.031
	(.016)	(.028)	(.023)	(.023)
Repair Services	−.126	−.026	−.056	−.087
	(.021)	(.032)	(.034)	(.034)
Personal Services	−.216	−.107	−.154	−.194
	(.015)	(.025)	(.025)	(.025)
Entertainment	−.145	−.078	−.141	−.163
	(.023)	(.036)	(.034)	(.034)
Medical Services	−.052	−.039	−.082	−.078
	(.015)	(.022)	(.023)	(.023)
Hospitals	.039	.063	.059	.062
	(.013)	(.018)	(.023)	(.023)
Welfare Services	−.333	−.190	−.246	−.330
	(.022)	(.032)	(.027)	(.027)
Education Services	−.127	−.185	−.194	−.216
	(.016)	(.019)	(.028)	(.028)
Professional Services	.085	.060	.062	.023
	(.016)	(.029)	(.026)	(.026)
Weighted Adjusted Standard Deviation of Premiums	.132**	.108**	.140**	.177**

See Table I notes. Sample sizes are the same as in Table I.

regression that already controls for occupation, human capital, and demographic factors (the complete variable list is given in note a of Table I). In comparison, the union variable only decreases the standard error of the regression by 1.6 percentage points, the human capital controls reduce the standard error by 5.1 percentage points, and race and sex controls reduce the standard error by .2 percentage points when they are added to the same regression. This suggests that if industry wage differences are noncompetitive they have far greater impacts on the allocation of resources than do the wage differences associated with unions or discrimination.

Some general observations can be made about the industry wage structure. Durable manufacturing products and chemical industries tend to be high wage industries while wholesale, retail, and service industries tend to be low wage industries. In 1984, for instance, workers in the capital intensive, technologically sophisticated chemical industry were paid 22 per cent more than the average employee, while workers in the customer oriented retail trade industries were paid 16 per cent to 19 per cent less than the average employee, all else constant.

To summarize the overall variability in industry wages we focus on the standard deviation of the industry wage differentials. Although for each industry $i = (1, \dots, K)$ the estimated wage differential $\hat{\beta}_i$ is an unbiased estimate of the true wage differential β_i, the standard deviation of $\hat{\beta}$ is an upwardly biased estimate of the standard deviation of β. This bias occurs because $\hat{\beta}_i$ equals $\beta_i + \hat{\varepsilon}_i$, where $\hat{\varepsilon}_i$ is a least squares sampling error.

We adjust the standard deviation of $\hat{\beta}$ by using the formula:

$$(10) \qquad SD(\beta) \approx \sqrt{\operatorname{var}(\hat{\beta}) - \sum_{i=1}^{K} \hat{\sigma}_i^2 / K}$$

where $\hat{\sigma}_i$ is the standard error of $\hat{\beta}_i$. Because this adjustment neglects the covariances among the ε_i, it slightly underestimates the standard deviation of β.[6]

Industry variations in relative wages are substantial. In 1984 the employment-weighted standard deviation of two digit CIC industry wage differentials was 14 per cent, in 1979 the standard deviation was 11 per cent, and in 1974 the standard deviation was 13 per cent. Thus cross-sectional estimates imply that changing between typical industries has about the same impact on wages as does changing union status.

Nonwage Compensation

Fringe benefits are an important component of compensation, accounting for as much as 40 to 50 per cent of total compensation in some companies. To adjust for variation in fringes across industries, we multiplied the CPS hourly wage data for each worker by the ratio of total labor costs to wages in the corresponding industry. The industry labor cost and wage data are reported in the National Income and Product Accounts (NIPA).

The results of wage regressions with the dependent variable adjusted to reflect nonwage compensation are reported in column (4) of Tables I and II. Since the NIPA and CPS classification schemes do not match perfectly, caution should be taken in comparing these results to the CPS results. Nonetheless, Tables I and II show that consideration of nonwage compensation reinforces rather than reduces industries wage differences. For instance, the wage differential in primary metals

[6] The expected value of the variance of $\hat{\beta}$ is given by

$$E\left[\operatorname{var}(\hat{\beta})\right] = \operatorname{var}(\beta) + \sum_{i=1}^{K} \frac{\sigma_i^2}{K} - \sum_{i=1}^{K} \sum_{j=1}^{K} \frac{\sigma_{ij}}{K^2}$$

where $\sigma_i^2 = E(\hat{\varepsilon}_i^2)$ and $\sigma_{ij} = E(\hat{\varepsilon}_i \hat{\varepsilon}_j)$. Since $\Sigma(\sigma_i^2/K) - \Sigma\Sigma(\sigma_{ij}/K^2) \geqslant 0$, it follows that $E[\operatorname{var}(\hat{\beta})] \geqslant \operatorname{var}(\beta)$. Standard deviations reported in the text do not adjust for covariance terms in the above equation and thus in expected value underestimate the true standard deviation. However, experimentation with the 1984 CPS shows that accounting for covariance terms increases the estimated standard deviation by only .0007.

increases from 16 per cent above the mean to 26 per cent above the mean when we take account of nonwage compensation. Accounting for nonwage benefits tends to increase industry wage dispersion.

Wage Differences Through Time

Over time both the one and two digit CIC industries show a stable pattern of inter-industry wage variability. The standard deviation of estimated wage differentials shows no trend during the years we studied and the differentials are highly correlated from year to year. Between 1984 and 1979 the correlation in estimated industry wage differentials is .915 and between 1984 and 1974 the correlation is .911. As further evidence of the stability of the inter-industry wage structure over time, Krueger and Summers (1986) find a correlation of .56 between the industry wage differentials for 1984 and the average wage of unskilled male manufacturing workers in 1923.[7] Like Slichter, we conclude that the industry wage structure remains fairly constant over time.

The stability of the industry wage structure casts doubt on explanations of wage differentials based on the short run immobility of labor or transitory labor demand shocks. It is unlikely that labor is sufficiently immobile over several decades or even one decade to allow such large differentials to persist.

In apparent contrast to the predictions of a naive competitive model, we find that the industry an employee is in has a statistically significant and sizable impact on wages even after controlling for supply-side factors. Furthermore, these relative wage differentials persist at about the same level over time, which is inconsistent with explanations based on the short run immobility of labor and the effects of transitory demand shocks. Next we examine other possible competitive rationalizations for our results.

3. LABOR QUALITY EXPLANATIONS OF INDUSTRY WAGE DIFFERENTIALS

Perhaps the most plausible competitive explanation for our findings is that there are differences in unmeasured aspects of labor quality across industries. The limited human capital variables available in the Current Population Survey may not adequately control for labor quality. It could be argued that unmeasured labor quality differences, such as motivation and innate ability, vary systematically across industries and are being "picked-up" by the industry controls rather than the human capital controls.

As a first approach to this problem, Table III explores the impact of alternative degrees of control for human capital on inter-industry wage variation. If industry wage differentials were due to measured and unmeasured labor quality differences across industries we would expect a substantial fall in the dispersion of industry wages once we control for measured human capital. However, the

[7] It should be noted that these raw correlations are underestimates due to sampling errors.

TABLE III
ALTERNATIVE DEGREES OF CONTROL FOR LABOR QUALITY—MAY 1979 CPS, PENSION SUPPLEMENT

Controls	Weighted Adjusted SD of Industry Wage Differentials	Correlation With Table II
(1) 8 occupation dummies, sex, nonwhite, region dummies (3), central city dummy, union dummy, ever married, ever married* sex, and veteran status	.114**	.994
(2) Row (1) controls plus 12 age structure variables	.108**	.998
(3) Row (2) controls plus 4 education variables	.108**	1.000
(4) Row (3) controls plus 4 tenure variables	.104**	.995

** F test that industry wage differentials jointly equal 0 rejects at the .00001 level.

addition of human capital controls—education, tenure, and age—results in only a one percentage point drop in the standard deviation of the wage differentials in the 1979 CPS Pension Supplement. Despite the increased controls for labor quality the standard deviation of industry wages remains above 10 per cent. Unless one believes that variation in unmeasured labor quality is vastly more important than variation in age, tenure, and schooling, this evidence makes it difficult to attribute inter-industry wage differences to differences in labor quality.[8]

We further address the problem of unmeasured, unchanging labor quality by analyzing longitudinal data. With these data we can compare the wages of the same person as he or she switches industries. The longitudinal analysis addresses the problem of unmeasured labor quality in the cross-sectional results, but is not without potential biases. These biases include the selectivity of job switchers and increased measurement error. These issues are addressed in the results reported below.

Two longitudinal data sets are analyzed. The primary data set was created by pooling three matched May CPS data sets. Since CPS cannot match individuals who changed their address during the year, the sample is not completely representative. Nonetheless, the Census Bureau reports that about 70 per cent of respondents were matched from one year to the next. The data set contains 18,541 employees, and 2,137 of these workers report changes in their one digit industry during the year. However, evidence from Mellow and Sider (1983) who used direct evidence obtained from the employers of a subset of a CPS sample to

[8] Evidence suggests that unmeasured ability and upbringing have surprisingly little power in explaining wages. For instance, results presented in Taubman (1977) suggest that the expected difference in earnings between identical twins is about two-thirds as great as between randomly chosen members of the population. Jencks (1972) reports similar results for a host of other variables.

TABLE IV

THE EFFECTS OF UNMEASURED LABOR QUALITY[a]

Industry	(1) Fixed Effects Unadjusted for Measurement Error	(2) Fixed Effects Adjusted for Measurement Error I[b]	(3) Fixed Effects Adjusted for Measurement Error II[c]	(4) Levels
Construction	.063	.098	.174	.174
	(.033)	(.060)	(.060)	(.024)
Manufacturing	.028	.055	.107	.064
	(.031)	(.058)	(.058)	(.022)
Transportation and	.019	.060	.049	.114
Public Utilities	(.035)	(.059)	(.059)	(.024)
Wholesale and	−.042	−.068	−.125	−.133
Retail Trade	(.031)	(.056)	(.056)	(.023)
Finance, Insurance	.027	.017	.018	.035
and Real Estate	(.036)	(.061)	(.061)	(.025)
Services	−.040	−.088	−.128	−.079
	(.032)	(.056)	(.057)	(.023)
Mining	.067	.122	.142	.156
	(.004)	(.057)	(.058)	(.040)

[a] Data set is three matched May CPS's pooled together: 1974–1975, 1977–1978, and 1979–1980. Sample size is 18,122. Levels are 1974, 1977, and 1979 data pooled. Results of the 1975, 1978, and 1980 sample are qualitatively the same. Controls for fixed effects regressions are change in education and its square, change in occupation, 3 region dummies, change in union membership, experience squared, change in marital status, year dummies, and a constant. Controls for level regressions are the same as Table I plus year dummies.
[b] Adjustment I assumes 3.4 per cent error rate and that misclassifications are proportional to industry size. See Appendix for description.
[c] Adjustment II assumes average error rate is 3.4 per cent and misclassifications are allocated according to employer-employee mismatches. See Appendix for description.

estimate the extent of measurement error in answers to CPS questions about industry suggests that a large fraction of reported industry switches do not reflect genuine movements between industries but are instead the result of classification errors. As a result, it is necessary to correct our estimates for measurement error.

We make use of the prior information provided by Mellow and Sider on the extent of reporting errors to correct our estimates of industry wage differentials for the effects of measurement error. The correction differs from the standard one because the independent variables we examine are dichotomous. It is detailed in the Appendix. The procedure is implemented under two different assumptions about the nature of the process generating industry classification errors. In Case I we assume the error rate is the same in all industries and that the chance of being misclassified into an industry is proportional to the industry's employment share. In Case II we estimate the chance of spurious classification between industry i and industry j directly from the data used by Mellow and Sider.

Table IV presents the results of longitudinal analysis with the matched CPS data. We report the first difference results adjusted for measurement error under our two alternative assumptions. In addition, we report the fixed effects results without adjusting for measurement error, and report the results of a wage regression using levels. The results show that the first difference and level regressions are similar, and in both cases the industry variables are jointly statistically significant.[9] For all industries, the measurement error adjusted first difference and level results have the same sign and about the same magnitude. For instance, the longitudinal results with measurement error correction II show that workers who join (leave) the manufacturing sector gain (lose) a 10.7 per cent pay increase (decrease), while a regression on the levels shows a 6.4 per cent pay premium for manufacturing workers. In some cases, the measurement error corrected results actually suggest that the unmeasured labor quality is lower in the high pay industries.

Using data from 1979, Gottschalk and Maloney (1985) find that nearly 70 per cent of job changes are voluntary. There are potentially important selection problems involved in studying workers who voluntarily change industries. For instance, if there is uncertainty as to workers' ability, workers who move from the apparent high wage industries to the low wage industries may be low quality workers, while workers who move from low wage to high wage industries may benefit from better matches. As a partial test for the importance of these problems, we examined the impact on wages of changing industries separately for leavers and joiners. The selection effects operating on workers moving from industry i to j are likely to be different from those operating on workers going from industry j to industry i. We were unable, however, to reject the hypothesis that wage changes were the same for joiners and leavers. This suggests that selectivity forces are not very important in the longitudinal analysis and provides some support for the first difference specification.

Longitudinal Evidence from Displaced Workers

Perhaps more convincing evidence on the same issue comes from our analysis of a sample of displaced workers. The second longitudinal data set we use is the January 1984 CPS survey of displaced workers. The Census Bureau asked a sequence of retrospective questions to workers who lost their job because their plant closed, they were permanently laid off, or their job was abolished. This data set helps solve the problem of selective job changers because only workers who were involuntarily displaced from their jobs are in the sample. One disadvantage of the data set, however, is that the workers' hourly wage rate and weekly hours are not available. Instead, we use the weekly wage as the dependent variable and restrict the sample to full-time (more than 35 hours per week) workers. On the other hand, the data set has the advantage of following workers who moved to a new location and contains job tenure on the initial job.

Table V reports the results of our longitudinal analysis of displaced workers. The first difference estimates are corrected for measurement error in the same fashion as the estimates in Table IV. Because a high proportion (more than half) of the workers in this sample switched industries, measurement error has a

[9] A preferable alternative to first-differencing would be to examine changes in wages for workers who move in all directions. Unfortunately, measurement error and the small sample of industry changers makes such an approach infeasible.

TABLE V[a]
THE EFFECTS OF UNMEASURED LABOR QUALITY FOR A SAMPLE OF DISPLACED WORKERS

Industry	(1) Fixed Effects Unadjusted for Measurement Error	(2) Fixed Effects Adjusted for Measurement Error I[b]	(3) Fixed Effects Adjusted for Measurement Error II[c]	(4) 1984 Cross-Section
Construction	.000	.001	.005	.174
	(.051)	(.051)	(.052)	(.060)
Manufacturing	.053	.058	.059	.055
	(.049)	(.048)	(.050)	(.060)
Transportation and	.010	.011	.013	.117
Public Utilities	(.054)	(.054)	(.055)	(.064)
Wholesale and	−.058	−.062	−.068	−.097
Retail Trade	(.050)	(.049)	(.050)	(.061)
Finance, Insurance	.015	.015	.016	−.024
and Real Estate	(.056)	(.055)	(.056)	(.067)
Services	−.062	−.067	−.065	−.097
	(.050)	(.050)	(.051)	(.062)
Mining	.289	.306	.330	.366
	(.036)	(.036)	(.037)	(.137)

[a] Control variables for fixed effects models are tenure on previous job, age, 8 occupation change dummy variables, a dummy variable indicating whether the worker moved to a new location, 4 dummy variables for year of displacement, and a constant. Control variables for 1984 cross-section are years since displacement and its square, education, race, sex, 3 region dummy variables, marital status, 8 occupation dummy variables, age and its square, and a constant. Sample size for fixed effects regressions is 2,318 and for 1984 cross-section is 2,592. We are grateful to Doug Kruse for preparing this table.
[b] Adjustment I assumes 3.4 per cent error rate and that misclassifications are proportional to industry size. See Appendix for description.
[c] Adjustment II assumes average error rate is 3.4 per cent and misclassifications are allocated according to employer-employee mismatches. See Appendix for description.

substantially smaller effect on the first difference estimates than it does in the first CPS data set, where the rate of true industry mobility is much lower. The industry variables are jointly highly significant in both levels and first-differences. Although the construction and transportation industries appear to be anomalies, these results suggest that workers who are involuntarily displaced from their jobs and switch industries experience substantial wage changes that closely parallel the industry wage structure found in cross-sectional analyses. We interpret this as additional evidence that observed cross-sectional industry wage differences do not only reflect differences in average labor quality.[10]

There is a final point that militates against the unmeasured labor quality explanation for industry wage differentials. Evidence surveyed in Krueger and Summers (1986) and Dickens and Katz (1986b) indicates that there are strong

[10] We note, however, the contrasting findings by Murphy and Topel (1986) who conclude that two-thirds of observed industry annual earnings differences are due to unobserved individual components. There are two major differences in their analysis that might account for these findings. First, Murphy and Topel use an instrumental variable procedure to adjust for measurement error. Second, and probably more importantly, Murphy and Topel focus on changes in occupation-industry cells without controlling for changes in workers' occupations. It is plausible that unobserved worker-specific differences bias cross-sectional estimates of the occupational wage structure but not the industry wage structure.

regularities in the pattern of industrial wages. More profitable industries, those with more monopoly power, and those where labor's share is smaller pay higher wages. The regularities appear to be statistically significant, to hold in different times and places, and to account for a fairly large fraction of inter-industry wage variations. Since it is hard to see why there would be a correlation between unmeasured labor quality and product market characteristics, these results cast further doubt on the unmeasured quality explanation for wage differentials.

4. ALTERNATIVE EXPLANATIONS OF INDUSTRY WAGE DIFFERENTIALS

In this section we examine whether the substantial industry wage differentials discussed in Sections 2 and 3 can be given competitive or institutional explanations. We examine the importance of compensating differentials, unions, and other factors. The major conclusion is that industry wage differentials appear robust to additional competitive and institutional explanations.

Compensating Differentials

Logically, the finding of stable inter-industry wage differentials could be explained by pointing to compensating differentials. The compensating differentials argument is that agreeable and disagreeable job attributes vary systematically with one's industry of employment, and therefore necessitate wage differentials to compensate employees for nonwage aspects of the industry. Since the results considered so far do not control for working conditions, it could be argued that the observed industry wage differentials merely represent compensating differentials.

Although Brown (1980), Smith (1979), and several other studies have not been able to document compensating differentials for a range of job attributes, we examine this possibility. We base our analysis of working conditions on the University of Michigan's Quality of Employment Survey (QES). The 1977 QES cross-section contains data on a wide range of working conditions. Several other studies of compensating differentials have relied on QES, such as Preston (1985) and Brown and Medoff (1985). We focus on ten potentially important job attributes—weekly hours, a variable indicating whether health hazards are present on the job, and another indicating whether the hazard is serious, second and third shift dummies, commuting time, two variables indicating the extent of choice of overtime, and two catch-all variables indicating whether the physical work conditions are pleasant.[11] These are the same variables Brown and Medoff (1985) hold constant.

If the industry differentials do not change substantially once the working condition measures are added to the regression, we would conclude that compensating differentials are not playing an important role in determining the industry wage differentials.

[11] Although the weekly hours variable is possibly endogenous, results are qualitatively the same when it is omitted from the regression.

TABLE VI

ANALYSIS OF INDUSTRY WAGE DIFFERENTIALS WITH AND WITHOUT CONTROLS FOR WORKING CONDITIONS—QES 1977[a]

	Coefficient (SE)	
Industry	(1)	(2)
Construction	.113	.100
	(.098)	(.100)
Manufacturing	.050	.046
	(.086)	(.087)
Transportation	.113	.124
	(.095)	(.096)
Wholesale & Retail Trade	−.056	−.061
	(.090)	(.091)
Finance, Insurance and Real Estate	.071	.053
	(.104)	(.105)
Services	−.107	−.104
	(.090)	(.091)
Mining	.233	.308
	(.205)	(.220)
10 Working Condition Variables[b]	no	yes
Weighted Adjusted Standard Deviation of 2-Digit Industry Premiums	.113*	.118*
R^2	.496	.519

[a] Other explanatory variables are education and its square, derived experience and its square, sex, race, 3 region dummies, tenure with employer and its square, union status, and 8 occupation dummies. Sample size is 1,033.

[b] Working condition variables are weekly hours, variables indicating dangerous or unhealthy conditions on the job and whether the danger/threat is serious, commuting time, second and third shift dummies, two dummies indicating extent of choice of overtime, and two dummies indicating whether the physical working conditions are pleasant.

* F test that industry wage differentials jointly equal 0 is rejected at .00005 level.

Table VI reports results of standard wage regressions with and without the ten working condition variables. Because the QES sample is much smaller than the CPS samples (1,033 usable observations compared to more than 9,000 in CPS), these estimates are less precise than our other results. However, as can be seen from comparing Table I to Table VI, the industry wage structure estimated with the QES is highly correlated with our results from CPS. Furthermore, the industry dummy variables are jointly statistically significant. The F statistic of the joint significance of the industry wage effects in column (2) is $F(6{,}996) = 6.30$. By comparing column (1) and column (2) of Table VI it is clear that the working condition variables do not substantially alter the pattern of industry wages. The standard deviation of the industry log wage premiums actually increases from 0.11 to 0.12 when the working conditions controls are added to the equation.

Another possible compensating differential is for full-time versus part-time work. We examined this possibility by narrowing the CPS sample to only full-time employees. The industry pay premiums in this subsample are not substantially different from the full sample. Consequently, we conclude that this is not a major determinant of industry wage differentials. Lastly, variation in the risk of unemployment across industries might provide an explanation for industry wage differences. However, Murphy and Topel (1986) find that variables measuring the probability and duration of unemployment do not substantially reduce the effect of industry and occupation affiliation on wages. A similar conclusion follows from estimates presented in Abowd and Ashenfelter (1981).

Evidence considered here does not support the view that industry wage differentials are due to omitted working condition variables. It is not likely that the basic results reported in Section 2 would change if we could control for working conditions. Indeed, our finding that controlling for working conditions raises the dispersion of wages suggests that looking across industries, wage differentials are additional rather than compensating.

Union Threats

For many years institutional economists have stressed the role of unions in wage determination. A recent paper in this tradition by William Dickens (1985) argues that varying costs of union avoidance across sectors will lead some firms to offer pay premiums to avoid unionization. Firms that find it costly to defeat a union will offer supra-competitive wages to prevent unionization. According to this theory, the ease with which an industry can defeat a union drive has a negative relationship with its wage differential. The testable implication of Dickens' model is that inter-industry wage variability should be low where the threat of unionization is low.

Time series evidence does not support the union threat explanation of industry wage differentials. Between 1970 and 1980 the percentage of workers who were in union representation election victories fell from .6% to .2% of the private sector workforce, yet our earlier results show that industry wage structure remained remarkably stable. This finding should not be surprising in light of Sumner Slichter's (1950) finding that the industry wage structure hardly changed after the passage of the Wagner Act and the unprecedented unionization in the 1930's and 1940's.

Table VII provides additional cross-sectional evidence on the industry wage structure and union threats. Firms in southern states have a great legal and cultural edge over the rest of the country in avoiding unions. In 1978, for instance, nonsouthern workers were 2.5 times more likely to belong to a union than southern private sector wage and salary workers. Consequently, the threat effect model predicts that industry wage differentials would be less important for a sample of southern employees. Row (1) contains the standard deviation of industry wage differentials in southern states after controlling for other factors. Contrary to the predictions of the union threat model, we find a substantial amount of variation in relative wages across industries for this subsample, and we also find that the industry wage structure in the south is highly correlated with the industry wage structure in the rest of the country. Similar results were

TABLE VII

ALTERNATIVE SAMPLES AND UNION THREAT—MAY 1984 CPS[a]

Sample	Weight Adjusted Standard Deviation of Industry Wage Differentials[b]	Weighted Correlation with Complement[c]
(1) Southern States	.133**	.92
(2) Nonunion Employees	.144**	.60
(3) Union Employees	.137**	.60

a Other explanatory variables are the same as in Table I. Each row was estimated from a separate cross-sectional regression.
b Weights are 1984 employment.
c Complements for rows (1) through (3) are nonsouthern states, union employees and nonunion employees, respectively. Sample size is 3,310 for row (1), 9,709 for row (2), and 1,803 for row (3).
** F test that industry wage differentials jointly equal 0 is rejected at .00001 level.

obtained using a subsample of SMSA's with very low unionization rates. And in all cases F tests of the joint significance of the industry wage differentials are decisively rejected.

We also address the question of whether industry wage differentials result from varying degrees of union bargaining power across industries. If the industry wage differences are due to "strong" unions that can raise wages without suffering severe employment losses in certain industries (i.e. because of varying elasticities of labor demand), we would expect to find less variability in wages across industries for nonunion workers. Rows (2) and (3) of Table VII show that this is not the case. Instead, we find that nonunion workers have slightly greater dispersion in industry wage differentials than union workers, and that there is a high correlation between industry wages for union and nonunion employees. This finding has also been corroborated by Dickens and Katz (1986a).

Lastly, evidence on the industry wage structure worldwide surveyed in Krueger and Summers (1986) militates against an explanation of industry wage premia based on unions. Nations such as South Korea and Poland that vigorously oppose unions have a very similar wage structure to nations like Great Britain and West Germany that have widespread and legally protected collective bargaining.

On balance, a fair judgment is that industry wage differentials exist to about the same extent in union and nonunion environments, and in situations where the credibility of union threats differs widely, and therefore do not appear to be a union phenomenon.

Other Issues

A plausible way to gain further insights into the inter-industry wage structure is to examine how it varies across different types of workers and establishments. In general, we find that the inter-industry wage structure is quite stable.

It is natural to conjecture that industry wage differences have something to do with patterns of human capital accumulation. Firms may be forced to share rents with older workers who have acquired substantial firm specific capital. This

TABLE VIII
ALTERNATIVE SAMPLES[a]

Sample	Adjusted Standard Deviation of Industry Wage Differentials[b]	Weighted Correlation with Complement[c]
Age		
(1) Age 20–35	.148**	.85
(2) Age 50–65	.128**	
Tenure		
(3) Tenure ⩽ 1	.087**	.75
(4) Tenure > 10	.096**	
Firm Size		
(5) 1–99 Employees	.073**	.78
(6) 1,000 or More Employees	.111**	
Types of Employment		
(7) Self Employed	.097**	.84
(8) Privately Employed	.133**	
Occupation		
(9) Blue Collar	.108**	.79
(10) White Collar	.136**	

[a] Other explanatory variables are the same as in Table I. Year dummies are also included in rows (7) and (8). Sample sizes for rows (1) through (10), respectively, are 5,534, 1,998, 3,311, 1,619, 3,752, 3,497, 3,378, 46,232, 5,607, and 5,905. Rows (1) and (2), (9) and (10) are 1984 CPS. Rows (3) through (6) are 1979 CPS. Rows (7) and (8) are May 1975, 1976, 1977, and 1978 CPS. Each row was estimated from a separate cross-sectional regression.
[b] Rows (7) and (8) are unweighted; all other rows are weighted by 1984 employment.
[c] Complement is the other reported subsample.
** F test that industry wage differentials jointly equal 0 rejects at the .00001 level.

would lead to inequality in wages across industries. In this case our wage equation might not be accurately measuring inter-industry differences in the expected lifetime income of new workers entering different industries. In order to examine these possibilities, we examine industry effects on the wages of young and old workers, and on workers with short and long job tenure. Rows (1) and (2) of Table VIII show that wage premia across industries for the young and old are highly correlated. Furthermore, the standard deviation of the estimated industry wage differential is about 14 per cent for both groups of workers. Similarly, we find that workers with one year or less of job tenure or more than ten years of job tenure have almost equally variable and highly correlated industry wage structures. Again, F tests of the overall significance of the industry wage differentials find that industry of employment has a statisically significant effect on wages for all groups of workers. Varying patterns of human capital accumulation do not appear to provide an explanation for the inter-industry wage structure.[12]

An important institution that affects wages is company and plant size. Several studies have documented large employer size-wage differentials. For our purposes, the size-wage differential is an important dimension of the wage structure

[12] Note also that these findings belie human capital explanations holding that differences in the level of wages across industries are caused by differences in the slope of age or tenure wage profiles.

because several explanations of the size-wage differential are based on efficiency wages that result from more costly monitoring in larger establishments. (See Calvo and Wellisz (1978), Oi (1983), and Bulow and Summers (1986) for examples of efficiency wage models applied to different size firms.) Rows (5) and (6) of Table VIII show that industry wage dispersion increases sharply with firm size. This suggests that monitoring difficulties may in fact increase with firm size in some industries. Corroborating evidence comes from an analysis of self-employed workers. Despite the fact that skills are likely to be diverse among the self employed, and the substantial errors in reporting self employment, inter-industry wage variations are about one-quarter smaller among the self employed than among other workers.

Rows (9) and (10) of Table VIII show that the industry wage structure is fairly uniform for both blue collar and white collar employees. We also reached the same conclusion when we examined more detailed occupations. Industries which pay workers in one occupation group above their alternative wage tend to pay workers in other occupations above their alternative wage as well. This finding supports the conclusions of Dickens' and Katz' (1986) more extensive examination of industry wage patterns across different occupations for nonunion workers. Since it is unlikely that workers in different occupations within an industry have similar quantities of unmeasured ability, this finding is further evidence against an unmeasured labor quality explanation of industry wage premia. The similarity of the industry wage structure for workers in different occupations suggests that the factor that is responsible for industry wage differences cuts across occupational lines. This may cast some doubt on efficiency wage theories based on differences in monitoring technologies, since monitoring costs are likely to vary somewhat across occupations. It militates in favor of sociological explanations such as that of Akerlof (1984).

5. INDUSTRY WAGE EFFECTS AND TURNOVER

The previous sections were aimed at documenting substantial variations in wages across industries that are not explained by the standard competitive model. If workers in high wage industries truly receive economic rents we would expect to find a negative relationship between turnover and industry wage differentials. On the other hand, if the observed wage differentials merely reflect compensating differentials for unobserved and undesirable working conditions we would expect to find no relationship between turnover and industry wage differentials. The relationship between wage premiums and turnover thus provides an alternative test of the textbook competitive model of industry wage determination. It is also of interest because turnover reductions are one possible reason why firms might pay supra-competitive wages.

The relationship between wages and turnover is well established in the literature (see Pencavel (1970), Freeman (1980), and Viscusi (1980) for examples). In this section we specifically examine the relationship between industry wage premia and quits and length of employment. In principle, this way we do not capture any effect of human capital on quit behavior. Our approach to analyzing

TABLE IX
THE EFFECT OF INDUSTRY WAGE DIFFERENTIALS ON JOB TENURE AND QUITS

Independent Variables	Dependent Variable[a] (1) Tenure	(2) Quit[b]
Industry wage premium	2.198	−.073
	(.676)	(.135)
Union (1 = yes)	3.179	−.164
	(.157)	(.037)
Other variables	Age dummies (6), Age * Sex (6), Education, Education Squared * Sex, Region Dummies (3), Race Dummy, Sex Dummy, Central City Dummy, Firm Size Dummies (4), Plant Size Dummies (4), Marriage Dummy, Marriage * Sex, Veteran Status Dummy	Education, Education Squared, Region Dummies (3), Race Dummy, Sex Dummy, SMSA Dummy, (Age—Education—5) and its square
Sample Size	8,978	633
R^2	.40	.20

[a] Mean (SD) of Tenure is 5.70 (7.61); Mean (SD) of Quit is .26 (.44).
[b] Quit equation was estimated with a linear probability model.

turnover is to estimate a linear probability model where the dependent variable equals 1 if the employee voluntarily quit his job between 1973 and 1977 and 0 if he remains on the same job. The key independent variable is the industry wage premium, which equals the wage differential (reported in Table II) associated with the employee's industry in 1973. In addition, we control for other factors that influence employee turnover, such as experience, occupation, and education (a complete list of regressors is given in Table IX). The quit analysis is performed on individual-level data from the QES 1973–1977 panel.

In addition, we estimate regressions of tenure on industry wage differentials and several other variables. Since a lower turnover rate is reflected in longer job tenure, a finding of a positive relationship between the length of job tenure and industry wage differentials would be consistent with the view that industry wage differentials represent economic rents. Tenure regressions have the advantage of being estimable using the larger sample available in the May 1979 CPS Supplement.

Table IX reports the results of the tenure and quit regressions. The effect of industry wage premiums on job tenure is positive and statistically significant, while their effect on quits is negative but statistically insignificant. The statistically insignificant finding for quit rates in part reflects the relatively small sample used for the quit analysis. The quit and especially tenure regressions provide additional evidence that wage premiums do not reflect compensating differentials, since such differentials would not induce reduced turnover.

The reduced turnover that appears to accompany higher wages may at least partially offset some of the cost of higher wages. Turnover is costly to firms. Employee separations cost the firm in terms of search, lost production during vacancies, and a loss of specific training. (See Salop (1979) for a formal efficiency wage model based on turnover.) Brown and Medoff (1978) estimate that the elasticity of output with respect to the quit rate is about $-.1$. The quit analysis implies that at the mean the elasticity of quits with respect to the wage premium is $-.07/.26 = -.27$. Dickens and Katz (1986b) find qualitatively similar results for nonunion workers. Taken together, these results imply that a 10 per cent increase in the wage differential brings about a .3 per cent increase in output through reduced quits alone. This suggests that although turnover does adversely affect output, reductions in turnover alone are not sufficient to justify wage premiums of the magnitude actually observed unless fixed costs of hiring are very high or labor's share in output is very low. Raff and Summers (1987) show that at Ford Motor Company high turnover was a visible manifestation of problems with very large consequences for output. In this case actions which reduced turnover also produced very large output gains.

6. CONCLUSIONS

We believe the results here call into serious question the view that industry wage differentials can plausibly be rationalized with textbook competitive models. These differentials appear to be a pervasive empirical regularity. As we have noted and document more fully in Krueger and Summers (1986), the industry wage structure is remarkably stable across space and time. As Dickens and Katz (1986a) stress, the pattern of industry wage differentials is very similar for workers in different occupations. At a minimum, these findings shift the burden of proof to those wishing to interpret wage differentials in terms of simple competitive models.

We have already argued that in a tautologous sense almost any explanation for wage differentials that is consistent with profit maximization must rely in some way on efficiency wages. The failure of wages to adjust to excess supply in the labor market is often discussed in terms of rent sharing. This is the essence of the insider-outsider theories developed in order to explain involuntary unemployment by Lindbeck and Snower (1984 and 1986). The rent sharing explanation for industry wage differentials is discussed in Krueger and Summers (1986), and modelled formally in Rotemberg and Saloner (1986).

Rent sharing explanations are intimately related to efficiency wage theories in two senses. First, a reason firms share rents is presumably that failure to do so will result in their work force not cooperating with it by quitting, shirking, or otherwise interfering with production. By paying a higher wage, firms may elicit effort and avoid these consequences. Second, rent sharing is less expensive for firms in an efficiency wage environment where changes in wages have no first order effect on costs than it would be in a standard competitive situation. We prefer to regard rent sharing as a species of efficiency wage theory rather than as an alternative explanation for wage differentials.

The demonstration of important inter-industry wage differentials, if accepted, creates a *prima facie* case for the existence of involuntary unemployment. Unemployment may be thought of as employment in home production. It is no more surprising that workers should be confined to this "industry" than to other low wage industries. There is a more subtle linkage between inter-industry wage differentials and involuntary unemployment as well. The existence of wage differentials can provide the motivation for "wait" unemployment of the type considered by Hall (1975) and Bulow and Summers (1986). In the presence of involuntary unemployment, there is a case for policies directed at increasing employment. The natural rate of unemployment is likely to be inefficiently high. As Akerlof and Yellen (1985) emphasize, efficiency wage models can illuminate cyclical fluctuations in unemployment as well. The finding here of large inter-industry wage differentials suggests that profits may be relatively insensitive to wages over a wide range. This attenuates firms' incentives to adjust wages in the face of unemployment.

The results in this paper suggest an important direction for future research. The sources of wage differentials need to be isolated. As Stiglitz (1984) notes, different efficiency wage models have somewhat different implications for a number of positive and normative issues. Alternative noncompetitive, non-efficiency wage theories, while difficult to specify, undoubtedly also have differing implications. Moreover, linking wage premia to variables suggested by efficiency wage theories, if possible, would strengthen the argument by elimination presented here. For example, Krueger (1987) examines differences in wages and turnover between company-owned and franchisee-owned fast food restaurants because the presence of franchisees is likely to facilitate monitoring. Alternatively, to overcome difficulties of identification it may be useful to rely on case studies to test efficiency wage theories. To this end, Raff (1986) and Raff and Summers (1987) present a case study of Henry Ford's introduction of the five dollar day. Finally, production function estimates of the type presented by Brown and Medoff (1978) might permit estimates of at least some efficiency wage effects.

Woodrow Wilson School, Princeton University, Princeton, NJ 08544, U.S.A.
and
Department of Economics, Harvard University, Cambridge, MA 02138, U.S.A.

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TABLE A1

ESTIMATED WAGE DIFFERENTIALS FOR THREE-DIGIT CIC INDUSTRIES—MAY 1984 CPS[a]
(Standard Errors in Parentheses)

CIC	Industry (SIC)	Wage Differential	
	MINING		
040	Metal mining (10)	.296	(.070)
041	Coal mining (11, 12)	.253	(.087)

TABLE A1 (*Continued*)

CIC	Industry (SIC)	Wage Differential	
042	Crude petroleum and natural gas extraction (13)	.256	(.043)
050	Nonmetallic mining and quarrying, except fuel (14)	.070	(.095)
060	CONSTRUCTION (15, 16, 17)	.129	(.025)
	MANUFACTURING		
	Nondurable Goods		
	Foods and kindred products		
100	Meat products (201)	−.028	(.056)
101	Dairy products (202)	.176	(.067)
102	Canned and preserved fruits and vegetables (203)	.042	(.060)
110	Grain mill products (204)	.099	(.097)
111	Bakery products (205)	.011	(.065)
112	Sugar and confectionary products (206)	.116	(.104)
120	Beverage industries (208)	.126	(.066)
121	Miscellaneous food preparations and kindred products (207, 209)	.004	(.070)
122	Not specified food industries	NA	NA
130	Tobacco manufacturers (21)	.339	(.128)
	Textile mill products		
132	Knitting mills (225)	−.079	(.072)
140	Dyeing and finishing textiles, except wool and knit goods (226)	.200	(.171)
141	Floor coverings, except hard surface (227)	.011	(.122)
142	Yarn, thread and fabric mills (228, 221–224)	.036	(.056)
150	Miscellaneous textile mill products (229)	.032	(.097)
	Apparel and other finished textile products		
151	Apparel and accessories, except knit (231–238)	−.137	(.037)
152	Miscellaneous fabricated textile products (239)	−.102	(.079)
	Paper and allied products		
160	Pulp, paper, and paperboard mills (261–263, 268)	.177	(.057)
161	Miscellaneous paper and pulp products (264)	.112	(.072)
162	Paperboard containers and boxes (265)	.136	(.072)
	Printing, publishing, and allied industries		
171	Newspaper publishing and printing (271)	−.020	(.049)
172	Printing, publishing, and allied industries, except newspapers (272–279)	.144	(.036)
	Chemicals and allied products		
180	Plastics, synthetics, and resins (282)	.070	(.100)
181	Drugs (283)	.225	(.085)
182	Soaps and cosmetics (284)	.296	(.092)
190	Paints, varnishes, and related products (285)	.252	(.116)
191	Agricultural chemicals	−.129	(.111)
192	Industrial and miscellaneous chemicals (281, 286, 289)	.292	(.046)
	Petroleum and coal products		
200	Petroleum refining (291)	.374	(.074)
201	Miscellaneous petroleum and coal products (295, 299)	.598	(.381)
	Rubber and miscellaneous plastic products		
210	Tires and inner tubes (301)	.306	(.116)
211	Other rubber products, and plastics footwear and belting (302–304, 306)	.016	(.090)
212	Miscellaneous plastics products (307)	.027	(.050)

TABLE A1 (*Continued*)

CIC	Industry (SIC)	Wage Differential	
	Leather and leather products		
220	Leather tanning and finishing (311)	−.027	(.381)
221	Footwear, except rubber and plastic (313, 314)	−.088	(.067)
222	Leather products, except footwear (315–317, 319)	−.074	(.145)
	Durable Goods		
	Lumber and wood products, except furniture		
230	Logging (241)	.089	(.085)
231	Sawmills, planing mills, and millwork (242, 243)	.001	(.049)
232	Wood buildings and mobile homes (245)	−.039	(.116)
241	Miscellaneous wood products (244, 249)	−.099	(.088)
242	Furniture and fixtures (25)	−.008	(.050)
	Stone, clay, glass, and concrete products		
250	Glass and glass products (321–323)	.012	(.076)
251	Cement, concrete, gypsum, and plaster products (324, 327)	.072	(.075)
252	Structural clay products (325)	.385	(.220)
261	Pottery and related products (326)	.067	(.171)
262	Miscellaneous nonmetallic mineral and stone products (328, 329)	.174	(.089)
	Metal industries		
270	Blast furnaces, steelworks, rolling and finishing mills (331)	.208	(.054)
271	Iron and steel foundries (332)	.105	(.083)
272	Primary aluminum industries (3334, pt 334, 3353–3355, 3361)	.259	(.107)
280	Other primary metal industries (3331–3333, 33339, pt 334, 3351, 3356, 3357, 3362, 3369, 339)	.112	(.069)
281	Cutlery, hand tools, and other hardware (342)	.037	(.103)
282	Fabricated structural metal products (344)	.106	(.051)
290	Screw machine products (345)	.137	(.171)
291	Metal forgings and stampings (346)	.036	(.088)
292	Ordnance (348)	.134	(.116)
300	Miscellaneous fabricated metal products (341, 343, 347, 349)	.048	(.058)
301	Not specified metal industries	−.097	(.381)
	Machinery, except electrical		
310	Engines and turbines (351)	.293	(.104)
311	Farm machinery and equipment (352)	.278	(.075)
312	Construction and material handling machines (353)	.174	(.068)
320	Metalworking machinery (354)	.020	(.067)
321	Office and accounting machines (357, except 3573)	.371	(.103)
322	Electronic computing equipment (3573)	.252	(.043)
331	Machinery, except electrical, n.e.c. (355, 356, 358, 359)	.152	(.037)
332	Not specified machinery	NA	NA
	Electrical machinery, equipment, and supplies		
340	Household appliances (363)	.035	(.090)
341	Radio, TV, and communication equipment (365, 366)	.220	(.044)
342	Electrical machinery, equipment, and supplies, n.e.c. (361, 362, 364, 367, 369)	.066	(.034)
350	Not specified electrical machinery, equipment, and supplies	.423	(.380)

TABLE A1 (*Continued*)

CIC	Industry (SIC)	Wage Differential	
	Transportation equipment		
351	Motor vehicles and motor vehicle equipment (371)	.244	(.037)
352	Aircraft and parts (372)	.210	(.050)
360	Ship and boat building and repairing (373)	.058	(.068)
361	Railroad locomotives and equipment (374)	.273	(.269)
362	Guided missiles, space vehicles, and parts (376)	.004	(.061)
370	Cycles and miscellaneous transportation equipment (375, 379)	−.025	(.107)
	Professional and photographic equipment, and watches		
371	Scientific and controlling instruments (381, 382)	.108	(.065)
372	Optical and health services supplies (383, 384, 385)	.109	(.062)
380	Photographic equipment and supplies (386)	.290	(.100)
381	Watches, clocks, and clockwork operated devices (387)	.342	(.270)
382	Not specified professional equipment	NA	NA
390	Toys, amusement, and sporting goods (394)	.121	(.087)
391	Miscellaneous manufacturing industries (39, except 394)	−.040	(.067)
392	Not specified manufacturing industries	−.070	(.269)
	TRANSPORTATION, COMMUNICATIONS, AND OTHER PUBLIC UTILITIES		
	Transportation		
400	Railroads (940)	.268	(.052)
401	Bus service and urban transit (41, except 412)	.073	(.065)
402	Taxicab service (412)	−.203	(.146)
410	Trucking service (421, 423)	.074	(.035)
411	Warehousing and storage (422)	.095	(.095)
420	Water transportation (44)	.114	(.082)
421	Air transportation (45)	.320	(.047)
422	Pipe lines, except natural gas (46)	−.253	(.171)
432	Services incidental to transportation (47)	−.026	(.072)
	Communications		
440	Radio and television broadcasting (483)	−.132	(.061)
441	Telephone (wire and radio) (481)	.301	(.037)
442	Telegraph and miscellaneous communication services (482, 489)	.049	(.075)
	Utilities and sanitary services		
460	Electric light and power (491)	.277	(.043)
461	Gas and steam supply systems (492, 496)	.301	(.068)
462	Electric and gas, and other combinations (493)	.300	(.073)
470	Water supply and irrigation (494, 497)	.081	(.122)
471	Sanitary services (495)	.062	(.191)
472	Not specified utilities	.498	(.270)
	WHOLESALE TRADE		
	Durable Goods		
500	Motor vehicles and equipment (501)	−.006	(.072)
501	Furniture and home furnishings (502)	.051	(.116)
502	Lumber and construction materials (503)	.115	(.089)
510	Sporting goods, toys, and hobby goods (504)	.139	(.220)
511	Metals and minerals, except petroleum (505)	.071	(.136)
512	Electrical goods (506)	.123	(.059)

TABLE A1 (*Continued*)

CIC	Industry (SIC)	Wage Differential	
521	Hardware, plumbing and heating supplies (507)	.013	(.070)
522	Not specified electrical and hardware products	NA	NA
530	Machinery, equipment, and supplies	.068	(.040)
531	Scrap and waste materials (5093)	−.033	(.100)
532	Miscellaneous wholesale, durable goods (5094)	.164	(.156)
	Nondurable Goods		
540	Paper and paper products (511)	.003	(.111)
541	Drugs, chemicals, and allied products (512, 516)	.033	(.076)
542	Apparel, fabrics, and notions (513)	−.007	(.112)
550	Groceries and related products (514)	.019	(.047)
551	Farm products—raw materials (515)	−.109	(.074)
552	Petroleum products (517)	.159	(.073)
560	Alcoholic beverages (518)	.138	(.083)
581	Farm supplies (5191)	.063	(.100)
582	Miscellaneous wholesale, nondurable goods (5194, 5198, 5199)	−.081	(.082)
571	Not specified wholesale trade	.366	(.269)
	RETAIL TRADE		
580	Lumber and building material retailing (521, 523)	−.109	(.055)
581	Hardware stores (525)	−.304	(.063)
582	Retail nurseries and garden stores (526)	−.184	(.094)
590	Mobile home dealers (527)	−.276	(.191)
591	Department stores (531)	−.190	(.029)
592	Variety stores (533)	−.103	(.082)
600	Miscellaneous general merchandise stores (539)	−.268	(.100)
601	Grocery stores (541)	−.121	(.028)
602	Dairy products stores (245)	−.135	(.145)
610	Retail bakeries (546)	−.131	(.089)
611	Food stores, n.e.c. (52, 543, 544, 549)	−.254	(.076)
612	Motor vehicle dealers (551, 552)	−.023	(.038)
620	Auto and home supply stores (553)	−.040	(.057)
621	Gasoline service stations (554)	−.269	(.047)
622	Miscellaneous vehicle dealers (555, 556, 557, 559)	−.268	(.122)
630	Apparel and accessory stores, except shoe (56, except 566)	−.229	(.041)
631	Shoe stores (566)	−.232	(.086)
632	Furniture and home furnishings stores (571)	−.102	(.058)
640	Household appliances, TV, and radio stores (572, 573)	−.169	(.060)
641	Eating and drinking places (58)	−.201	(.068)
642	Drug stores (591)	−.246	(.045)
650	Liquor stores (592)	−.450	(.086)
651	Sporting goods, bicycles, and hobby stores (5941, 5945, 5946)	−.323	(.095)
652	Book and stationery stores (5942, 5943)	−.223	(.097)
660	Jewelry stores (5944)	−.089	(.082)
661	Sewing, needlework, and piece goods stores (5949)	−.371	(.116)
662	Mail order houses (5961)	−.269	(.103)
670	Vending machine operators (5962)	−.147	(.145)
671	Direct selling establishments (5963)	.129	(.094)
672	Fuel and ice dealers (598)	−.144	(.108)
681	Retail florists (5992)	−.150	(.083)
682	Miscellaneous retail stores (593, 5947, 5948, 5993, 5994, 5999)	−.143	(.058)
691	Not specified retail trade	−.010	(.381)

TABLE A1 (*Continued*)

CIC	Industry (SIC)	Wage Differential	
	FINANCE, INSURANCE, AND REAL ESTATE		
700	Banking (60)	.048	(.030)
701	Savings and loan associations (612)	.078	(.058)
702	Credit agencies, n.e.c. (61, except 612)	.049	(.056)
710	Security, commodity brokerage, and investment companies (62, 67)	.185	(.055)
711	Insurance (63, 64)	.116	(.030)
712	Real estate, including real estate-insurance-law offices (65, 66)	.004	(.033)
	BUSINESS AND REPAIR SERVICES		
721	Advertising (731)	.092	(.074)
722	Services to be dwellings and other buildings (734)	−.140	(.053)
730	Commercial research, development, and testing labs (7391, 7397)	.199	(.079)
731	Personnel supply services (736)	−.157	(.049)
732	Business management and consulting services (737)	.024	(.064)
740	Computer and data processing services (737)	.214	(.054)
741	Detective and protective services (7393)	−.021	(.059)
742	Business services, n.e.c. (732, 733, 735, 7394, 7395, 7396, 7399)	−.007	(.042)
750	Automotive services, except repair (751, 752, 754)	−.151	(.080)
751	Automotive repair shops (762, 7694)	−.058	(.050)
752	Electrical repair shops (762)	.224	(.122)
760	Miscellaneous repair services (763, 764, 7692, 7699)	−.062	(.058)
	PERSONAL SERVICES		
761	Private households (88)	−.382	(.032)
762	Hotels and motels (701)	−.148	(.034)
770	Lodging places, except hotels and motels (702, 703, 704)	−.484	(.107)
771	Laundry, cleaning, and garment services (721)	−.214	(.055)
772	Beauty shops (723)	−.037	(.050)
780	Barber shops (724)	−.035	(.191)
781	Funeral service and crematories (726)	−.261	(.103)
782	Shoe repair shops (725)	NA	NA
790	Dressmaking shops (pt 729)	−.584	(.269)
791	Miscellaneous personal services (722, pt 729)	−.219	(.083)
	ENTERTAINMENT AND RECREATION SERVICES		
800	Theaters and motion pictures (78, 792)	−.056	(.069)
801	Bowling alleys, billiard and pool parlors (793)	−.391	(.116)
802	Miscellaneous entertainment and recreation services (791, 794, 799)	−.147	(.040)
	PROFESSIONAL AND RELATED SERVICES		
812	Offices of physicians (801, 803)	−.076	(.040)
820	Offices of dentists (802)	.053	(.057)
821	Offices of chiropractors (8041)	−.340	(.171)
822	Offices of optometrists (8042)	−.363	(.269)
830	Offices of health practitioners, n.e.c. (8049)	−.400	(.270)
831	Hospitals (806)	.063	(.025)
832	Nursing and personal care facilities (805)	−.135	(.032)
840	Health services, n.e.c. (807, 808, 809)	−.023	(.046)
841	Legal services (81)	.079	(.044)
842	Elementary and secondary schools (821)	−.216	(.039)
850	Colleges and universities (822)	−.132	(.039)

TABLE A1 (*Continued*)

CIC	Industry (SIC)	Wage Differential	
851	Business, trade, and vocational schools (824)	−.128	(.128)
852	Libraries (823)	−.095	(.156)
860	Educational services, n.e.c. (829)	−1.489	(.220)
861	Job training and vocational rehabilitation services (833)	−.194	(.136)
862	Child care services (835)	−.275	(.056)
870	Residential care facilities, without nursing (836)	−.288	(.079)
871	Social services, n.e.c. (832, 839)	−.166	(.048)
872	Museums, art galleries, and zoos (84)	−.194	(.145)
880	Religious organizations (866)	−.276	(.039)
881	Membership organizations (861–865, 869)	−.070	(.055)
882	Engineering, architectural, and surveying services (891)	.206	(.050)
890	Accounting, auditing, and bookkeeping services (892)	.051	(.055)
891	Noncommercial educational and scientific research (892)	−.055	(.122)
892	Miscellaneous professional and related services (899)	.241	(.156)
Weighted Adjusted Standard Deviation[b]		.160**	

[a] Other explanatory variables are education and its square, 6 age dummies, 8 occupation dummies, 3 region dummies, sex dummy, race dummy, central city dummy, union member dummy, ever married dummy, veteran status, marriage × sex interaction, education × sex interaction, education squared × sex interaction, and 6 age × sex interactions.
[b] Weights are employment shares for each industry.
** F test that industry wage differentials jointly equal 0 is rejected at the .000001 level.

APPENDIX

Correcting for Measurement Error in Dummy Variables in Longitudinal Data

Economic variables are frequently measured with error. In this Appendix, we derive a first difference estimator that is consistent if a set of dummy variables is measured with error.[13]

The Statistical Model

Consider the following linear first difference model:[14]

$$\Delta w_t = \Delta D_t^{*\prime}\alpha + \Delta \varepsilon_t \qquad (t = 1, \ldots, N), \tag{1}$$

where Δw_t is the change in log wage, ΔD_t^* is a K vector of change in industry dummy variables, α is a K vector of parameters, and $\Delta \varepsilon_t$ is a mean 0 iid disturbance. The symbol Δ denotes a change in a variable. There are $K+1$ industries and N observations. Because of collinearity, only K industries are in equation (1).

[13] We are grateful to Bruce Meyer, Aaron Han, and Chris Cavanagh who provided indispensible assistance in the derivation of the techniques described here. See Freeman (1984) for the one dummy variable case.

[14] Since the change in industry status is probably orthogonal to the change in other independent variables, such as marital status and education, equation (1) may be a reasonable approximation.

To facilitate the subsequent analysis, we shall write (1) in matrix notation as

(1′) $$\Delta w = \Delta D^{*}\alpha + \Delta \varepsilon$$

where Δw and $\Delta \varepsilon$ are $N \times 1$ vectors and ΔD^{*} is an $N \times K$ matrix.

Because industry status is reported with error, ΔD_t^{*} is not observable. Instead, for each industry i we observe ΔD_{it}, which is the true change in industry status plus a classification error Δe_{it}:

(2) $$\Delta D_{it} = \Delta D_{it}^{*} + \Delta e_{it} \qquad (i = 1, \ldots, K+1;\ t = 1, \ldots, N).$$

The values ΔD_{it}, ΔD_{it}^{*}, and Δe_{it} can take on are limited:

$$\Delta D_{it} = \begin{cases} 1, \\ 0, \\ -1; \end{cases} \qquad \Delta D_{it}^{*} = \begin{cases} 1, \\ 0, \\ -1; \end{cases} \qquad \Delta e_{it} = \begin{cases} 2, \\ 1, \\ 0, \\ -1, \\ -2. \end{cases}$$

ASSUMPTION 1: *Industry classification errors e_{it} are independently and identically distributed over time.*

We introduce the following notation:

r_{ij}^{t} = prob [worker t is classified in industry j given that he truly is in industry i at a point in time];

$$r_{ii}^{t} = \sum_{j \neq 1}^{k+1} r_{ij}^{t};$$

F_{ij}^{t} = prob [worker t initially in industry i moves to industry j].

We further assume that all individuals have the same error and transition probabilities so $r_{ij}^{t} = r_{ij}$ and $F_{ij}^{t} = F_{ij}$ for all t.

The distribution of Δe_t conditional on ΔD_i^{*} is given in Table A2. The expected value of Δe_{it} conditional upon $\Delta D_{it}^{*} = (-1, 0, 1)$ is

$$E(\Delta e_{it} | \Delta D_{it}^{*}) = \begin{cases} -\sum_{j \neq 1}^{K+1} \dfrac{F_{ji}}{\left(\sum_{j \neq 1}^{K+1} F_{ji}\right)} (r_{ji} + r_{ii}), & \text{if } \Delta D_{it}^{*} = 1, \\ 0, & \text{if } \Delta D_{it}^{*} = 0, \\ \sum_{j \neq 1}^{K+1} \dfrac{F_{ij}}{\left(\sum_{j \neq 1}^{K+1} F_{ji}\right)} (r_{ji} + r_{ii}), & \text{if } \Delta D_{it}^{*} = -1. \end{cases}$$

Since Δe_{it} is not independent of ΔD_{it}^{*} this problem differs from a textbook measurement error problem.

We make two further assumptions about the misclassification process.

ASSUMPTION 2: $E(\Delta e_{it}) = 0$ *for* $i = 1, \ldots, K+1$. *This is equivalent to assuming that the observed net industry flows are an unbiased estimate of the true net industry flows.*

ASSUMPTION 3: *Prob* $(\Delta D_i^{*} = 1) =$ *prob* $(\Delta D_t^{*} = -1)$ *for* $i = 1, \ldots, K+1$. *The distribution of industry employment is in a dynamic steady state. Although this assumption is clearly violated over a long time period, it is probably a reasonable assumption over the short time periods considered in the empirical work.*

With these two assumptions, the conditional expectation of Δe_{it} can be compactly expressed as

$$E(\Delta e_{it} | \Delta D_{it}^{*}) = (r_{i,\,i} + r_{i,\,\bar{i}})\, \Delta D_{it}^{*},$$

where

$$r_{\bar{i},\,i} = \frac{1}{2}\left[\sum_{j \neq 1}^{K+1} \frac{F_{j,\,i}}{\sum_{j \neq 1}^{K+1} F_{j,\,i}} r_{ji} + \sum_{j \neq 1}^{K+1} \frac{F_{i,\,j}}{\sum_{j \neq 1}^{K+1} F_{i,\,j}} r_{ji}\right].$$

TABLE A2

CONDITIONAL DISTRIBUTION OF e_i

e_i	Frequency of Error Assuming Value of ΔD_i^*: 1	0	-1
-2	$\sum_{j\neq i}\frac{F_{ji}}{\left(\sum_{j\neq i}F_{ji}\right)}r_{ji}r_{i\bar{i}}$	0	0
-1	$\sum_{j\neq i}\frac{F_{ji}}{\left(\sum_{j\neq i}F_{ij}\right)}(r_{ji}(1-r_{i\bar{i}})+(1-r_{ji})r_{i\bar{i}})$	$\frac{F_{ii}}{F_{ii}+F_{i\bar{i}}}((1-r_{i\bar{i}})r_{i\bar{i}})+\frac{\sum_{j\neq i}F_{ji}}{F_{ii}+F_{i\bar{i}}}(r_{ji}(1-r_{ji}))$	0
0	$1-\sum_{j\neq i}\frac{F_{ji}}{\left(\sum_{j\neq i}F_{ij}\right)}(r_{ji}+r_{i\bar{i}}-r_{i\bar{i}}r_{ji})$	$\frac{F_{ii}}{F_{ii}+F_{i\bar{i}}}((1-r_{i\bar{i}})^2+r_{i\bar{i}})^2+\frac{\sum_{j\neq i}F_{ji}}{F_{ii}+F_{i\bar{i}}}((1-r_{ji})^2+r_{ji})^2$	$1-\sum_{j\neq i}\frac{F_{ij}}{\left(\sum_{j\neq i}F_{ij}\right)}(r_{ji}+r_{i\bar{i}}-r_{i\bar{i}}r_{ji})$
1	0	$\frac{F_{ii}}{F_{ii}+F_{i\bar{i}}}((1-r_{i\bar{i}})r_{i\bar{i}})+\frac{\sum_{i\neq j}F_{ji}}{F_{ii}+F_{i\bar{i}}}((1-r_{ji})r_{ji})$	$\sum_{j\neq i}\frac{F_{ij}}{\left(\sum_{j\neq i}F_{ij}\right)}(r_{ji}(1-r_{i\bar{i}})+(1-r_{ji})r_{i\bar{i}})$
2	0	0	$\sum_{j\neq i}\frac{F_{ij}}{\left(\sum_{j\neq i}F_{ij}\right)}r_{ji}r_{i\bar{i}}$

Thus ΔD_{it} can be written

(3) $$\Delta D_{it} = (1 - r_{\bar{i},i} - r_{i,\bar{i}})\,\Delta D_{it}^{*} + \nu_{it}$$

where ν_{it} is a mean 0 disturbance that is uncorrelated with ΔD_{it}^{*} and ν_{is} for $s \neq t$.

Equation (3) can be expressed in matrix notation for the K industries and N observations as

(4) $$\Delta D = \Delta D^{*}[I - R] + \nu,$$

where

$\Delta D^{*} = N \times K$ matrix with ΔD_{it}^{*} a typical element;
$I = K \times K$ identity matrix;
$R = K \times K$ diagonal matrix with $(r_{\bar{i},i} + r_{i,\bar{i}})$ on the diagonal;
$\nu = N \times K$ matrix of disturbances.

Solving (4) for ΔD^{*} and substituting the result in (1′) yields

(5) $$\Delta w = \Delta D[I - R]^{-1}\alpha - \nu[I - R]^{-1}\alpha + \Delta\varepsilon.$$

From (5) it is apparent that an OLS regression of Δw on ΔD yields a biased and inconsistent estimate of α because ΔD and ν are correlated. But a consistent estimate can be obtained if prior information is available on the r_{ij}.

ESTIMATOR: A consistent estimator of α is given by $\hat{\alpha}_c$:

(6) $$\hat{\alpha}_c = (\Delta D^{*\prime}\Delta D^{*})^{-1}[I - R]^{-1}(\Delta D'\Delta D)\,\hat{\alpha}_{\mathrm{OLS}}.$$

PROOF: Substitution of $\hat{\alpha}_{\mathrm{OLS}} = (\Delta D'\Delta D)^{-1}\Delta D'\Delta w$ yields

$$\hat{\alpha}_c = (\Delta D^{*\prime}\Delta D^{*})^{-1}[I - R]^{-1}\Delta D'\Delta w.$$

Substitution of (1′) for Δw gives

$$\hat{\alpha}_c = (\Delta D^{*\prime}\Delta D^{*})^{-1}[I - R]^{-1}\Delta D'\{\Delta D^{*}\alpha + \Delta\varepsilon\}.$$

Finally, substitution for ΔD′ gives

(7) $$\begin{aligned}\hat{\alpha}_c &= (\Delta D^{*\prime}\Delta D^{*})^{-1}[I - R]^{-1}\{\nu' + [I - R]\Delta D^{*\prime}\}\{\Delta D^{*}\alpha + \Delta\varepsilon\}\\ &= \alpha + (\Delta D^{*\prime}\Delta D^{*})^{-1}\left\{[I - R]^{-1}\nu'\Delta D^{*}\alpha + [I - R]^{-1}\nu'\Delta\varepsilon + \Delta D^{*\prime}\Delta\varepsilon\right\},\end{aligned}$$

and the probability limit of (7) is

$$\begin{aligned}\operatorname{plim}(\hat{\alpha}_c) &= \alpha + \operatorname{plim}\left(\frac{1}{N}\Delta D^{*\prime}\Delta D^{*}\right)\left\{[I - R]^{-1}\operatorname{plim}\left(\frac{1}{N}\nu'\Delta D^{*}\right)\alpha\right.\\ &\qquad \left. + [I - R]^{-1}\operatorname{plim}\left(\frac{1}{N}\nu'\Delta\varepsilon\right) + \operatorname{plim}\left(\frac{1}{N}\Delta D^{*}\Delta\varepsilon\right)\right\}\\ &= \alpha.\end{aligned}$$

Q.E.D.

Limiting Variance / Covariance Matrix

To simplify the problem of deriving the variance/covariance matrix of $\hat{\alpha}_{c'}$ we assume $\Delta D^{*\prime}\Delta D^{*}[I - R]$ is known with certainty. We also assume $\operatorname{plim}((1/N)\Delta e\,\Delta e') = \sigma_{\Delta\varepsilon}I_{N\times N}$. The asymptotic variance/covariance matrix V of $\hat{\alpha}_c$ is then given in (8)

(8) $$V = A\alpha'\Omega\alpha\Lambda A' + A\sigma_{\Delta\varepsilon}^{2}\Lambda + \sigma_{\Delta\varepsilon}^{2}\Omega$$

where $A = \operatorname{plim}(1/N)(\Delta D^{*\prime}\Delta D^{*})^{-1}[I - R]^{-1}$, $\Lambda = \operatorname{plim}((1/N)\nu'\nu)$, and $\Omega = \operatorname{plim}((1/N)\Delta D^{*\prime}\Delta D^{*})$.[15]

Intuitively, the last term of (8) equals the variance/covariance matrix of $\hat{\alpha}_{\mathrm{OLS}}$ if all variables are correctly measured, while the first two terms reflect the additional uncertainty due to measurement error.

To estimate V note that $\Lambda = \operatorname{plim}(1/N)(\Delta D'\Delta D - [I - R]\Delta D^{*\prime}\Delta D^{*}[I - R])$ and $\sigma_{\Delta\varepsilon}^{2} = \operatorname{plim}(1/N)\{\Delta\hat{u}'\Delta\hat{u} - \hat{\alpha}_{\mathrm{OLS}}\nu'\nu\hat{\alpha}_{\mathrm{OLS}} + (\hat{\alpha}_c - [I - R]\hat{\alpha}_{\mathrm{OLS}})'\Delta D^{*\prime}\Delta D^{*}(\hat{\alpha}_c - [I - R]\hat{\alpha}_{\mathrm{OLS}})\}$ where $\Delta\hat{u}$ is an $N \times 1$ vector of residuals from an OLS regression of Δw on ΔD.

[15] Λ can be shown to be heteroskedastic, but this is probably of little consequence because we find that Λ has a very small effect on V.

TABLE A3

RESULTS OF MEASUREMENT ERROR CORRECTION III
FIXED EFFECTS ESTIMATES

	Sample	
Industry	Matched CPS[a]	Displaced Workers Survey[b]
Construction	.091	.002
	(.039)	(.050)
Manufacturing	.045	.056
	(.037)	(.048)
Transportation and	.027	.012
Public Utilities	(.041)	(.053)
Wholesale and	−.061	−.062
Retail Trade	(.037)	(.048)
Finance, Insurance	.029	.017
and Real Estate	(.043)	(.055)
Services	−.060	−.063
	(.038)	(.049)
Mining	.094	.295
	(.042)	(.036)

[a] See Table IV notes.
[b] See Table V notes.

Application

We estimate $(\Delta D^{*\prime}\Delta D^{*})$ and $[I-R]$ using varying assumptions about industry misclassifications. In Correction I we make the simple assumption that there is a constant misclassification rate, r for all industries and that the misclassifications are distributed in proportion to each industry's size, so $r_{ij}=p_r r$ where p_k is the fraction of workers in industry j. Using matched employer-employee data from the January 1977 CPS supplement we estimate that 6.8 per cent of employee responses to the industry question do not match employer responses to the same question. However, the mismatches are not all employee errors and may not be independent over time, so the 6.8 per cent estimate may overstate the true error rate. In fact, a 6.8 per cent error rate generates an implausibly large number of spurious industry changers for many industries. Consequently, we use 3.4 per cent as a rough estimate of r.

In Correction II we continue to assume that on average 3.4 per cent of workers are misclassified, but now r_{ij} is proportional to the matrix of employer-employee mismatches. This is accomplished by decreasing the observed employer-employee mismatches by 50 per cent for each pair of industries. Finally, Correction III uses the full matrix of employer-employee mismatches, but decreases the error rates by 75 per cent so only 1.7 per cent of workers are misclassified on average.

Once r_{ij} is estimated, $\Delta D^{*\prime}\Delta D^{*}$ is derived as follows. First, we estimate the industry gross transition matrix F^{*}. Let ρ be a $K\times K$ matrix with r_{ij} as a typical element and let F be a $K\times K$ matrix of observed industry transitions with F_{ij} as a typical element. Then the true transition matrix $F^{*}=(\rho')^{-1}F\rho^{-1}$. (See Meyer, 1986, and Poterba and Summers, 1986, for further exposition of this technique.) The i,jth off-diagonal element of $\Delta D^{*\prime}\Delta D^{*}$ is $-(F_{ij}+F_{ji})$, while the i,ith element of $\Delta D^{*\prime}\Delta D^{*}$ is $\Sigma_{j\neq i}^{K+1}(F_{ij}+F_{ji})$.

The results of Corrections I and II are reported in Tables IV and V and the results of Correction III are reported in Table A3.

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