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EFFICIENCY WAGES AND THE WAGE STRUCTURE

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Efficiency Wages and the Wage Structure

ABSTRACT

This paper examines differences in pay for equally skilled workers in different industries. The major finding is that there is substantial dispersion in wages across industries, even after allowing for measured and unmeasured labor quality, working conditions, fringe benefits, transitory demand shocks, threat of unionization, union bargaining power, firm size and other factors. Some direct evidence in favor of efficiency wage theories is presented. The evidence suggests that industry wage differentials are successful in eliciting better performance through reduced turnover and increased effort.

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Lawrence H. Summers Department of Economics Harvard University Cambridge, MA 02138 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 (1984) 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 (1984), 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.

This paper examines the magnitude of non-competitive wage differentials. We focus on the role of industry and occupational variables in explaining relative wages. Our findings suggest that a worker's industry and occupation exert a substantial impact on his wage even after controlling for human capital 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, Brown and Medoff (1984), and of large intra-industry wage differences, Dunlop (1957) and Groshen (1986) in suggesting the importance of developing models of non-competitive wage setting even in non-union settings.

We focus on efficiency wage theories as an explanation for the setting of non-competitive wages. Any economic theory that explains why wages deviate from their competitive level must in a tautologous sense explain why firms find it profitable to pay non-competitive wages. In this sense, any explanation of non-competitive 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 principle 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 and eliciting more effort from their workers 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 interindustry and inter-occupational variations in wages. Section 3 considers and rejects a number of possible reconciliations of the results with competitive theory. By providing fixed effects estimates we cast serious doubt on "unmeasured labor quality" explanations for inter-industry wage differences. We also present evidence strongly suggesting that wage differentials cannot

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all be attributed to union effects, the short run immobility of labor or compensating differentials. Section 4 provides some evidence that high wages are efficacious in eliciting effort from workers and reducing turnover and thus provides some support for efficiency wage theories. Section 5 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. <u>Efficiency Wage Theories</u>

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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 package which provided equal levels of utility. Wages would depend only on workers' abilities and not on characteristics of their employers which did not influence other non-pecuniary 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 non-competitive wages. Our

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goal in this paper is to demonstrate the potential importance of efficiency wages not to distinguish between 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 job 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 firms 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 effects. 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. د

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If all firms or occupations were identical, one would not expect to see different firms or occupations 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 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 or occupations which 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 or occupation has on wages to test segmented labor market theories that are closely related to the efficiency wage model considered here. Summer 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

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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

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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.¹ 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 separation.

The empirical work reported below takes up Cain's challenge and examines possible competitive explanations for inter-industry wage differences. We also extend previous work by testing efficiency wage explanations for the existence of segmented labor markets.

2. Data, Methodology, and Basic Results

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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 or occupation is a significant factor in determining wages after controlling for labor quality and working conditions we must look beyond simple competitive theories and ask why firms choose to pay workers more than their opportunity cost.

Our initial empirical analysis of industry and occupational wage differentials is based on cross sectional data on individuals collected by the

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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.² The samples we analyze contain full and part-time private nonagricultural 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 than \$1.00 or greater than \$250.00 an hour outliers and eliminated them from the sample.

We estimate several standard wage equations in order to examine the importance of industry and occupation 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 and occupation dummy variables on relative wages. We normalize the estimated industry and occupation wage differentials as deviations from the (weighted) mean differential.³

Table 1 presents results of 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 include education, age, sex, race, union status, a central city dummy, marital status, veteran status, and several interaction terms.⁴ Table 2 presents comparable results for two-digit CIC industries and Appendix Table A1 contains comparable results for 1984 for three digit CIC industries. As a group the industry

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dummy variables are statistically significant and they are generally significant individually.

Furthermore, the industry variables have a sizable impact on relative wages. The coefficient for mining in Table 2 for 1984, for instance, implies that the average employee in the mining industry earns wages that are 26% 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 38% above the mean in the petroleum industry to a low of 37% below the mean in private household services. These wage differentials suggest that other factors besides opportunity cost are important in explaining wages.

The industry and occupation variables are very important in explaining variations in log earnings. As an indication of their importance, the standard error of the regression falls nearly 10% when the industry and occupation controls are added to the equation, and two digit industry controls alone lead to 4.5% reduction in the standard error of the regression after controlling for occupation and other factors. In comparison, the union variable only has a 1.5% effect on the standard error of the regression, the human capital controls have only a 4.4% effect, and race and sex controls have less than a .2% effect. This suggests that if industry and occupational wage differences are non-competitive 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

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(1) 1974	(2) 1979	(3) 1984	(4) 1984 Total Compensation
		_	
.195 (.021)	.126 (.031)	.135 (.038)	.119 (.039)
.055	.044	.080	.119
(.020)	(.029)	(.035)	(.035)
.111	.081	.178	.247
(.021)	(.031)	(.038)	(.038)
128	082	118	147
(.020)	(.030)	(.036)	(.036)
.047	010	.061	.076
(.022)	(.035)	(.037)	(.037)
070	055	064	092
(.021)	(.030)	(.035)	(.036)
.179	.229	.241	.250
(.035)	(.058)	(.090)	
.097	.069	.094	.125
29,945	8,978	10,289	10,283
	1974 .195 (.021) .055 (.020) .111 (.021) 128 (.020) .047 (.022) 070 (.021) .179 (.035) .097	1974 1979 .195.126(.021)(.031).055.044(.020)(.029).111.081(.021)(.031)128082(.020)(.030).047010(.022)(.035)070055(.021)(.030).179.229(.035)(.058).097.069	1974 1979 1984 .195.126.135(.021)(.031)(.038).055.044.080(.020)(.029)(.035).111.081.178(.021)(.031)(.038)128082118(.020)(.030)(.036).047010.061(.022)(.035)(.037)070055064(.021)(.030)(.035).179.229.241(.035)(.058)(.090).097.069.094

Table 1: Estimated Wage Differentials for One-Digit Industries May CPS (Standard Errors in Parentheses)

^aControls include education and its square, 6 age dummies, 8 occupation dummies, sex dummy, race dummy, central city dummy, union member dummy, ever married dummy, veteran status, marriage x sex interaction, education x sex interaction, education squared x sex interaction, and 6 age x sex interactions.

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^bWeights are employment shares for each year.

Industry	(1) 1974	(2) 1979	(3) 1984	(4) Total Compen- sation
Mining	.203	.263	.262	0.274
	(.022)	(.031)	(.036)	(.036)
Construction	.228 (.011)	.137 (.016)	.153 (.022)	0.140 (.022)
Ordnance	.202 (.040)	.091 (.067)	.115 (.118)	NA NA
Lumber	.003 (.021)	035 (.037)	048 (.045)	-0.011 (.045)
Furniture	059 (.025)	120 (.036)	033 (.052)	-0.013 (.052)
Stone & Clay	.032 (.022)	.052 (.034)	.082	0.135 (.051)
Primary Metals	.082 (.016)	.114 (.026)	.170 (.041)	0.270
Fabricated Metals	.057 (.015)	.039 (.026)	.061 (.036)	0.122
Machinery, excl. elec.	.083 (.013)	.092	.187 (.025)	0.223 (.025)
Electrical Machinery	.055 (.013)	.045	.105 (.027)	0.134
Fransport Equipment	.120 (.014)	.156 (.021)	.087 (.027)	0.263 (.027)
Instruments	.086 (.025)	.137 (.040)	.131 (.042)	0.160
lisc. Manufacturing	116 (.024)	110 (.042)	.001 (.054)	(.042) 0.021 (.054)
ood	.010 (.015)	.019 (.026)	.072 (.031)	(.054) 0.125 (.031)

Table 2: Estimated Wage Differentials for Two-Digit Industries -- May Cps (Standard Errors in Parentheses)

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Industry	(1) 1974	(2) 1979	(3) 1984	(4) Total Compen- sation
Торассо	007	040	.294	0.482
	(.063)	(.156)	(.173)	(.173)
Apparel	087	132	156	-0.152
	(.016)	(.030)	(.033)	(.033)
Paper	.057	.088	.126	0.163
	(.020)	(.033)	(.042)	(.042)
Printing	.052	.039	.083	0.087
	(.017)	(.028)	(.029)	(.029)
Chemical	.157	.148	.238	0.283
	(.018)	(.029)	(.034)	(.034)
Petroleum	.238	.278	.382	0.631
	(.036)	(.062)	(.077)	(.077)
Rubber	.007	.023	.035	0.079
	(.021)	(.036)	(.043)	(.043)
Leather	097	233	126	-0.106
	(.034)	(.051)	(.062)	(.062)
Railroad	.200 (.023)	.120 (.037)	NA	NA
Other Transport	.090 (.014)	.120	.161 (.028)	0.190 (.028)
Communications	.159	.064	.194	0.317
	(.016)	(.027)	(.030)	(.030)
Public Utilities	.138	.068	.287	0.364
	(.021)	(.028)	(.033)	(.033)
Wholesale Trade	.035	015	.065	0.043
	(.012)	(.020)	(.022)	(.022)
Eating & Drinking	267	125	188	-0.218
	(.012)	(.020)	(.023)	(.023)
Other Retail	141	093	156	-0.187
	(.030)	(.050)	(.081)	(.081)

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Industry	(1) 1974	(2) 1979	(3) 1984	(4) Total Compen- sation
Banking	.081	063	.077	
	(.014)	(.031)	(.023)	0.105 (.023)
Insurance	.048	.022	.080	0.084
	(.013)	(.027)	(.022)	(.022)
Private Household	151	259	367	-0.517
	(.019)	(.034)	(.101)	(.101)
Business Services	053	067	.013	-0.017
	(.016)	(.028)	(.024)	(.024)
Repair Services	126	026	007	-0.038
	(.021)	(.032)	(.036)	(.036)
Personal Services	216	107	163	-0.202
	(.015)	(.025)	(.026)	(.026)
Entertainment	145	078	143	-0.165
	(.023)	(.036)	(.036)	(.038)
Medical Services	052	039	073	-0.069
	(.015)	(.022)	(.024)	(.024)
lospitals	.039	.063	.064	0.068
	(.013)	(.018)	(.023)	(.023)
Welfare Services	333	190	254	-0.338
	(.022)	(.032)	(.028)	(.023)
ducation Services	127	185	189	-0.211
	(.016)	(.019)	(.029)	(.027)
rofessional Services	.085	.060	.071	0.032
	(.016)	(.029)	(.027)	(.027)
Inbiased Weighted Standar				
eviation of Premiums	.132	.108	.146	.185

Note: Controls and sample sizes are the same as in Table 1.

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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 24% percent above the average employee, while workers in the customer oriented retail trade industries were paid 16% to 19% 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. A simple calculation of the standard deviation of the estimated industry differentials is upwardly biased because the industry differentials cannot be estimated precisely. We therefore adjust the standard deviation of estimated ceofficients to reflect sampling error.⁵

Industry variations in relative wages are substantial. In 1984 the employment-weighted standard deviation of two digit CIC industry wage differentials was almost 15%, in 1979 the standard deviation was 11%, and in 1974 the standard deviation was 13%. Changing industries has about the same impact on wages as does changing union status, on average.

Focusing on occupation rather than industry, Table 3 shows that occupation wage differentials are also large. In 1984, wage premiums ranged from a high of 22% above the mean for managers and administrators to a low of 21% below the mean for transport operatives. The standard deviation of the occupational wage differentials in that year was about 12%. As was the case with the industry wage differentials, the occupation premiums are highly correlated from year to year.

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Occupation	(1) 1974	(2) 1979	(3) 1984
Professional & Technical			
Professional & lechnical	.177 (.010)	.194 (.016)	.211 (.018)
Management & Administration	.218	.106	.216
	(.001)	(.022)	(.020)
Sales	002	105	.148
	(.010)	(.019)	(.024)
Crafts	.044	.092	034
	(.009)	(.013)	(.016)
Operatives excl. Transport	090	024	166
	(.009)	(.013)	(.106)
Transport Operatives	~.083	033	211
	(.013)	(.020)	(,043)
Laborers	090	060	146
	(.012)	(.017)	(.019)
Service Workers	119	114	066
	(.010)	(.014)	(.017)
Clerical	023	010	.003
	(.030)	(.049)	(.081)
Unbiased Weighted			
Standard Deviation	. 107	.085	. 117

Table 3: Estimated Wage Differentials for Occupations May CPS (Standard Errors in Parentheses)

^aControls are the same as in Table 1.

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^bSamples sizes for 1974, 1979, and 1984 are 29,945, 8,978 and 10,294, respectively.

Non-Wage Compensation

Fringe benefits are an important component of compensation, accounting for as much as 40% to 50% 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 1 and 2. Since the NIPA and CPS classification schemes do not match perfectly, care should be used in comparing these results to the CPS results. Nonetheless, Tables 1 and 2 show that consideration of nonwage compensation reinforces rather than reduces industries wage differences. For instance, the wage differential in primary metals increases from 17% above the mean to 27% above the mean when we take account of nonwage compensation.

<u>Wage Differences Through Time</u>

Over time both the one and two digit CIC industries show a stable pattern of inter-industry wage variability. The standard deviation of 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 is .998 and between 1984 and 1974 the correlation is .970. 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

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manufacturing workers in 1923. Like Slichter, we conclude that the industry wage structure remains 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, transitory labor demand shocks, and rent sharing. It is unlikely that labor is sufficiently immobile over several decades or even one decade to allow such large differentials to persist. And stock market data suggest that the rents available in different industries fluctuate widely through time. The standard deviation in stock market return between 1984 and 1979 of 23 selected industries surveyed by Standard and Poor's was 78%. The great variability in rents available in an industry over time would make a rent-sharing explanation of the industry wage differences implausible.

In contrast to the predictions of the competitive model, we find that the industry or occupation an employee is in has a statistically significant and sizable impact on wages. 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, transitory demand shocks, or rent sharing. Next we examine whether these findings hold up under closer scrutiny.

3. <u>Alternative Explanations of Industry Wage Differentials</u>

In this section we examine whether the substantial industry wage differentials discussed in Section 2 can be given competitive or institutional explanations. This section is divided into four subsections. The first

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considers issues of measured and unmeasured labor quality, the second examines the importance of compensating differentials, the third section explores the union threat effect, and the fourth section addresses other issues. The major conclusion is that industry wage differentials are robust to additional competitive and institutional explanations.

Labor Quality

Perhaps the most plausible competitive explanation for our findings is that there are differences in unmeasured aspects of labor quality across industries. Tables 4A and 4B explore the impact of alternative degrees of control for human capital on inter-industry and occupation wage variation. If industry wage differentials were due to measured and unmeasured labor quality differences across industries we would expect a significant fall in the dispersion of industry wages once we control for measured human capital. However, the addition of human capital controls -- education, tenure, and age -- results in only a 1% 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%. And variation in occupational wage differences is also substantial despite increased labor quality controls. Unless one believes that age tenure and schooling account for only a negligible amount of the variation in labor quality, this evidence makes it implausible to attribute inter-industry wage differences to differences in labor quantity.

It might still be argued that our results do not adequately control for labor quality -- that unmeasured labor quality differences, such as motivation

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	Controls	Weighted Unbiased SD of Industry Wage Differentials	Raw Correlation With Table 2
(1)	Occupation, sex, nonwhite, central city dummy, union dummy, ever married, ever married* sex, and veteran status	. 114	- 994
(2)	Row (2) controls plus 12 age structure variables	.108	.998
(3)	Row (2) plus 4 education variables	.108	1.0
(4)	Row (3) controls plus 4 tenure variables	.104	.995

Table 4A: Alternative Degrees of Control for Labor Quality - Industry Analysis May 1979 CPS - Pension Supplement

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Table 4B: Alternative Degrees of Control for Labor Quality - Occupation Analysis May 1979 CPS - Pension Supplement

	Controls	Weighted Unbiased SD of Industry Wage Differentials	Raw Correlation With Table 2
(1)	Occupation, sex, nonwhite, central city dummy, union dummy, ever married, ever married* sex, and veteran status	.111	. 991
(2)	Row (2) controls plus 12 age structure variables	. 102	.992
(3)	Row (2) plus 4 education variables	.085	1.0
(4)	Row (3) controls plus 4 tenure variables	.081	. 999

and innate ability, vary systematically with industry and are being "picked-up" by the industry variables instead of the human capital controls.

We 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 industry. The longitudinal analysis addresses the problem of unmeasured labor quality in the cross-sectional results reported above, but is not without potential biases. These biases include the selectivity of job switchers and increased measurement error.

We have created a large longitudinal data set by pooling together three matched CPS data sets. Since CPS cannot match individuals who change their address, the sample is not completely representative and probably under-represents job switchers. Nonetheless, CPS reports that about 70% of respondents were matched from one year to the next year. Of the 18,541 employees in our data set, 2,137 reported changing major industries. However, evidence from Mellow and Sider (1983) on measurement error in answering questions about industry suggests that many of these reported industry switchers truly did not switch industry affiliation, and are instead the result of classification errors. As a result, it is necessary to correct our estimates for measurement error.

Table 5 presents the results of our analysis of longitudinal data. Since measurement error is a severe problem in looking at persons who report changes in industry, we report results with and without adjustment for measurement error. The correction for measurement error in more than one dummy variable in longitudinal data is derived in the Appendix. Our results show that the longitudinal and level regressions are very similar. In all industries except

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	<u>Estim</u>	<u>ating Techn</u> ique	
Taduatav	(1) Fixed Effects Without Correction	(2) Fixed Effects Corrected	(3)
Industry	for Measurement Errors	for Measurement Error ^b	Levels ^o
Construction	.063	.123	176
	(.033)	(.074)	.176 (.023)
Manufacturing	.028	.097	.059
	(.031)	(.072)	(.021)
Transportation and	.019	. 229	.110
Public Utilities	(.035)	(.248)	(.022)
Wholesale and	042	093	126
Retail Trade	(.031)	(.074)	(.021)
F.I.R.E.	.027	132	.029
	(.036)	(.243)	(.023)
Services	040	164	070
	(.032)	(.010)	(.022)
Mining	.067	.193	.134
	(.004)	(.070)	(.044)

Table 5: The Effects of Unmeasured Labor Quality

^aData set is three matched May CPS's pooled together. 1974-1975, 1977-1978 and 1979-1980. Sample size is 18,122.

^bSee Appendix I for description of correction technique.

^CLevels are 1974, 1977 and 1979 data pooled. The 1975, 1978 and 1980 sample was qualitatively the same.

^dControls for fixed effects regressions include change in education and its square, change in occupation, change in union membership, change in experience squared, change in marital status, change in veteran status and year dummies. Controls for level regressions are the same as Table 1 plus year dummies.

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finance, insurance and real estate the level and adjusted longitudinal results have the same sign and about the same magnitude. For instance, the measurement error corrected results show that employees who leave (join) the manufacturing sector gain (lose) a 9.7% pay increase (decrease), while a regression on the levels shows a 5.9% pay premium for manufacturing employees. For some industries the measurement error corrected results actually suggest that the unmeasured labor quality is lower in the high pay industries.

There are potentially important selection problems involved in studying workers who change industries. 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. Along with the similarity of the cross-sectional and longitudinal results, we find this evidence supportive of the view that observed industry differences in wages do not reflect differences in average labor quality.

B. <u>Compensating Differentials</u>

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, 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

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could be argued that the industry wage differentials we observe 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. 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.

Table 6 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), our estimates are less precise than our other results. However, as can be seen from comparing Table 1 to Table 6 the industry wage structure in QES is highly correlated with our results from CPS. By comparing column (1) and

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column (2) of Table 6 it is clear that the working condition variables do not substantially alter the pattern of industry wages. The standard deviation of the industry premiums actually increases from 0.11 to 0.12 when the working condition controls are added to the equation.

Table 7 reports occupation pay premiums with and without the ten working condition controls. The results of this exercise are less convincing. The standard deviation of the differentials drops from 6.2% to 4.9% once working conditions are controlled for. These pay premiums are much less important than industry premiums and than our earlier occupation results. However, the attenuated occupational wage differentials may result from the imprecision in the estimates. Even with working condition controls, the occupation variables are statistically significant.

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 and occupation 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 and occupation 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.

Evidence considered in this subsection does not support the view that industry and occupation wage differentials are due to omitted working condition variables. It is not likely that the basic results reported in

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	<u> </u>	
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)
F.I.R.E.	.071	.053
	(.104)	(.105)
Services	107	104
	(.090)	(.091)
Mining	.233	.308
	(.205)	(.220)
10 Working Condition Variables ^a	no	yes
Unabiased Weighted Standard Deviation of 2-Digit Industry		
Premiums	.113	.118
R ²	.496	.519

Table 6: Analysis of Industry Wage Premiums With and Without Controls for Working Conditions OES 1977

^aWorking condition variables include 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.

^bOther controls include 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.

^CSample size is 1,033.

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	Coefficient (SE)		
Occupation	(1)	(2)	
Professional & Technical			
	.144 (.055)	.128 (.055)	
Management & Administration	.155	.164	
	(.057)	(.057)	
Sales	.025	.033	
	(.071)	(.070)	
Crafts	.019	.022	
	(.053)	(.053)	
Operatives excl. Transport	098	073	
	(.058)	(.058)	
Transport Operatives	163	124	
	(.074)	(.075)	
Laborers	040	045	
	(.080)	(.079)	
Service Workers	179	197	
	(.061)	(.060)	
Clerical	021	037	
	(.192)	(.202)	
10 Working Condition Variables	no	yes	
Unabiased Weighted Standard			
Deviation of Occupation Wage Premiums	.062	040	
	.002	.049	

Table 7: Analysis of Occupation Wage Premiums With and Without Controls for Working Conditions QES 1977

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Note: See Table 5 notes. Sample size equals 1,033.

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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.

C. Union Threat

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 industry's ease of defeating a union drive has a negative relationship with wage differentials. 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 the industry wage structure remained remarkably stable during this time period. This finding should not be surprising in light of Sumner Slichter's (1950) finding that the industry wage structure did not change substantially after the passage of the Wagner Act and unprecedented unionization in the 1930's and 1940's. These results strongly suggest that the industry wage structure exists independent of union activity.

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Table 8 provides additional cross-sectional evidence on the industry wage structure and unions. Firms in southern states have a great legal and cultural edge over the rest of the country in avoiding unions. In 1978, for instance, non-southern 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. In row (1) we present the standard deviation of industry wage differentials in southern states after controlling for other factors. Contrary to the predictions of the 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 obtained using a subsample of SMSAs with very low unionization rates. It does not appear that the threat of unionization is an important explanation of the inter-industry wage structure.

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 who can raise wages without suffering severe employment losses in certain industries (i.e. because of varying elasticity of labor demand), we would expect to find less variability in wages across industries for nonunion workers. Rows (2) and (3) of Table 8 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

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Samp ———)]e	Adjusted Weighted Standard Deviation of Industry Wage Differentials ^a	Weighted Correlation with Complement ^b
(1)	Southern States	.136	.91 (1.0)
(2)	Nonunion Employees	- 148	.68 (.99)
(3)	Union Employees	.127	.68 (.99)

Table 8: Alternative Samples and Union Threat May 1984 CPS

^aweights are 1984 employment.

^bComplements for rows (1) through (3) are nonsouthern states, union employees and nonunion employees, respectively. Consistent correlations are reported in parentheses.

union and nonunion employees.

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 which vigorously oppose unions have almost an identical wage structure to nations that have widespread and legally protected collective bargaining such as England and West Germany.

Industry wage differentials exist to about the same extent in union and nonunion environments and in situations where the credibility of union threats differ widely, and therefore do not appear to be a union phenomenon.

D. 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 plants. In general, we find that 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 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 separately industry effects on the wages of young and old workers, and on workers with short and long tenure. Rows (1) and (2) of Table 9 show that wage premium across industries for the young and old are highly correlated. Furthermore,

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the standard deviation of industry wages is about 14% 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. Varying patterns of human capital accumulation do not appear to provide an explanation for the inter~industry wage structure.⁶

An important institution that affects wages is company and plant size. Several studies have documented sizable size-wage differentials. For our purposes, the size-wage differential is an important dimension of the wage structure 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 9 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 most likely to be diverse among the self employed, and the substantial reporting 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 9 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

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Sample	Adjusted Standard Deviation of Industry Wage Differentials	Weighted Correlatior with Complement ^b	
Age			
(1) Age 20-35 (2) Age 50-65	.139 .134	.85	
Tenure			
(3) Tenure ≼ 1 (4) Tenure > 10	.087 .096	. 75	
<u>Firm Size</u>			
(5) 1-99 Employees (6) 1,000 or More E	.073 mployees .111	. 78	
Types of Employment			
(7) Self Employed (8) Privately Emplo	.097 yed .133	.84	
Occupation			
(9) Blue Collar (10) White Collar	.126 .140	. 63	

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^aRows (7) and (8) are unweighted; all other rows are weighted by 1984 employment.

^bComplement is the other reported subsample. Correlations are not adjusted.

^CControls are the same as in Table 1. Year dummies were also included in rows (7) and (8).

^dSample sizes for rows (1) through (10), respectively, are 4,932, 1,811, 5,116, 1,619, 3,752, 3,497, 3,378, 46,232, 3,959, and 6,335. Rows (1), (2), (7) and (8) are 1984 CPS. Rows (3) through (6) are 1979 CPS. Rows (7) and (8) are May 1975, 1976, 1977, and 1978 CPS.

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wage tend to pay workers in other occupations above their alternative wage as well. This finding supports the conclusions of Dickens' and Katz's (1986) more extensive examination of this issue. 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.⁷ 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).

4. <u>Direct Evidence</u>

The previous sections were aimed at documenting substantial variations in wages across industries and occupations that are not explained by the standard competitive model. In this section we examine whether it is profitable to pay these wage premia. Specifically, we test efficiency wage models that are based on reduced turnover costs and improved performance. First we consider the relationship between pay premiums and turnover and then we examine effort and performance. The direct evidence that we present suggests that wage premiums contribute to increased employee productivity and some limited support for efficiency wage theories.

Turnover is costly to firms. Increased quits cost the firm in terms of

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recruitment, lost production and lost specific training. While the relationship between wages and turnover is well established in the literature (see Pencavel (1970) and Viscusi (1980) for instance), we specifically examine the relationship between turnover and industry and occupation wage premia. Our approach to analyzing turnover is to regress tenure and quit rates on an employee's wage premium and other controls. The wage premium is the sum of industry and occupation wage differentials that we report in Tables 2 and 3.

Table 10 shows that the wage premium variable is a significant factor in explaining tenure and quits. The premium variable has an impact on tenure and quits even after controlling for individual specific wage rates. Industry and occupation wage premia thus have a stronger impact on turnover that goes beyond the general effect of increased wages. This finding, at a minimum, provides further evidence that wage premiums do not reflect compensating differentials, since such differentials would not induce reduced turnover. The results imply that a 75% increase in the wage premium, which equals the change in wages of moving from the lowest paid industry to the highest paid industry in 1984, would result in an estimated 38% increase in tenure and a 63% decrease in quit rates, all else equal. Brown and Medoff (1978) estimate that the elasticity of output with respect to the quit rate is about .1. This implies that reductions in turnover alone are not sufficient to justify wage premiums of the magnitude actually observed if labor's share is substantial. Although this is slightly more than the impact of changing from nonunion to union status, higher wages do not appear to bring about a big enough reduction in turnover to justify their cost unless they bring other benefits.

In Table 11 we consider the effect of industry and occupation wage

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		Deper	Dependent Variables ^a	
Independent Var i ab les	(1) Tenure	(2) Tenure	(3) Quit	(4) Quit
Wage premiums ^b	2.94 (0.46)	.81 (.49)	21 (.11)	13 (.11)
Union	2.34 (0.16)	1.88 (.16)	15 (.04)	13 (.04)
Log hourly wage	;	2.22 (.20)	1	14 (.04)
Other controls:	Age dummies (6), Age * Sex (6), Education, Education Squared, Education Squared * Sex, Region Dummies (3), Race Dummiey, Sex Dummy, Central City Dummy, Firm Size Dummies (4), Marriage Dummy, Marriage * Sex, Veteran Status Dummy	Same as (1) my, irm nt Size Dummy, an	Education, Education Squared, Region Dummies (3), Race Dummy, Sex Dummy, SMSA Dummy, Derived Experience, and Derived Experience Squared	Same as (3)
R ²	.42	.42	.17	.18
	181.8	182.7	9.21	9.38
Data Set	May 1979 CPS Pension Supplement	May 1979 CPS Pension Sumlement	QES 1973-1977 Panel	QES 1973-1977 Panel

^aMean (SD) of Tenure equals 5.7 (7.6); Mean (SD) of Quit equals .24 (.43). ^bPremium variable is the sum of 2-digit industry and occupation wage

cdifferentials. Sample size is 8,978 for tenure regressions and 571 for quit regression.

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Table 10: Regressions on Tenure and Quits

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premiums on several self-reported measures of performance and job characteristics, holding human capital, individual wages, and demographic factors constant. For comparison, we also report the effect of union membership on these same performance measures and job characteristics.

We find that industry and occupation premiums are postiively related to self-reported work effort. This is true even after holding constant the level of wages. Furthermore, workers in better paying occupations and industries are more likely to report that their work is "meaningful" to them and that they think about their work during their leisure time than workers in low paying occupations and industries. These findings suggest that wage premiums are successful in eliciting better performance from workers.

Lastly, we find that workers in better paying industries and occupations tend to have less repetitious work and greater freedom to determine their work speed. While this result is contrary to an equalizing differences view of industry and occupation wage differences, it is consistent with efficiency wages based on varying monitoring costs since workers with greater discretion are more difficult to monitor than workers with well defined, repetitious job tasks.

The direct evidence reported in this section provides some support for efficiency wage theory by showing a link between wage premiums and reduced turnover, increased work effort, and more job discretion. It is certainly not clear, however, that these responses to high wages are sufficiently large to make raising wages profitable.

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Table 11: Direct Evidence on Wage Premiums and Effort

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Independent Variables	(1) I put a lot of effort beyond what is required into my job (1,2,3,4)	<pre>(2) The work I do on my job is mean- ingful to me (1,2,3,4)</pre>	<pre>(3) My job does not require that I do the same things over and over (1,2,3,4)</pre>	<pre>(4) I determine the speed at which I work (1,2,3,4)</pre>	<pre>(5) I often think about my job when I'm busy doing something else (1,2,3,4)</pre>
Premium ^a	.171	.411	,636	.193	.466
	(.153)	(.154)	(.180)	(.149)	(.219)
Log Hourly Wage	.015	.031	.181	.018	.027
	(.056)	(.057)	(.066)	(.055)	(.081)
Union Members	119	206	365	167	190
	(.052)	(.052)	(.061)	(.051)	(.075)
R ²	.04	.07	.16	, 04	.06
Mean (SD) of	3.47	3.05	2.63	2.95	2.25
Dependent Variable	(.69)	(.71)	(.87)	(.67)	(1.00)

^aPremium variable is the sum of CPS industry and occupation wage differentials in 1974. ^bThe sample size is 937. Controls include potential experience and its square, tenure and its square, 3 region dummies, sex, nonwhite, and education and its square.

5. <u>Conclusions</u>

The empirical results in this paper suggest that non-competitive considerations play an important part in wage setting. After controlling for labor quality and compensating differentials to the maximum extent possible with available data we find that variables related to job characteristics but not to workers' utility on the job have very substantial effects on wages. Differences in industry have effects on wages that are comparable in magnitude to the effects of unionism, firm size, sex or race. In Krueger and Summers (1986), industry wage differences are remarkably stable over time and remarkably similar across countries. There is some evidence that firms paying wage premiums reap some gains in terms of lower turnover and better performance as a result.

These results have important implications for both micro and macro economic policy. It is well known (e.g Bhagwhati and Srinivasan (1983)) that in the presence of inter-industry wage differentials, a variety of subsidies, tariffs, or other protectionist policies may be desirable in the sense that they raise total economic welfare. Bulow and Summers (1986) demonstrate that it is even possible that subsidies to high wage industries financed by universal lump sum taxes will represent a Pareto-improvement. Traditionally, these results have not been thought of as having much policy relevance. Inter-industry wage differentials have been viewed as distortions which are best attacked directly and which may be exacerbated by second-best policies. Efficiency wage models suggest that inter-industry wage differentials may not be the result of imperfections in competition but of deeper information and

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contracting problems. In this case, second best industrial subsidies may be the only available policy instruments. Of course, it is far from clear that governments have the ability to actually use such policies in a desirable way.

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 attentuates 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 noncompetitive 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 non-competitive, non-efficiency wage theories, while difficult to specify, undoubtedly also have differing implications. Moreover, linking wage

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premia to variables suggested by efficiency wage theories, if possible, would strengthen the argument by elimination presented here. There are, of course, formidable difficulties of identification so it may be necessary to rely on case studies to test efficiency wage theories. To this end, Summers (1986) presents a case study of Henry Ford's introduction of the five dollar day. Alternatively, production function estimates of the type presented by Brown and Medoff (1978) might permit estimates of at least some efficiency wage effects.

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Table A1: Estimated Wage Differentials for Three-Digit CIC Industries -- May 1984 CPS

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CIC	Industry (SIC)		lage erential
	MINING		
040	Metal mining (10)	.255	(.079)
041	Coal mining (11, 12)	.264	(.098)
042	Crude petroleum and natural gas extraction (13)	. 284	(.047)
050	Nonmetallic mining andquarrying, except fuel (14)	.050	(.112)
B (060)	CONSTRUCTION (15, 16, 17)	.144	(.027)
	MANUFACTURING		
	Nondurable Goods		
	Foods and kindred products		
100	Meat products (201)	059	(.061)
101	Dairy products (202)	.181	(.088)
102	Canned and preserved fruits and vegetables (203)	.041	(.070)
110	Grain mill products (204)	.201	(.117)
111	Bakery products (205)	.011	(.077)
112	Sugar and confectionary products (206)	.091	(.108)
120	Beverage industries (208)	.152	(.073)
121	Miscellaneous food prepareations and kindred products (207, 209)	.066	
122	Not specifed food industries	.088 NA	(.084)
130	Tobacco manufacturers (21)	.286	NA (.172)
	Textile mill products		
132	Knitting mills (225)	169	(.074)
140	Dyeing and finishing textiles, except		(,)
	wool and knit goods (226)	.127	(.172)
141	Floor coverings, except hard surface (227)	033	(.123)
142	Yarn, thread and fabric mills (228, 221-224)	009	(.060)
150	Miscellaneous textile mill products (229)	023	(.101)
	Apparel and other finished textile products		
151	Apparel and accessories, except knit (231-238)	181	(.038)
152	Miscellaneous fabricated textile products (239)	145	(.079)
	Paper and allied products		
160	Pulp, paper, and paperboard mills (261-263, 268)	.164	(.061)
161	Miscellaneous paper and pulp products (264)	.075	(.079)
62	Paperboard containers and boxes (265)	.094	(.076)

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(Standard Errors in Parentheses)

Table A1, Continued

<u>cic</u>	Industry (SIC)		age rential
	Printing, publishing, and allied industries		
C (171) 172	Newspaper publishing and printing (271) Printing, publishing, and allied industries,	-,049	(.051)
	except newspapers (272-279)	.123	(.037)
	Chemicals and allied products		
180	Plastics, synthetics, and resins (282)	.026	(.101)
181	Drugs (283)	.221	(.086)
182	Soaps and cosmetics (284)	.280	(.095)
190	Paints, varnishes, and related products (285)	.236	(.122)
191	Agricultural chemicals	016	(.136)
192	Industrial and miscellaneous chemicals (281,		
	286, 289)	.290	(.047)
	Petroleum and coal products		
200 201	Petroleum refining (291) Miscellaneous petroleum and coal products	.370	(.079)
201	(295, 299)	.637	(.383)
	Rubber and miscellaneous plastic products		
210 211	Tires and inner tubes (301)	.339	(.129)
211	Other rubber products, and plastics footwear and belting (302-304, 306)	026	(000)
212	Miscellaneous plastics products (307)	026	(.090) (.052)
<u> </u>	Priscertaneous prastres products (307)	000	(1052)
	Leather and leather products		·
220	Leather tanning and finishing (311)	107	(.382)
221	Footwear, except rubber and plastic (313,314)		
222	Leather products, except footwear (315-317, 319)	132	(.157)
	Durable Goods		
	Lumber and wood products, except furniture		
230	Logging (241)	043	(.172)
231	Sawmills, planing mills, and millwork (242, 243)		(.056)

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	Industry (SIC)		age rential
	Lumber and wood products, except furniture (Continu	ed)	
232	Wood buildings and mobile homes (245)	067	(.117)
241	Miscellaneous wood products (244, 249)	191	(.108)
242	Furniture and Fixtures (25)	047	(.054)
	Stone, clay, glass, and concrete products		
250	Glass and glass products (321–323)	035	(.090)
251	Cement, concrete, gypsum, and plaster products		
	(324, 327)	.060	(.086)
252	Structural clay products (325)	.263	(.271)
261	Pottery and related products (326)	.046	(.172)
262	Miscellaneous nonmetallic mineral and stone		·
	products (328, 329)	.216	(.101)
	Metal industries		
270	Blast furnaces, steelworks, rolling and		
	finishing mills (331)	.233	(.060)
271	Iron and Steel foundries (332)	.128	(.090)
272	Primary aluminum industries (3334, pt 334,		
200	(3353-3355, 3361)	.256	(.117)
280	Other primary metal industries (3331-3333, 33339, pt 334, 3351, 3356, 3357, 3382,		
	3369, 339)	.052	(.074)
281	Cutlery, hand tools, and other hardware (342)	012	(.104)
282	Fabricated structural metal products (344)	.090	(.053)
290	Screw machine products (345)	.103	(.172)
291	Metal forgings and stampings (346)	.000	(.088)
292	Ordnance (348)	.118	(.117)
300	Miscellaneous fabricated metal products (341, 343, 347, 349)	.035	(064)
801	Not specified metal industries	165	(.064) (.382)
	Machinery, except electrical		
810	Engines and turbines (351)	.270	(.104)
311	Farm machinery and equipment (352)	.324	(.081)
312	Construction and material handling machines (353)	.145	(.070)
320	Metalworking machinery (354)	.020	(.072)

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Table A1, Continued

CIC	Industry (SIC)		age rential
	Machinery, except electrical (Continued)		
321	Office and accounting machiens (357, except 3573)	.349	(.108)
322	Electronic computing equipment (3573)	.243	(.044)
331	Machinery, except electrical, n.e.c. (355, 356,		
	358, 359)	.133	(.038)
332	Not specified machinery	· NA	NA
	Electrical machinery, equipment, and supplies		
340	Household appliances (363)	015	(.093)
341	Radio, TV, and communication equipment (365,		
	366)	.202	(.045)
342	Electrical machinery, equipment, and supplies, n.e.c. (361, 362, 364, 367, 369)	.051	(.035)
350	Not specified electrical machinery, equipment, and supplies	.498	(.382)
	Transportation equipment		
351	Motor vehicles and motor vehicle equipment (371)	. 220	(.038)
352	Aircraft and parts (372)	.198	(.050)
360	Ship and boat building and repairing (373	.057	(.073)
361	Railroad locomotives and equipment (374)	.230	(.270)
362	Guided missiles, space vehicles, and parts (376)	.180	(.061)
370	Cycles and miscellaneous transportation equipment		•
	(375, 379)	030	(.108)
	Professional and photographic equipment, and watches		
371	Scientific and controlling instruments (381, 382)	.074	(.067)
372	Optical and health services supplies (383, 384,		
200	385)	.097	(.062)
380	Photographic equipment and supplies (386)	.277	(.101)
381	Watches, clocks, and clockwork operated devices		
	(387)	.321	(.271)
382	Not specified professional equipment	NA	NA

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	Industry (SIC)		age rential
390	Toys, amusement, and sporting goods (394)	. 104	(.088)
391	Miscellaneous manufacturing industries (39,	. 104	(.000)
	except 394)	077	(.070)
392	Not specified manufacturing industries	073	(.271)
	TRANSPORTATION, COMMUNICATIONS, AND OTHER PUBLIC UTILITIES		
	Transportation		
400	Railroads 940)	.227	(.067)
401	Bus service and urban transit (41, except 412)	.086	(.122)
402	Taxicab service (412)	573	(.382)
410	Trucking service (421, 423)	.079	(.050)
411	Warehousing and storage (422)	020	(.172)
420	Water transportation (44)	.087	(.112)
421	Air transportation ()45)	.331	(.049)
422	Pipe lines, except natural gas (46)	116	(.192)
432	Services incidental to transportation (47)	037	(.073)
	Communications		
440	Radio and Television broadcasting (483)	144	(.062)
441	Telephone (wire and radio) (481)	.312	(.038)
442	Telegraph and miscellaneous communication		••••••
	services (482, 489)	.039	(.079)
	Utilities and sanitary services		
460	Electric light and power (491)	. 289	(.045)
461	Gas and steam supply systems (492, 496)	.291	(.070)
462	Electric and gas, and other combinations (493)	.319	(.074)
470	Water supply and irrigation (494, 497)	.083	(.129)
471	Sanitary services (495)	.455	(.382)
472	Not specified utilities	.494	(.271)
	WHOLESALE TRADE		
	<u>Durable Goods</u>		
500	Motor Vehicles and equipment (501)	013	(.084)
501	Furniture and home furnishings (502)	.066	(.122)

CIC	Industry (SIC)		age rential
502	Lumber and construction materials (503)	.123	(.104)
510	Sporting goods, toys, and hobby goods (504)	.178	(.270)
511	Metals and minerals, except petroleum (505)	.119	(.146)
512	Electrical goods (506)	.107	(.061)
521	Hardware, plumbing and heating supplies (507)	.039	(.076)
522	Not specified electrical and hardware products	NA	NA
530	Machinery, equipment, and supplies	.073	(.041)
531	Scrap and waste materials (5093)	.109	(.136)
532	Miscellaneous wholesale, durable goods (5094, ????)	.185	(.172)
	Nondurable Goods		
540	Paper and paper products (511)	.011	(.122)
541	Drugs, chemicals, and allied products (512, 516)	024	(.082)
542	Apparel, fabrics, and notions (513)	.092	(.137)
550	Groceries and relatedproducts (514)	020	(.057)
551	Farm productsraw materials (515)	146	(.090)
552	Petroleum products (517)	.182	(.078)
560	Alcoholic beverages (518)	.072	(.108)
58 <u>1</u>	Farm supplies (5191)	.055	(.113)
582	Miscellaneous wholesale, nondurable goods (5194, 5198, 5199)	0.11	
571	Not specified wholesale trade	.041	(.104)
571		.354	(.270)
	RETAIL TRADE		
580	Lumber and building material retailing (521, 523)	119	(.061)
581	Hardware stores (525)	305	(.068)
582	Retail nurseries and garden stores (526)	121	(.129)
590 D (501)	Mobile home dealers (527)	276	(.192)
D (591)	Department stores (531)	203	(.031)
592	Variety stores (533)	138	(.098)
600	Miscellaneous general merchandise stores (539)	266	(.117)
E (601)	Grocer stores (541)	144	(.032)
602	Dairy products stores (245)	234	(.157)
610	Retail bakeries (546)	145	(.095)
611	Food stores, n.e.c. (52, 543, 544, 549)	282	(.086)
612	Motor vehicle dealers (551, 552)	023	(.040)
620	Auto and home supply stores (553)	105	(.067)
62 <u>1</u>	Gasoline service stations (554)	278	(.061)
622	Miscellaneous vehicle dealers (555, 556, 557, 559)	258	(.122)

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CIC	Industry (SIC)		age rential
			_
630	Apparel and accessory stores, except shoe (56,		
	except 566)	237	(.042)
631	Shoe stores (566)	237	(.086)
632	Furniture and home furnishings stores (571)	112	(.062)
640	Household appliances, TV, and radio stores (572,		
	573)	172	(.061)
F (641)	Eating and drinking places (58)	213	(.083)
642	Drug stores (591)	258	(.047)
650	Liquor stores (592)	488	(.088)
651	Sporting goods, bicycles, and hobby stores (5941,		
~~~	5945, 5946)	338	(.098)
652	Book and stationery stores (5942, 5943)	199	(.104)
660	Jewelry stores (5944)	094	(.082)
661	Sewing, needlework, and piece goods stores (5949)	403	(.123)
662	Mail order houses (5961)	287	(.108)
670	Vending machine operators (5962)	174	(.157)
671	Direct selling establishments (5963)	.117	(.095)
672	Fuel and ice dealers (598)	284	(.172)
681	Retail florists (5992)	173	(.086)
682	Miscellaneous retail stores (593, 5947, 5948,		-
601	5993, 5994, 5999)	121	(.060)
691	Not specified retail trade	041	(.382)
	FINANCE, INSURANCE, AND REAL ESTATE		
G (700)	Banking (60)	.048	(.031)
701	Savings and loan associations (612)	.082	(.059)
702	Credit agencies, n.e.c. (61, except 612)	.045	(.056)
710	Security, commodity brokerage, and investment		
	companies (62, 67)	.175	(.056)
H (711)	Insurance (63, 64)	.107	(.034)
712	Real estate, including real estate-insurance-law		( ,
	offices (65, 66)	.005	(.034)
	BUSINESS AND REPAIR SERVICES		<b>,</b> ,
	BUSINESS AND REPAIR SERVICES		
721	Advertising (731)	.087	(.076)
722	Services to be dwellings and other buildings (734)	160	(.054)
730	Commercial research, development, and testing		
	labs (7391, 7397)	.209	(.081)
731	personnel suply services (736)	142	(.052)
732	Business management and consulting services (737)	.015	(.064)
740	Computer and data processing services (737)	.220	(.054)

Table A1, Continued

.

CIC	Industry (SIC)		age rential
741 742	Detective and protective services (7393) Business services, n.e.c. (732, 733, 735, 7394,	.015	(.071)
	7395, 7396, 7399)	029	(.044)
750	Automotive services, except repair (751, 752, 754)	079	(.101)
751	Automotive repair shops (762, 7694)	.034	(.051)
752	Electrical Repair Shops (762)	.220	(.122)
760	Miscellaneous repair services (763,764, 7692, 7699)	030	(.061)
	PERSONAL SERVICES		
J (761)	Private households (88)	388	(.100)
762	Hotels and motels (701)	168	(.034)
770	Lodging places, except hotels and motels (702,		
	703, 704)	510	(.116)
771	Laundry, cleaning, and garment services (721)	285	(.059)
772	Beauty shops (723)	057	(.050)
780	Barber shops (724)	054	(.191)
781	Funeral service and crematories (726)	268	(.116)
782	Shoe repair shops (725)	NA	NA
790	Dressmaking shops (pt 729)	561	(.271)
791	Miscellaneous personal services (722, pt 729)	243	(.083)
	ENTERTAINMENT AND RECREATION SERVICES		
800	Theaters and motion pictures (78, 792)	074	(.069)
801 802	Bowling alleys, billiard and pool parlors (793) Miscellaneous entertainment and recreation	417	(.122)
	services (791, 794, 799)	167	(.043)
	PROFESSIONAL AND RELATED SERVICES		
812	Offices of physicians (801, 803)	082	(.041)
820	Offices of dentists (802)	.053	(.057)
821	Offices of chiropractors (8041)	354	(.172)
822	Offices of optometrists (8042)	335	(.271)
830	Offices of health practitioners, n.e.c. (8049)	436	(.271)
K (831)	Hospitals (806)	.055	(.026)
832	Nursing and personal care facilities (805)	142	(.032)
840	Health services, n.e.c. (807, 808, 809)	020	(.047)
841	Legal services (81)	.072	(.045)
L (842)	Elementary and secondary schools (821)	225	(.040)
M (850)	Colleges and universities (822)	147	(.040)

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CIC	Industry (SIC)		age rential
851	Business, trade, and vocational schools (824)	139	( 120)
852	Libraries (823)	040	(.129)
860	Educational services, n.e.c. (829)	-1.505	(.172)
861	Job training and vocational rehabilitation services (833)		(.221)
862	Child care services (835)	218	(.146)
870	Residential care facilities, without nursing (836)	302	(.057)
871	Social services, n.e.c. (832, 839)	315	(.080)
872	Museums, art galleries, and zoos (84)	178	(.049)
880	Religious organizations (866)	144	(.192)
881	Membership opgenizations (000)	308	(.040)
882	Membership organizations (861-865, 869) Engineering, architectural, and surveying services (891)	077	(.055)
890	Accounting, auditing, and bookkeeping services (892)	.186	(.051)
891	Noncommercial educational and scientific research (892)	.043	(.056)
892	Miscellaneous professional and realted services	018	(.137)
	(899)	.241	(.157)
Weighted	Adjusted Standard Deviation	.164	

Note: Controls are the same as in Table 1.

### APPENDIX

# CORRECTING FOR MEASUREMENT ERROR IN DUMMY VARIABLES IN LONGITUDINAL DATA

Under usual assumptions, measurement error bias is exacerbated in longitudinal data because random misclassification in both periods increases noise while a smaller number of changers reduces signal. Due to the restricted status of a dummy variable, measurement error is correlated with the change in a dummy variable in fixed effects models. Freeman (1984) derives the correction for measurement in this case. The effect of measurement error on a set of mutually exclusive and exhaustive dummy variables is a more complicated problem because the measurement error is correlated across the dummy variables. In this appendix we derive the correction for measurement error in more than one dummy variable in longitudinal data. The procedure is then applied to adjust the estimated fixed effects results in Section 3.

We have the following problem. In either time period an individual can belong to one of k+1 industries. If a worker joins industry i, the change in dummy variable i is 1; if he leaves industry i the change in dummy variable i registers a -1; and if he remains in industry i both periods or never is in industry i, the change in dummy variable registers a 0. For simplicity, we assume the true model is equation (1), where the change in log wage  $\Delta W$  is a function of k industry dummy variables  $\Delta D^*$ , and a random disturbance  $\Delta \epsilon$ .  $\alpha$  is the vector of coeficients we want to estimate. All k+1 industry dummies cannot be in equation (1) because they are colinear -- if you leave one industry you must join another. Since the change in industry status is

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probably orthogonal to the change in other independent variables, such as marital status and education, equation (1) is a reasonable approximation.

(1)  $\Delta W = \Delta D \star \alpha + \Delta \epsilon$ 

The measurement error problem arises because industry status is reported with error in both time periods. For industry i we know the reported  $\Delta D_i$ , which is the true change in status plus the classification error,  $e_i$ .

(2) 
$$\Delta D_{i} = \Delta D_{i}^{*} + e_{i}$$
  
 $e_{i} = \begin{cases} 0 \\ 1 \\ 2 \end{cases}$   
 $\Delta D_{i} = \begin{cases} 0 \\ 1 \\ 1 \\ 2 \end{cases}$ 

Following Freeman (1984), we assume that measurement error is independent over time and random. We further assume that the measurement error is proportional to the industry's size and that transitions from industry i to j equal transitions from j to i. Under these assumptions, the distribution of  $e_i$  conditional upon the true transition is reported in Table A2 below. In the table  $r_{\bar{1},i}$  is the weighted probability an employee who is not in industry i is misclassified in industry i, while  $r_{i,\bar{1}}$  is the probability of being classified as not in industry i conditional upon being in industry i.  $T_{i,j}$  is the true transition probability. The expected value of  $e_i$  is equation (3):

(3)  $E(e_i) = -(r_{\overline{i},i} + r_{i,\overline{i}})\Delta D_i^*$ 

And thus  $\Delta D_i$  can be written as:

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

Table A2: Distribution of e_i

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$\begin{bmatrix} \mathbf{e}_{i} & 1 & 0 & 0 & 0 \\ -2 & \mathbf{r}_{i}^{2}, \mathbf{r}_{i}^{2}, 1^{2} \\ -1 & \mathbf{r}_{i}^{2}, 1^{2}, 1^{2} \\ -1 & \mathbf{r}_{i}^{2}, 1^{2} (1^{-r}_{i}, 1^{2}) + (1^{-r}_{i}, 1^{2}) \mathbf{r}_{i}, 1^{2} \\ + \frac{\mathbf{r}_{i}^{2}, 1^{2}}{\mathbf{r}_{i}, 1^{2} + \mathbf{r}_{i}, 1^{2}} & 0 & 0 \\ -1 & \mathbf{r}_{i}^{2}, 1^{2} (1^{-r}_{i}, 1^{2}) + (1^{-r}_{i}, 1^{2}) \mathbf{r}_{i}, 1^{2} \\ + \frac{\mathbf{r}_{i}^{2}, 1^{2}}{\mathbf{r}_{i}, 1^{2} + \mathbf{r}_{i}, 1^{2}} & (1^{-r}_{i}, 1^{2}) + (1^{2}, 1^{2}) + (1^{2}, 1^{2}) \\ + \frac{\mathbf{r}_{i}^{2}, 1^{2}}{\mathbf{r}_{i}, 1^{2} + \mathbf{r}_{i}, 1^{2}} & (1^{-r}_{i}, 1^{2})^{2} + \mathbf{r}_{i}, 7^{2} \\ + \frac{\mathbf{r}_{i}, 1^{2}, 1^{2}}{\mathbf{r}_{i}, 1^{2} + \mathbf{r}_{i}, 7^{2}} & 1^{-(r}_{i}, 1^{2}) + (1^{-r}_{i}, 1^{2}) + (1^{-r}_{i}, 1^{2}) + (1^{2}, 1^{2}) + (1^{2}, 1^{2}) + (1^{2}, 1^{2}) + (1^{2}, 1^{2}) + (1^{2}, 1^{2}) + (1^{2}, 1^{2}) + (1^{2}, 1^{2}) + (1^{2}, 1^{2}) + (1^{2}, 1^{2}) + (1^{2}, 1^{2}) + (1^{2}, 1^{2}) + (1^{2}, 1^{2}) + (1^{2}, 1^{2}) + (1^{2}, 1^{2}) + (1^{2}, 1^{2}) + (1^{2}, 1^{2}) + (1^{2}, 1^{2}) + (1^{2}, 1^{2}) + (1^{2}, 1^{2}) + (1^{2}, 1^{2}) + (1^{2}, 1^{2}) + (1^{2}, 1^{2}) + (1^{2}, 1^{2}) + (1^{2}, 1^{2}) + (1^{2}, 1^{2}) + (1^{2}, 1^{2}) + (1^{2}, 1^{2}) + (1^{2}, 1^{2}) + (1^{2}, 1^{2}) + (1^{2}, 1^{2}) + (1^{2}, 1^{2}) + (1^{2}, 1^{2}) + (1^{2}, 1^{2}) + (1^{2}, 1^{2}) + (1^{2}, 1^{2}) + (1^{2}, 1^{2}) + (1^{2}, 1^{2}) + (1^{2}, 1^{2}) + (1^{2}, 1^{2}) + (1^{2}, 1^{2}) + (1^{2}, 1^{2}) + (1^{2}, 1^{2}) + (1^{2}, 1^{2}) + (1^{2}, 1^{2}) + (1^{2}, 1^{2}) + (1^{2}, 1^{2}) + (1^{2}, 1^{2}) + (1^{2}, 1^{2}) + (1^{2}, 1^{2}) + (1^{2}, 1^{2}) + (1^{2}, 1^{2}) + (1^{2}, 1^{2}) + (\mathbf$			Frequency of Error Assuming True Value of AD* i	lue of AD* i
$ \begin{array}{cccc} & \overline{r_{1,i}}, \overline{r_{1,i}} & & & & & \\ & \overline{r_{1,i}}, \overline{r_{1,i}} + (1 - r_{1,i}) + (1 - r_{1,i}) r_{1,i}, \overline{r_{1,i}} & & \\ & & \overline{r_{1,i}}, \overline{r_{1,i}} + (1 - r_{1,i}) + (1 - r_{1,i}) r_{1,i}, \overline{r_{1,i}} \\ & & & + \frac{\overline{r_{1,i}}, \overline{r_{1,i}}}{\overline{r_{1,i}} + \overline{r_{1,i}}, \overline{r_{1,i}}} & (1 - r_{1,i}) r_{1,i}, \overline{r_{1,i}} \\ & & & & \\ 1 - (r_{1,i}, r_{1,i}, r_{1,i}, r_{1,i}) & & & & \\ & & & \frac{\overline{r_{1,i}}, \overline{r_{1,i}}}{\overline{r_{1,i}} + \overline{r_{1,i}}, \overline{r_{1,i}}} & ((1 - r_{1,i}))^2 + r_{1,i}, \overline{r}^2) \\ & & & & \\ & & & & \\ \end{array} $	ы.	1	0	-1
$ \begin{array}{cccc} \Gamma_{\overline{1},1}(1-\Gamma_{1,\overline{1}})+(1-\Gamma_{\overline{1},1})\Gamma_{1,\overline{1}} & & & & & & & \\ \overline{1}_{1,1}+\overline{1}_{1,\overline{1}},1& & & & & \\ & & & & & & & \\ \overline{1}_{1,1}+\Gamma_{1,\overline{1}},1& & & & & \\ & & & & & & & \\ \hline 1-(\Gamma_{\overline{1},1}+\Gamma_{1,\overline{1}},\Gamma_{1,\overline{1}})& & & & & & \\ & & & & & & & \\ \hline 1-(\Gamma_{\overline{1},1}+\Gamma_{1,\overline{1}},\Gamma_{1,\overline{1}})& & & & & \\ & & & & & & & \\ \hline 1+\overline{1}_{1,1}+\overline{1}_{1,\overline{1}}& & & & \\ & & & & & & \\ \hline 1+\overline{1}_{1,1}+\overline{1}_{1,\overline{1}}& & & \\ & & & & & \\ \hline 1+\overline{1}_{1,1}+\overline{1}_{1,\overline{1}}& & & \\ \end{array} \right)^{-1} \begin{pmatrix} \Gamma_{1}\Gamma_{1,1}\\\Gamma_{1,1}\\\Gamma_{1,1}\\\Gamma_{1,1}\\\Gamma_{1,1}\\\Gamma_{1,1}\\\Gamma_{1,1}\\\Gamma_{1,1}\\\Gamma_{1,1}\\\Gamma_{1,1}\\\Gamma_{1,1}\\\Gamma_{1,1}\\\Gamma_{1,1}\\\Gamma_{1,1}\\\Gamma_{1,1}\\\Gamma_{1,1}\\\Gamma_{1,1}\\\Gamma_{1,1}\\\Gamma_{1,1}\\\Gamma_{1,1}\\\Gamma_{1,1}\\\Gamma_{1,1}\\\Gamma_{1,1}\\\Gamma_{1,1}\\\Gamma_{1,1}\\\Gamma_{1,1}\\\Gamma_{1,1}\\\Gamma_{1,1}\\\Gamma_{1,1}\\\Gamma_{1,1}\\\Gamma_{1,1}\\\Gamma_{1,1}\\\Gamma_{1,1}\\\Gamma_{1,1}\\\Gamma_{1,1}\\\Gamma_{1,1}\\\Gamma_{1,1}\\\Gamma_{1,1}\\\Gamma_{1,1}\\\Gamma_{1,1}\\\Gamma_{1,1}\\\Gamma_{1,1}\\\Gamma_{1,1}\\\Gamma_{1,1}\\\Gamma_{1,1}\\\Gamma_{1,1}\\\Gamma_{1,1}\\\Gamma_{1,1}\\\Gamma_{1,1}\\\Gamma_{1,1}\\\Gamma_{1,1}\\\Gamma_{1,1}\\\Gamma_{1,1}\\\Gamma_{1,1}\\\Gamma_{1,1}\\\Gamma_{1,1}\\\Gamma_{1,1}\\\Gamma_{1,1}\\\Gamma_{1,1}\\\Gamma_{1,1}\\\Gamma_{1,1}\\\Gamma_{1,1}\\\Gamma_{1,1}\\\Gamma_{1,1}\\\Gamma_{1,1}\\\Gamma_{1,1}\\\Gamma_{1,1}\\\Gamma_{1,1}\\\Gamma_{1,1}\\\Gamma_{1,1}\\\Gamma_{1,1}\\\Gamma_{1,1}\\\Gamma_{1,1}\\\Gamma_{1,1}\\\Gamma_{1,1}\\\Gamma_{1,1}\\\Gamma_{1,1}\\\Gamma_{1,1}\\\Gamma_{1,1}\\\Gamma_{1,1}\\\Gamma_{1,1}\\\Gamma_{1,1}\\\Gamma_{1,1}\\\Gamma_{1,1}\\\Gamma_{1,1}\\\Gamma_{1,1}\\\Gamma_{1,1}\\\Gamma_{1,1}\\\Gamma_{1,1}\\\Gamma_{1,1}\\\Gamma_{1,1}\\\Gamma_{1,1}\\\Gamma_{1,1}\\\Gamma_{1,1}\\\Gamma_{1,1}\\\Gamma_{1,1}\\\Gamma_{1,1}\\\Gamma_{1,1}\\\Gamma_{1,1}\\\Gamma_{1,1}\\\Gamma_{1,1}\\\Gamma_{1,1}\\\Gamma_{1,1}\\\Gamma_{1,1}\\\Gamma_{1,1}\\\Gamma_{1,1}\\\Gamma_{1,1}\\\Gamma_{1,1}\\\Gamma_{1,1}\\\Gamma_{1,1}\\\Gamma_{1,1}\\\Gamma_{1,1}\\\Gamma_{1,1}\\\Gamma_{1,1}\\\Gamma_{1,1}\\\Gamma_{1,1}\\\Gamma_{1,1}\\\Gamma_{1,1}\\\Gamma_{1,1}\\\Gamma_{1,1}\\\Gamma_{1,1}\\\Gamma_{1,1}\\\Gamma_{1,1}\\\Gamma_{1,1}\\\Gamma_{1,1}\\\Gamma_{1,1}\\\Gamma_{1,1}\\\Gamma_{1,1}\\\Gamma_{1,1}\\\Gamma_{1,1}\\\Gamma_{1,1}\\\Gamma_{1,1}\\\Gamma_{1,1}\\\Gamma_{1,1}\\\Gamma_{1,1}\\\Gamma_{1,1}\\\Gamma_{1,1}\\\Gamma_{1,1}\\\Gamma_{1,1}\\\Gamma_{1,1}\\\Gamma_{1,1}\\\Gamma_{1,1}\\\Gamma_{1,1}\\\Gamma_{1,1}\\\Gamma_{1,1}\\\Gamma_{1,1}\\\Gamma_{1,1}\\\Gamma_{1,1}\\\Gamma_{1,1}\\\Gamma_{1,1}\\\Gamma_{1,1}\\\Gamma_{1,1}\\\Gamma_{1,1}\\\Gamma_{1,1}\\\Gamma_{1,1}\\\Gamma_{1,1}\\\Gamma_{1,1}\\\Gamma_{1,1}\\\Gamma_{1,1}\\\Gamma_{1,1}\\\Gamma_{1,1}\\\Gamma_{1,1}\\\Gamma_{1,1}\\\Gamma_{1,1}\\\Gamma_{1,1}\\\Gamma_{1,1}\\\Gamma_{1,1}\\\Gamma_{1,1}\\\Gamma_{1,1}\\\Gamma_{1,1}\\\Gamma_{1,1}\\\Gamma_{1,1}\\\Gamma_{1,1}\\\Gamma_{1,1}\\\Gamma_{1,1}\\\Gamma_{1,1}\\\Gamma_{1,1}\\\Gamma_{1,1}\\\Gamma_{1,1}\\\Gamma_{1,1}\\\Gamma_{1,1}\\\Gamma_{1,1}\\\Gamma_{1,1}\\\Gamma_{1,1}\\\Gamma_{1,1}\\\Gamma_{1,1}\\\Gamma_{1,1}\\\Gamma_{1,1}\\\Gamma_{1,1}\\\Gamma_{1,1}\\\Gamma_{1,1}\\\Gamma_{1,1}\\\Gamma_{1,1}\\\Gamma_{1,1}\\\Gamma_{1,1}\\\Gamma_{1,1}\\\Gamma_{1,1}\\\Gamma$	-2	רה, ורו, ה	0	o
$0 \qquad \qquad$	-1		-	o
$1 - (r_{\overline{1}, i} + r_{i, \overline{1}} - r_{i, \overline{1}} + r_{i, 1$			T _{1,1} 1,1+T _{1,1}	
$0 \qquad \frac{T_{1,i}T_{1,i}}{T_{1,i}T_{1,i}}((1-r_{1,i})^{2}+r_{1,i}^{2})^{2}$ $\frac{T_{1,i}T_{1,i}}{T_{1,i}T_{1,i}}((1-r_{1,i})^{2}+r_{1,i}^{2})^{2}$ $\frac{T_{1,i}T_{1,i}}{T_{1,i}T_{1,i}}((1-r_{1,i})^{2})^{2}$	0	1-(rī, i+r1, ī-ri, īrī, i)		1-(rī, †+r _† , ī ^{-r} i, ī ^r ī, i
$0 \qquad \frac{T_{i,i}T_{i,i}}{T_{i,i}+T_{i,i}} \{(1-r_{i,T})r_{i,T}, T_{i,T}, T_{i$			+ $\frac{T_{\bar{1},\bar{1}}}{T_{i,i}+T_{\bar{1},\bar{1}}}((1-r_{\bar{1},i})^2 + r_{\bar{1},i}^2)$	
$+ \frac{T_{\overline{1}, \overline{1}}}{T_{\overline{1}, \overline{1}} + \overline{T_{\overline{1}, \overline{1}}}} (1 - r_{\overline{1}, \overline{1}}) r_{\overline{1}, \overline{1}}$	F	O	T _{i,i} +T _{ī,i} {(1-r _{i, ī} )r _{i,ī}	r ₁ , ī(1-rī, i)+(1-r _i , ī)rī, i
0			+ T _{1,1} ,1,(1-r _{1,1} )r _{1,1}	
	5	0	o	ri,īrī,i

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where  $\nu_i$  is an orthogonal disturbance.

In matrix notation we have:

(5)  $\Delta D = \Delta D \star [I-R] + v$ 

where:  $R = K \times K$  diagonal matrix with  $(r_{\overline{i},i} + r_{i,\overline{i}})$  on the diagonal. I = K × K identity matrix.

 $\nu$  = Matrix of disturbances which are orthogonal to  $\Delta D^*$ .

Solving for  $\Delta D^*$  and substituting the result into the true model we derive equation (6).

(6) 
$$\Delta W = \Delta D[I-R]^{-1}\alpha - \nu[I-R]^{-1}\alpha + \Delta \epsilon$$

From equation (6) it can be seen that an OLS regression of  $\Delta W$  on  $\Delta D$ yields a biased and inconsistent estimate of the wage differentials  $\alpha$  because (omitted)  $\nu$  and  $\Delta D$  are correlated. A consistent estimator of  $\alpha$  is given in equation (7).

(7) 
$$\hat{\alpha} = (\Delta D^{*} \Delta D^{*})^{-1} (\Delta D^{*} \Delta D) [I-R]^{-1} \hat{\alpha}_{OLS}$$

A proof of equation (7) is straightforward and useful for deriving the standard errors of the estimates. The proof is as follows. Substitution of the OLS estimate for  $\hat{\alpha}_{OLS}$  in equation (7) yields the following equation.

 $\hat{\alpha} = (\Delta D^{*} \Delta D^{*})^{-1} (\Delta D^{*} \Delta D) [I-R]^{-1} [(\Delta D^{*} \Delta D)^{-1} \Delta D^{*} \Delta \omega]$ 

And substitution of the true model, equation (1), for  $\Delta \omega$  in the above equation gives

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

Finally, substituting  $\Delta D' = [I-R]'\Delta D^*' + \nu'$  and cancelling terms results in equation (8). (This result relies on the fact that [I-R] is a diagonal matrix.) The probability limit of (8) is  $\alpha$ , and thus equation (7) is a consistent estimator.

(8) 
$$\hat{\alpha} = \alpha + [I-R]^{-1} (\Delta D^{\star} \Delta D^{\star})^{-1} ([I-R]^{\star} \Delta D^{\star} \Delta \epsilon + \nu^{\star} \Delta D^{\star} \alpha + \nu^{\star} \Delta \epsilon)$$

### Standard Errors

The asymptotic variance-covariance matrix, V of  $\alpha$  is  $E[(\alpha - \alpha)(\alpha - \alpha)']$ . This is presented in equation (9), where A =  $[I-R]^{-1}(\Delta D^*/\Delta D^*)^{-1}$ . This relies on the assumption that  $\Delta \epsilon$  is iid.

(9) 
$$V = A \{\sigma_{\Delta \epsilon}^2 \nu' \nu + \nu' \Delta D * \alpha \alpha' \Delta D * \nu + \sigma_{\Delta \epsilon}^2 [I-R]^2 \Delta D * \Delta D * \rangle A'$$

All of the terms of equation (9) can be estimated given information on  $\Delta D^* \Delta D^*$ ,  $\Delta \omega$ , and  $\Delta D$ , except for  $\nu' \Delta D^* \alpha \alpha' \Delta D^* \nu$ .⁷ However, ignoring this term will not have an important effect on V if, as is usually the case with longitudinal data, the variance of the noise is small relative to the residual variance.

The standard errors of the coefficients are the square root of the diagonal elements of (9).

### <u>Application</u>

In order to apply the correction technique we need an estimate of the misclassification probabilities and the moment matrix of the true industry change variables,  $\Delta D^{*} \Delta D^{*}$ . The moment matrix of reported changers,  $\Delta D' \Delta D$  is known. Mellow and Sider (1983) estimate that 7.7% of employee responses to the industry question in CPS do not match employer responses to the same

question for major industries. However, not all of these responses are employee errors. In fact, Mellow and Sider report some evidence that employers frequently misreport their employees' industry.

We use 5% as a rough estimate of random misclassification in reported industry status,  $r_{i,\bar{i}}$ . We further assume that  $r_{i,j}$  is proportional to the size of industry j. The i,jth off-diagonal element of  $\Delta D^{*'}\Delta D^{*}$  is the negative of the number of movers from industry i to j or j to i, while diagonal element i,i is the total number of joiners to i and leavers from i. We adjust  $\Delta D'\Delta D$ for spurious joiners and leavers to derive  $\Delta D^{*'}\Delta D^{*}$ . Workers who truly switched industry status are assumed to correctly report their industry status. Under these assumptions, the number of misclassified movers from industry i to j or j to i is:

 $2(1-r_{i,\bar{i}})N(T_{i,i}r_{i,j} + T_{j,j}r_{j,i}).$ 

The probability of remaining in industry i both periods, T_{i,i} is approximated by the reported probability of remaining in industry i both periods.

### Footnotes

1. In a recent paper, 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.

2. All results were qualitatively the same when the full 1979 sample was used.

3. Since the wage regressions include a constant, we treat the omitted industry variable as having a zero effect on wages, calculate the employmentweighted 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.

4. We return to the effects of unions in Section 3C.

5. To crudely adjust the variances for sampling error, we subtract the weighted average of the sampling variances of the differentials from the unadjusted variance. The raw correlations are biased for the same reason the standard deviation is biased. As a result, we adjust the correlation coefficient of differentials across samples by multiplying them by the ratio of the biased standard deviation to the unbiased standard deviations. This procedure can be shown to produce a slight underestimate of the variance of

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the true industry wage differentials because of its neglect of covariance terms.

6. Note also that these findings bely 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.

7.  $*\sigma_{\Delta\epsilon}^{2}$  can be estimated from available data because plim  $\sigma_{\Delta u}^{2} = \sigma_{\Delta\epsilon}^{2}$ +  $\hat{\alpha}_{OLS}^{\nu} \hat{\nu} \hat{\alpha}_{OLS}^{+} (\alpha - [I-R]\hat{\alpha}_{OLS})^{\dagger} \Delta D^{\dagger} \Delta D^{\dagger} (\alpha - [I-R]\hat{\alpha}_{OLS});$  and  $E(\nu'\nu) = \Delta D^{\dagger} \Delta D - \Delta D^{\dagger} \Delta D^{\dagger} [I-R]^{2}$ .  $\alpha$  is estimated from (7).

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