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Wage, Tenure, and Wage Growth Variation Within and Across Establishments

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We estimate employer-specific wage, tenure, and wage growth differentials using a unique Bureau of Labor Statistics establishment survey of full-time, white-collar workers. Employer wage and tenure differentials, conditional on worker characteristics, are substantial in these data. Education, potential experience, and tenure are highly correlated within an establishment. High-wage establishments generally employ higher quality workers, and the most skilled men and professionals typically work with the most skilled women and nonprofessionals. There is significant variation in wage growth rates across employers, and high wage growth establishments tend to have longer tenure, all else equal.

I. Introduction

The theory of compensating wage differentials suggests that the characteristics of workers and employers are important determinants of equilibrium wages. Average wages may also vary across employers, conditional on worker characteristics, because of unobserved differences in average

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skills across employers.[1] Although there has been much discussion about possible sources of employer pay differentials, few studies have measured wage differentials conditional on worker characteristics because of data limitations.[2] In this article we present some of the first empirical evidence on wage, tenure, and wage growth differentials across employers, conditional on worker characteristics.[3] Our study utilizes a unique cross-section data set of employers responding to the Bureau of Labor Statistics' White Collar Pay Survey (WCP). This establishment survey collects microeconomic data on current wages and detailed occupations for multiple white-collar workers per employer. In a pilot survey, employers were also asked to provide starting wages, tenure, race, sex, education, and age for a subsample of their employees.

This article has four purposes. First, we examine whether matched worker-employer data can be successfully obtained from an establishment survey such as the WCP. Although wages are likely to be reported accurately by establishments, employer-reported worker demographic characteristics may contain substantial measurement error. We compare the wage distribution in the WCP to the wage distribution of workers in similar occupations from the Current Population Survey (CPS), where wages and demographic characteristics are reported by households. We find significantly more wage dispersion in the CPS that is not explained by worker characteristics, industry, or location dummy variables. Demographic wage differentials are quite similar in the WCP and CPS. Thus WCP worker characteristics do not appear to contain more measurement error than CPS worker characteristics, but CPS wages appear to contain substantially more measurement error than WCP wages.

A second goal of this article is to measure employer wage and tenure differentials conditional on worker characteristics. Most of the unconditional across-employer variation in pay and tenure is explained by average differences in worker characteristics across employers. There are sizable conditional employer wage and tenure differentials, and most of this interemployer variation in pay and tenure occurs within two-digit SIC industries.

[1] A number of factors which we do not examine in this article could also contribute to cross-section employer wage differentials, such as differences in working conditions, fringe benefits, rent sharing, indexing provisions of labor contracts, or bargaining cycles.

[2] Until recently, researchers have used industry dummy variables to make inferences about employer wage differentials. See Dickens and Katz (1987), Murphy and Topel (1987), Krueger and Summers (1988), Gibbons and Katz (1989), Helwege (1992), Katz and Summers (1989), and Keane (1993).

[3] There has been some progress in the past decade in analyzing matched worker-employer data; see Abowd, Kramarz, and Margolis (1994), Groshen (1991), or Troske (1993, 1994), for example.

Next we examine the hypothesis that conditional employer wage differentials are largely explained by worker sorting and unobserved differences in productivity across employers. Some team production models predict that workers sort into firms based on their relative productivity within their occupation, for example, the best lawyers are paired with the best secretaries. Because unobserved skill differences across firms are reflected in conditional employer wage differentials, these models also predict that firms with high wage differentials employ the most skilled workers. We examine these predictions by estimating within-employer correlations in observed skills and correlations between indices of worker quality and pay differentials at an employer. We find that education, experience, and tenure are significantly positively correlated within an establishment. Average skill levels and wages by sex and occupation are significantly correlated across employers. The most skilled men and professionals tend to work with the most skilled women and nonprofessionals, and employers that pay higher wages to men and professionals also typically pay more to women and nonprofessionals.

The final goal of this article is to analyze wage growth differentials across employers. We estimate wage growth as the return to both experience and tenure at an employer for the portion of the WCP sample that reports starting wages. We find significant dispersion in wage growth differentials across employers, conditional on worker characteristics. Employers with higher average current tenure tend to have faster wage growth but do not pay significantly higher starting wages, ceteris paribus. If workers know of these across-employer differences in wage growth rates, jobs with high anticipated wage growth will be more likely to survive. Wage growth regressions using this selected sample will yield biased estimates of within-job wage growth and overestimate the anticipated returns to tenure. Thus tenure returns estimated from household panel data may be upward biased.

II. Data

The purpose of the Bureau of Labor Statistics' White Collar Pay Survey (WCP) is to obtain accurate straight time wages of full-time workers in narrowly defined occupations in private sector establishments.[4] The

[4] The WCP occupations are those that are similar to occupations in the federal sector: accountant, chief accountant, auditor, public accountant, personnel specialist, personnel supervisor/manager, director of personnel, attorney, buyer, computer programmer, computer systems analyst, computer systems analyst supervisor/manager, chemist, engineer, tax collector, registered nurse, licensed practical nurse, nursing assistant, medical machine operating technician, civil engineering technician, engineering technician, drafter, computer operator, photographer, accounting clerk, file clerk, key entry operator, messenger, secretary, typist, personnel clerk/assistant, purchasing clerk/assistant, and general clerk.

straight time wage excludes pay for overtime, performance bonuses, profit sharing, and tips, and the BLS converts all wages into monthly rates of pay. Bureau of Labor Statistics employees visit establishments in person and obtain wage, hours, and earnings data from payroll or other records. An establishment is defined by the BLS as an economic unit generally at a single physical location, where business is conducted or services are performed. A firm may consist of one or more establishments. We use the terms "employer" and "establishment" interchangeably in this article. The WCP samples goods-producing establishments in even-numbered years and service-producing establishments in odd-numbered years. The probability that an establishment is sampled is approximately proportional to its employment.[5]

Our data set is based on a supplement to the WCP survey conducted in 1989 and 1990. In this test survey, 354 establishments were asked questions about a random sample of their employees in "matched" white-collar occupations.[6] Employers were asked to report matched workers' starting pay, age, race, sex, years of education, highest educational degree obtained, and tenure with the employer, in addition to the usual current wage, hours, and occupation information.[7] Three hundred establishments provided information on tenure and worker demographic characteristics for 1,740 workers between the ages of 18 and 64.[8] Our final data set contains information on 1,681 workers in the 241 establishments that report information for multiple workers. The number of workers per establishment ranged between 2 and 32, though only three establishments reported information for more than 20 workers. The mean establishment reported information for 6.98 workers. The median worker in our sample has nine co-workers in the pilot survey.

Sample statistics for the WCP are reported in column 1 of table 1. The key dependent variables in our analysis are the logarithm of a worker's current monthly wage, measured in 1989 dollars, and the logarithm of

[5] See the BLS "Handbook of Methods" for a complete description of this survey.

[6] The number of workers per establishment in the pilot survey is increasing in establishment size.

[7] Note that union status was not collected. In a comparison CPS sample described below, we found that fewer than 5% of CPS workers in these white-collar occupations are union members.

[8] Establishments were asked to report demographic data for a total of 2,386 workers. In only 14 of the 354 establishments was average pay of workers in the survey supplement significantly different from the average pay of all WCP workers at the establishment. Five hundred seventy observations in the pilot survey were excluded because of missing age and education variables. Another 76 observations were excluded for missing race or tenure variables or because age, tenure, or experience variables fell outside valid ranges.

Table 1
WCP and CPS Sample Statistics and Mean Differences

	WCP Means (SD)	CPS Means (SD)	Difference between WCP and CPS Means (SE)
Real monthly wage	2,640.5 (1,204.1)	2,390.3 (1,238.2)	250.24 (31.63)
Log (real wage)	7.777 (.457)	7.654 (.516)	.123** (.013)
Tenure	8.670 (8.133)	...	...
Log tenure	1.666 (1.065)	...	...
Female	.468 (.499)	.513 (.500)	−.045** (.013)
Black	.071 (.258)	.064 (.245)	.007 (.007)
Other	.083 (.276)	.050 (.219)	.033** (.007)
Potential experience	18.517 (10.485)	16.378 (10.994)	2.139** (.270)
Education	14.459 (2.183)	14.225 (2.135)	.205** (.058)
Northeast	.238 (.426)	.239 (.427)	−.001 (.011)
Midwest	.334 (.472)	.222 (.416)	.112** (.012)
South	.302 (.459)	.295 (.456)	.007 (.012)
West	.126 (.332)	.243 (.429)	−.117** (.009)
Occupation:			...
Professional	.316 (.465)	.317 (.465)	
Administrative	.280 (.449)	.280 (.449)	...
Technical	.174 (.379)	.170 (.375)	...
Clerical	.230 (.421)	.233 (.423)	...
MSA size:			
Not in an MSA	.183 (.387)	.157 (.364)	.026** (.010)
Under 1 million	.233 (.423)	.236 (.425)	−.003 (.011)
1–5 million	.413 (.492)	.342 (.475)	.070** (.013)
Over 5 million	.171 (.376)	.264 (.441)	−.094** (.010)
Industry:			...
Durable goods manufacturing	.197 (.398)	.206 (.404)	
Nondurable goods manufacturing	.501 (.500)	.494 (.500)	...
Services	.146 (.353)	.144 (.351)	...
Mining and construction	.093 (.291)	.092 (.298)	...
Other	.063 (.243)	.064 (.244)	...
Establishment size:		...	...
Fewer than 500 employees	.389 (.488)		
500–999 employees	.167 (.373)	...	...
Over 1,000 employees	.444 (.497)	...	...
Number of co-workers	11.10 (6.61)	...	...
Sample size	1,681	16,424	

NOTE.—"Other" industry includes finance, insurance, real estate, wholesale and retail trade, transportation, communications, and utilities.
* Indicates significant at the 10% level.
** Indicates significant at the 5% level.

years of tenure with the employer.[9] Information on both highest degree attained and years of schooling were used to construct a measure of workers' educational attainment. Potential experience is measured as age minus years of education minus six. There are three racial groups: white,

[9] Interviewers coded years of tenure in integer values, and the minimum coded tenure is 1 year. We convert all current reported wages into 1989 dollars, using

black, and other. The average worker in the WCP sample earns just over $2,640 per month, has 8.67 years of tenure with their employer, 14.46 years of schooling and 18.52 years of potential labor market experience. Nearly 60% of the WCP workers are in professional or administrative occupations, 47% are female, and 7% are black. The industry composition is predominantly manufacturing because the WCP survey supplement was primarily conducted in 1990, when goods-producing industries were sampled: 50.1% of our sample is employed in nondurable goods and 19.7% in durable goods manufacturing.

III. Comparison with Current Population Survey

A. Comparison of Sample Statistics

Our WCP sample is one of the first in which a cross section of employers throughout the U.S. report their workers' wages and demographic characteristics. We compare this unique data set to a comparable sample from the Current Population Survey (CPS), a commonly used cross-section household survey. The primary focus of the CPS is to obtain accurate labor force status as of the survey week, and additional questions are asked each month (including hours worked) to clarify the information on labor force status. Data on hourly and weekly earnings are reported by a quarter of the sample—the outgoing rotation groups. A responsible person in each CPS household reports the wages, hours, and earnings data for all household members. The CPS interviewer asks this household member "how much does ——— usually earn per week" at their primary job last week before deductions, but including overtime pay, commissions, or tips usually received. Because this wage measure includes overtime pay, we limit our CPS sample to workers with 35–40 reported usual weekly hours of work.

Our comparable CPS sample consists of 16,424 private sector nonagricultural workers between the ages of 18 and 64, who usually work 35–40 hours per week, in white collar occupations similar to the WCP, from outgoing rotation groups in 1989. The composition of workers differs across the WCP and CPS in part because the WCP pilot survey was conducted primarily in 1990, when goods-producing industries were sampled. About 80% of WCP workers and 24% of CPS workers are employed in goods-producing industries. We construct sample weights for the CPS based on the fraction of WCP workers in 20 cells defined by major occupation and industry.[10]

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the December 1989 to December 1990 average change in the Employer Cost Index for wages and salaries of workers in goods-producing industries.

[10] Major occupation categories are professional, administrative, technical, and clerical, and major industry categories are durable goods manufacturing, nondurable goods manufacturing, mining and construction, services, and other (transpor-

Column 2 in table 1 presents weighted means and standard deviations for the CPS sample, and column 3 presents differences in means and corresponding standard errors across the WCP and CPS samples. Workers in the WCP have 2.14 more years of potential experience, .21 more years of education, are 4.5% less likely to be female, and earn 12.3% higher pay than CPS workers. The geographical distribution of workers also differs significantly across the CPS and WCP samples. The standard deviation of log wages is significantly higher in the CPS than in the WCP.

There is greater evidence of rounding of wages in the CPS than in the WCP: 42.3% of the workers in our CPS sample have reported usual weekly wages that are integer divisible by $50. In contrast, only 12.8% of WCP workers with a reported monthly wage have a monthly wage that is integer divisible by $50.[11]

B. Comparison of Log Wage Regressions

If demographic variables are reported with relatively more error by establishments than households we expect demographic wage differentials, estimated from standard log wage regressions, to be biased toward zero in the WCP relative to the CPS. Consider the log wage regression given by:

$$\ln W_{ij} = X_{ij}\beta + Z_{ij}\gamma + \delta_j + \nu_{ij}, \qquad (1)$$

where $\ln W_{ij}$ is the logarithm of worker i's current real monthly wage in industry j, X_{ij} is a vector of worker demographic characteristics, Z_{ij} is a vector of location characteristics (region and city size dummy variables), δ_j is industry j's wage differential, and ν_{ij} is an independently and identically distributed (i.i.d.) error term. The variables in X_{ij} include fourth-order polynomials in education and experience, and interactions between these polynomials and dummy variables for sex and race.[12] Just over 1% of our CPS sample and less than one-half of 1% of our WCP sample

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tation, communication, utilities, wholesale and retail trade, finance, insurance, and real estate). Sample weights match the occupation/industry distribution of the entire WCP sample, not the sample of multiworker establishments used in this article.

[11] Employers in the WCP pilot report annual wages for almost half of the workers, hourly wages for 16.9% of the workers, weekly wages for 8.8% of the workers, and monthly wages for 24.6% of the workers; 48.1% of the workers in our CPS sample report that they are paid by the hour.

[12] In the CPS sample, we reject cubic and quintic polynomials in favor of the quartic specification and reject the hypotheses that all coefficients on either sex or race interaction terms are jointly equal to zero.

Table 2
Comparison of WCP and CPS Log Wage Regressions

	WCP	CPS
Fraction of variance explained (R^2):		
Worker characteristics, industry, and location	.671	.519
Worker characteristics	.589	.452
(number of worker characteristics)	(61)	(61)
Industry dummy variables	.181	.149
(number of industry dummy variables)	(41)	(64)
Location dummy variables	.037	.055
(number of location dummy variables)	(6)	(6)
Marginal fraction of variance explained:		
Worker characteristics	.435	.329
Industry dummy variables	.069	.037
Location dummy variables	.019	.025
Standard deviations:		
Index of worker quality ($X_{ij}\, \hat{\beta}$)	.320	.314
Industry wage effects ($\hat{\delta}_j$)	.133	.104
Location wage effects ($\hat{\gamma}_j$)	.079	.086
Log wage residual ($\hat{v}_{ij}$)	.270	.360
Correlations:		
($\bar{X}_j\hat{\beta}$, $\hat{\delta}_j$)	.178	.236
($\bar{X}_j\hat{\beta}$, $\hat{\gamma}_j$)	.055	.082
($\hat{\gamma}_j$, $\hat{\delta}_j$)	−.200	.059

report fewer than 10 years of completed schooling, so we group workers with 10 or fewer years of education into a single category.[13]

We estimate identical specifications of (1) across the CPS and WCP data sets. Complete regression results for both samples are presented in appendix A, and table 2 presents summary information from these log wage regressions. We explain 67.1% of the variation in log wages in the WCP, and only 51.9% of the variation in the CPS. Demographic characteristics and two-digit SIC industry dummy variables account for a substantially higher fraction of the log wage variation in the WCP, and location effects account for a somewhat greater fraction of the variation in log wages in the CPS.

The variable ln W_{ij} can be decomposed into four components: an index of worker demographic characteristics, $X_{ij}\hat{\beta}$, an industry wage effect, $\hat{\delta}_j$, a location wage effect, $Z_{ij}\hat{\gamma}$, and the log wage residual, $\hat{v}_{ij}$. The expression $X_{ij}\hat{\beta}$ represents the wage that worker i expects to receive in the mean industry and location in the sample and can be viewed as an index of worker i's quality. Table 2 reports the standard deviation of each wage component for both samples. The standard deviation of the log wage

[13] We find that "bottom coding" education at 10 years (for workers with fewer than 10 years of completed schooling) yields the highest explained sum of squares in both the WCP and CPS samples.

residual is significantly higher in the CPS, and this accounts for the substantially lower explanatory power of the CPS wage regressions documented above. The standard deviations of the worker quality index and location wage effects are roughly equal across samples. The standard deviation of $\hat{\delta}$ is somewhat higher in the WCP (.133) than in the CPS (.104). These empirical standard deviations include dispersion due to sampling variation. The estimated standard deviation of δ, equally weighted across industries and adjusted for sampling error, is .158 in the WCP and .127 in the CPS.[14] These estimates are within the range of empirical results reported by Dickens and Katz (1987) and Krueger and Summers (1988).

Table 2 also reports the correlations between each of the wage components described above. In both samples, we find that workers with more highly valued demographic characteristics are more likely to work in industries and locations that pay higher wages, ceteris paribus. Again, our results corroborate the findings of Dickens and Katz (1987), who show that conditional industry wage premia are positively correlated with average education in the industry. High wage industries in the CPS tend to be located in areas where wages are higher, while high wage industries in the WCP tend to be located in areas with lower wages, all else equal.

Do the CPS and WCP estimates of (1) generate similar wage distributions? We first decompose the 12.3% difference in mean pay across the CPS and WCP samples. Differences in demographic characteristics, industry and location variables account for 5.9 percentage points of this wage differential, using estimated CPS coefficients. Thus, wages in the CPS are 6.4% significantly lower than in the WCP, conditional on worker, industry, and location characteristics. Second, we compare the predicted wages of all WCP workers using both the estimated CPS and WCP regression coefficients. The correlation between predicted wages based on CPS and WCP coefficients is .905.[15] Moreover, each component of a worker's predicted wage is highly correlated across sets of regression coefficients. The correlation between estimated indices of worker quality is .929, between estimated location effects is .906, and between estimated two-digit SIC industry effects is .604.[16] Thus, despite the significant differ-

[14] These adjusted standard deviations are equally weighted across industries, while the empirical standard deviations in table 2 are weighted by the number of workers in each industry. We adjust for sampling error using the expression in Krueger and Summers (1988), n. 6.

[15] The correlation between $(X^{\mathrm{WCP}}\hat{\beta}^{\mathrm{CPS}} + Z^{\mathrm{WCP}}\hat{\gamma}^{\mathrm{CPS}} + D^{\mathrm{WCP}}\hat{\delta}^{\mathrm{CPS}})$ and $(X^{\mathrm{WCP}}\hat{\beta}^{\mathrm{WCP}} + Z^{\mathrm{WCP}}\hat{\gamma}^{\mathrm{WCP}} + D^{\mathrm{WCP}}\hat{\delta}^{\mathrm{WCP}})$ is .905.

[16] The BLS, and most government agencies, code an establishment to an industry according to its primary product or activity. The relatively low correlation in industry wage differentials across samples may occur because CPS households report industry with some error. Mellow and Sider (1983) find that CPS respon-

ence in mean wages across samples, estimated WCP and CPS regression coefficients generate very similar relative wage patterns across workers.

Table 3 presents a further comparison of the estimated wage structure in the WCP and CPS samples. The first two columns report the estimated returns to education and experience, wage differentials by sex and race, and their standard errors using estimated WCP regression coefficients. The third and fourth columns present estimated wage differentials and standard errors based on estimated CPS coefficients. The final two columns of table 3 present differences in estimated returns across the WCP and CPS regressions and their corresponding standard errors. We present these estimated differentials evaluated at the mean level of education and experience in the WCP sample, at 12 and 16 years of education, and at 10 and 26 years of potential experience (the twenty-fifth and seventy-fifth percentiles of the education and experience distributions in the WCP).

The results in table 3 indicate a similar pattern of estimated demographic wage differentials across the WCP and CPS. Male-female wage differentials tend to increase with experience, black-white wage differentials tend to decrease with experience, and the return to an additional year of education is generally the lowest for workers with 12 years of schooling in both samples. There are some differences in the wage structure across samples that are worth noting. Wage differentials by sex and, to a lesser extent, race are significantly smaller in the WCP than in the CPS. The returns to education for men are generally higher in the WCP than in the CPS. Finally, although the returns to experience are similar across samples at both high and low levels of experience, the returns to experience are significantly higher in the WCP evaluated at mean years of experience.

C. Summary

This section has shown that the WCP sample contains higher paid and more skilled workers than a comparable CPS sample. Although differences in worker characteristics account for some of the mean wage differences across samples, the CPS may underreport wages by 6.4%.[17] The evidence also indicates that household reported wages in the CPS contain substantially more measurement error than establishment reported wages in the WCP. The variance of wages in the CPS is significantly higher than in the WCP, and virtually all of this additional variation is unexplained by worker characteristics, location effects, or industry effects. Our results

dents and their employers assign establishments to different industries 14% of the time.

[17] Polivka and Rothgev (1993) find that 30% of CPS respondents report net rather than gross pay.

Table 3
Demographic Wage Differentials in the WCP and the CPS (Standard Errors in Parentheses)

	WCP	CPS	Difference between WCP and CPS
Male-female differences:			
Exp = 10, Ed = 14.46	−.072* (.041)	−.213** (.015)	.141** (.044)
Exp = 18.52, Ed = 12	−.291** (.039)	−.387** (.016)	.096** (.042)
Exp = 18.52, Ed = 14.46	−.213** (.041)	−.295** (.016)	.082** (.044)
Exp = 18.52, Ed = 16	−.262** (.034)	−.261** (.017)	−.001 (.038)
Exp = 26, Ed = 14.46	−.305** (.044)	−.402** (.018)	.097** (.048)
Black-white differences:			
Exp = 10, Ed = 14.46	−.239** (.103)	−.290** (.032)	.051 (.108)
Exp = 18.52, Ed = 12	−.218** (.081)	−.208** (.032)	−.010 (.087)
Exp = 18.52, Ed = 14.46	−.178* (.091)	−.193** (.034)	.015 (.097)
Exp = 18.52, Ed = 16	−.070 (.074)	−.221** (.035)	.151* (.082)
Exp = 26, Ed = 14.46	−.132 (.089)	−.159** (.045)	.027 (.100)
White male returns to experience:			
Exp = 10, Ed = 14.46	.029** (.004)	.024** (.001)	.006 (.004)
Exp = 18.52, Ed = 12	.028** (.004)	.014** (.002)	.014** (.004)
Exp = 18.52, Ed = 14.46	.019** (.003)	.009** (.001)	.010** (.003)
Exp = 18.52, Ed = 16	.017** (.003)	.007** (.001)	.009** (.003)
Exp = 26, Ed = 14.46	.008** (.003)	.013** (.001)	−.005 (.004)
White male returns to education:			
Exp = 10, Ed = 14.46	.136** (.016)	.116** (.006)	.020 (.017)
Exp = 18.52, Ed = 12	−.009 (.036)	.045** (.012)	−.053 (.038)
Exp = 18.52, Ed = 14.46	.122** (.013)	.084** (.005)	.039** (.014)
Exp = 18.52, Ed = 16	.150** (.015)	.099** (.009)	.051** (.018)
Exp = 26, Ed = 14.46	.107** (.013)	.074** (.006)	.033** (.014)
White female returns to experience:			
Exp = 10, Ed = 14.46	.012** (.005)	.013** (.001)	−.001 (.005)
Exp = 18.52, Ed = 12	.017** (.003)	.001 (.001)	.016** (.003)
Exp = 18.52, Ed = 14.46	.004 (.003)	−.002** (.001)	.006 (.004)
Exp = 18.52, Ed = 16	.003 (.004)	−.006** (.002)	.009* (.005)
Exp = 26, Ed = 14.46	−.001 (.004)	−.003 (.002)	.002 (.005)
White female returns to education:			
Exp = 10, Ed = 14.46	.130** (.018)	.121** (.006)	.008 (.019)
Exp = 18.52, Ed = 12	.066** (.033)	.081** (.010)	−.016 (.034)
Exp = 18.52, Ed = 14.46	.110** (.013)	.112** (.006)	−.002 (.015)
Exp = 18.52, Ed = 16	.106** (.027)	.119** (.010)	−.013 (.029)
Exp = 26, Ed = 14.46	.091** (.017)	.094** (.008)	−.004 (.019)

* Indicates significant at the 10% level.
** Indicates significant at the 5% level.

suggest that the measurement error variance in CPS wages exceeds the error variance in WCP wages by .057 (the difference between $\mathrm{var}(\hat{v}^{CPS})$ and $\mathrm{var}(\hat{v}^{WCP})$). This corroborates the estimated variances of measurement error in CPS wages of .10 for men and .05 for women, reported by Bound and Krueger (1991). We find little evidence that worker demographic characteristics are reported with more error in the WCP. Demographic characteristics and location variables account for virtually the same amount of total wage variation in both samples, predicted wages are highly correlated across CPS and WCP regression coefficients, and there is no systematic evidence that estimated returns to education or experience are biased toward zero in the WCP.

IV. Employer Wage and Tenure Differentials

A. Literature Review

The best evidence on employer pay differentials is contained in Abowd et al. (1994), who estimate employer-specific log total compensation profiles using a longitudinal sample of over 1 million French workers and 500,000 firms. The standard deviation in log compensation is approximately .50 in their data. Education, tenure, experience, region and year dummy variables, and employer effects explain 57% of the variation in log compensation. Because workers change employers, they are able to include both worker- and employer-specific effects in their wage regressions. When person effects are included, 75%–80% of the variation in log compensation is explained, and the standard deviation of employer-specific intercepts is .10.

There are few studies of employer wage differentials using U.S. data, and each of these studies has substantial data limitations. Groshen (1991) uses micro data from the BLS Industry Wage Survey (IWS) and finds that the standard deviation of employer wage differentials, conditional on sex and occupation, is 14% of the average wage. The IWS reports only the sex and detailed occupation of workers and contains no other information on individual worker demographic characteristics. Troske (1994) matches data from the U.S. Census of Population to the Census of Manufacturers to obtain a large, but highly selected, matched sample of workers and employers in manufacturing. Troske finds evidence of significant employer pay differentials, conditional on worker characteristics. Neither of these data sets reports job tenure or wage growth variables.

Our WCP sample reports the wages, tenure, and demographic characteristics of multiple workers per employer. This allows us to address some questions that cannot be answered using household data sets such as the CPS, or the other matched worker-employer data sets in the United States: How much of the cross-section variation in wages and tenure, conditional on worker characteristics, can be explained by employer effects? How well do industry dummy variables proxy for these employer effects? Do high wage establishments have longer tenure, all else equal?

B. Empirical Results

There is a large employer-specific component of log wages in our sample; employer dummy variables alone can explain almost 45% of log wage variation, which is consistent with the range of results reported by

Groshen (1991). Log tenure is also highly correlated across workers within an establishment; 32% of the variation in log tenure can be explained by employer fixed effects.

We estimate employer wage differentials conditional on worker demographic characteristics using the following model of wage determination:

$$\ln W_{ik} = X_{ik}\beta + \alpha_k + \varepsilon_{ik}, \tag{2}$$

where $\ln W_{ik}$ is the log of the current wage of worker i at employer k, α_k is employer k's conditional wage differential, and ε_{ik} is an i.i.d. error term. The expression X_{ik} is a vector of worker i's characteristics that includes third-order polynomials in education and experience, interactions between these polynomials and a female dummy variable, and dummy variables for black and other racial groups.[18] We consider an alternative specification of X_{ik} that includes tenure variables: a third-order polynomial in tenure and education, and interactions between a female dummy variable and the polynomial terms in tenure and education.[19] The preferred specification of X_{ik} depends on the question being addressed, because wages and tenure are jointly determined. Below, we show that our empirical results are not sensitive to the inclusion of tenure variables in (2).

We reject the hypotheses that α_k equals zero and that α_k is uncorrelated with X_{ik}. These results hold whether or not tenure variables are included in X_{ik}.[20] We estimate (2) using employer fixed effects, for the two specifications of X_{ik}, and present coefficient estimates from each regression in appendix B.

Table 4 presents summary statistics from these log wage regressions. In column 1, where tenure variables are excluded from X_{ik}, worker demographic characteristics and employer effects account for 75.6% of the variation in log wages. In column 2, tenure variables are included in X_{ik}, the R^2 of the regression is .779, and demographic characteristics account

[18] The specification of X differs from (1) because, in the WCP sample, we fail to reject the hypotheses that all quartic polynomial terms equal zero and that all coefficients on race interaction terms equal zero. Misspecifications of X could lead to biased estimates of α_k. We also estimated log wage regressions with education categories (interacted with experience and tenure) to determine the robustness of our results. Employer wage differentials are quite similar, regardless of the specification of X.

[19] We fail to reject the hypothesis that coefficients on fourth-order polynomial terms in tenure and education are zero, and that interactions between race and tenure variables are equal to zero.

[20] We also reject the hypothesis that α_k and X_{ik} are uncorrelated when establishment size, region, city size, and industry dummy variables are included in the regression.

Table 4
Log Wage and Tenure Regressions

	Log Wage	Log Wage	Log Tenure
Fraction of variance explained (R^2):			
Worker characteristics and establishment dummy variables	.756	.779	.538
Worker characteristics	.573	.629	.340
(number of worker characteristics)	(21)	(33)	(21)
Establishment dummy variables	.447	.447	.321
(number of establishment dummy variables)	(240)	(240)	(240)
Marginal fraction of variance explained:			
Worker characteristics	.309	.332	.217
Establishment dummy variables	.183	.150	.198
Standard deviations:			
Index of worker characteristics ($X_{ik}\hat{\beta}$ or $X_{ik}\hat{\theta}$):			
Across workers	.301	.318	.565
Across establishments	.161	.178	.269
Establishment-specific effects ($\hat{\alpha}_k$ or $\hat{\tau}_k$)	.203	.189	.484
Residual ($\hat{\varepsilon}_{ik}$ or $\hat{u}_{ik}$)	.246	.215	.788
Correlations:			
($\bar{X}_k\hat{\beta}$, $\hat{\alpha}_k$) or ($\bar{X}_k\hat{\theta}$, $\hat{\tau}_k$)	.403	.385	.221
Tenure variables included in X?	No	Yes	No

for slightly more and employer effects account for slightly less of the marginal variation in log wages than in column 1. The majority of wage variation, both within and across employers, is explained by observed differences in worker characteristics. The variance decomposition described in table 4 implies that 65% of the across-employer variance in log wages is due to across-employer differences in worker characteristics and 60% of the within-employer variance in log pay is due to within-employer variation in worker characteristics.[21]

This variance decomposition can also be illustrated by separating ln W_{ik} into three components: $X_{ik}\hat{\beta}$, an index of worker i's quality (the wage she expects to receive from the mean WCP employer), $\hat{\alpha}_k$, employer k's wage differential, and $\hat{\varepsilon}_{ik}$, the log wage residual. Columns 1 and 2 of table 4 present the standard deviations of these components across workers. The standard deviation of $X_{ik}\hat{\beta}$ is .301 in column 1 and increases to .318 if tenure variables are included in X_{ik}. The standard deviation of $\hat{\alpha}_k$ is significantly reduced from .203 to .189 when tenure variables are included in X_{ik}.[22] These empirical standard deviations include dispersion

[21] If tenure variables are excluded from X_{ik}, worker characteristics account for 60% of the across-employer variation in pay and 55% of the within-employer variation in pay.

[22] The boot-strapped standard error of this change is .0035.

due to sampling variation. The estimated standard deviation of α_k, equally weighted across employers and adjusted for sampling error, is .183 (.170 when X_{ik} includes tenure). Conditional employer wage differentials are sizable: establishments that pay wages one standard deviation above the overall mean, conditional on worker characteristics, offer an 18.3% pay premium.

We analyze tenure differentials across employers, conditional on worker characteristics, by estimating:

$$\ln T_{ik} = X_{ik}\theta + \tau_k + u_{ik}, \tag{3}$$

where $\ln T_{ik}$ is the logarithm of a worker i's tenure with employer k, X_{ik} is the vector of worker characteristics described above, τ_k is employer k's conditional tenure differential, and u_{ik} is an i.i.d. error term. We reject the hypotheses that τ_k equals zero, and that τ_k is uncorrelated with X_{ik}, and estimate (3) using employer fixed effects.

Column 3 in table 4 reports summary statistics for the log tenure regression in (3), and complete regression results are presented in appendix B. Worker characteristics and employer effects account for 53.8% of the variation in log tenure. At the margin, worker characteristics and employer dummy variables account for roughly equal shares of the variation in log tenure. Column 3 also reports the empirical standard deviations of each of the three components of $\ln T_{ik}$: $X_{ik}\hat{\theta}$, a demographic component, $\hat{\tau}_k$, an employer effect, and $\hat{u}_{ik}$, the log tenure residual. The standard deviations in column 3 include dispersion due to sampling variation. The estimated standard deviation of τ_k, weighted equally across employers and adjusted for sampling error, is .388. Employer-specific log tenure differentials are substantial in the WCP: establishments that retain workers one standard deviation longer than average, conditional on worker characteristics, have 39% higher mean tenure.

Given the regression results from (2) and (3), we examine the relationship between wages and tenure across employers, conditional on worker characteristics other than tenure. There is a significant positive correlation between $\hat{\alpha}_k$ and $\hat{\tau}_k$: the correlation coefficient is .411. A one percentage point increase in an establishment's conditional wage differential is associated with a .98 percentage point increase in its conditional tenure differential.[23] High wage employers in the WCP have significantly longer tenure, holding constant worker characteristics.

Two-digit SIC dummy variables explain 35% of the variation in $\hat{\tau}_k$,

[23] If X includes tenure, the correlation between α_k and τ_k is .213, and the regression coefficient is .543. For each specification of X, the p-value for the test that the correlation equals zero is less than .001.

and 38–40% of the variation in $\hat{\alpha}_k$, depending on the specification of X_{ik}. When two establishment size dummy variables and dummy variables for establishments located in the South and in a Metropolitan Statistical Area (MSA) are included in these regressions, we account for 41% of the variation in $\hat{\tau}_k$, and 52–55% of the variation in $\hat{\alpha}_k$.[24] If X_{ik} excludes tenure, establishments with 1,000 or more workers have a wage differential 9.7% higher than establishments with fewer than 500 workers, and 5.4% higher than establishments with 500 to 999 workers. If X_{ik} includes tenure, these establishment size differentials are reduced by about one-fourth. Wage differentials are 16.6% higher in an MSA, and 5.4–5.5% lower in the South. Establishments with 1,000 or more workers have a tenure differential 29.8% higher than establishments with fewer than 500 workers, and 10.5% higher than establishments with 500–999 workers. We find no patterns in tenure differentials across regions or MSA size categories. Despite the significant pattern in employer wage and tenure differentials by industry, establishment size, and location, a substantial portion of the variation in $\hat{\tau}_k$ and $\hat{\alpha}_k$ remains unexplained.

C. Comparison of OLS and Fixed Effects Wage Regressions

Although it is unclear whether OLS or fixed effects estimates of β contain less bias,[25] it is still useful to compare these estimates. Appendix C presents OLS regression results that correspond to the fixed effects regressions in appendix B. Table 5 reports OLS and fixed effects estimates of the returns to education evaluated at mean tenure and experience. The inclusion of employer fixed effects changes only women's returns to education. For women with average education or more, the within-employer return is 4–5 percentage points lower than the OLS return, evaluated at mean tenure and experience. This suggests that obtaining a job at a high wage employer is an important aspect of educational investments for women. Men's returns to education are virtually identical across specifications and do not seem to be reduced by remaining at the same employer.

[24] These results are based on weighted least squares regressions with one observation per employer. Industry effects are significantly different from zero in all specifications. Coefficients on other region and MSA size dummies were insignificantly different from zero and, therefore, omitted from these regressions.

[25] The correlation between omitted and observed determinants of wages is likely to differ within and across employers, so within-employer regressions may mitigate or exacerbate omitted variable problems. If measurement error is i.i.d. and true worker characteristics are highly correlated within employers, observed within-employer differences in worker characteristics are probably due to measurement error, and within-employer regressions are likely to exacerbate measurement error problems. See Griliches (1979) for a related discussion of within-family estimators.

Table 5
Return to Education: Comparison of Fixed Effects and Pooled Regressions

	Ed = 12	Average Ed	Ed = 16
Male, pooled	−.001 (.026)	.127** (.010)	.142** (.012)
Male, fixed-effect	.108 (.024)	.133** (.009)	.138** (.011)
Female, pooled	.060** (.029)	.151** (.013)	.146** (.016)
Female, fixed-effect	.074** (.028)	.110** (.012)	.097** (.015)

* Indicates significant at the 10% level.
** Indicates significant at the 5% level.

Table 6 reports OLS and within-employer returns to tenure holding constant experience and returns to tenure and experience, evaluated at mean education. Although high wage establishments tend to have longer tenure, within-employer returns to tenure are still substantial. The inclusion of employer fixed effects has little impact on men's returns to tenure or experience. Women's within-employer returns to tenure are lower by one-third and returns to tenure and experience are lower by one-quarter relative to OLS estimates. We defer further discussion of returns to tenure and experience until Section VI, where we analyze workers' actual wage changes on the job.

Table 7 shows that male-female wage differentials within an employer are generally smaller than OLS differentials. At sample means for education, tenure, and experience the within-employer differential is 3.8 percentage points lower than the OLS differential. Differences between fixed effects and OLS estimates are substantial for less educated and experi-

Table 6
Return to Tenure: Comparison of Fixed Effects and Pooled Regressions

	Twenty-fifth Percentile: Tenure = 2; Exp = 10	Average Tenure and Experience	Seventy-fifth Percentile: Tenure = 13; Exp = 26
I. Return to tenure:			
Male, pooled	.010 (.007)	.011** (.002)	.010** (.003)
Male, fixed-effect	.016** (.006)	.012** (.002)	.010** (.003)
Female, pooled	.034** (.007)	.018** (.004)	.009** (.004)
Female, fixed-effect	.023** (.007)	.012** (.004)	.006 (.004)
II. Return to tenure and experience:			
Male, pooled	.038** (.006)	.023** (.003)	.013** (.003)
Male, fixed-effect	.041** (.006)	.027** (.003)	.016** (.003)
Female, pooled	.041** (.007)	.019** (.004)	.005 (.004)
Female, fixed-effect	.031** (.006)	.014** (.004)	.004 (.004)

NOTE.—Returns are evaluated at average education in the sample.
* Indicates significant at the 10% level.
** Indicates significant at the 5% level.

Table 7
Male-Female Differential: Comparison of Fixed Effects and Pooled Regressions

	Twenty-fifth Percentile: Tenure = 2; Exp = 10	Average Tenure and Experience	Seventy-fifth Percentile: Tenure = 13; Exp = 26
Ed = 12, pooled	−.289** (.044)	−.298** (.038)	−.306** (.040)
Ed = 12, fixed-effect	−.125** (.041)	−.185** (.035)	−.234** (.037)
Ed = 14.46, pooled	−.163** (.037)	−.195** (.035)	−.248** (.043)
Ed = 14.46, fixed-effect	−.056 (.034)	−.157** (.032)	−.244** (.039)
Ed = 16, pooled	−.185** (.033)	−.174** (.035)	−.214** (.043)
Ed = 16, fixed effects	−.156** (.030)	−.209** (.032)	−.265** (.039)

* Indicates significant at the 10% level.
** Indicates significant at the 5% level.

enced women. For example, at the twenty-fifth percentile of the tenure and experience distribution, OLS coefficients predict that female high school graduates earn 28.9% less than men, and fixed effects coefficients predict a 12.5% wage differential. A sizable portion of the male-female wage differential for less educated and experienced workers is due to the concentration of female workers at low wage employers.

Finally, the within-employer black dummy variable coefficient is −.088, and the OLS coefficient is −.129. Using the fixed-effects regression coefficients, black workers are employed in establishments that pay wages 5.2% lower than average, ceteris paribus, and black wages are 13.5% lower than white wages due to racial differences in worker characteristics. Therefore 5.2 percentage points of the 27.5% black-white pay differential is due to the relatively high concentration of black workers in low wage establishments.

V. Worker Sorting

A. *Literature Review*

Many team production models suggest that employer pay differentials are due to unobserved differences in average worker skills across establishments. For example, Rosen (1982) and Kremer (1993) hypothesize that workers sort into firms based on their relative ability and skills because of interdependencies in production, for example, the best lawyers will be paired with the best secretaries. An important empirical prediction of these models is that average wages and skill levels by occupation will be correlated across employers.

Using CPS data, Dickens and Katz (1987) find that conditional industry wage differentials are highly correlated across occupations; the median correlation in industry pay differentials across 12 occupational groups is

.79. Abowd et al. (1994) provide somewhat different evidence on worker sorting, by correlating the worker-specific and firm-specific components of compensation in their French longitudinal data. They find that highly paid and more skilled workers tend to be employed in higher compensation firms, ceteris paribus. Although the correlation between worker-specific and firm-specific compensation effects is .10, and high compensation firms are only slightly more likely to employ workers with greater observed skills, turnover patterns are quite different for high and low pay workers. Low compensation workers are significantly more likely to turn over and to move from one low compensation firm to another.

In this section we provide more direct tests of the theories of Kremer and Rosen by calculating within-employer correlations in skills. We also examine the across-employer correlation in wages and skills by sex and occupation, that is, whether the most skilled professionals work with the most skilled nonprofessionals, and the most able men work with the most able women.

B. Empirical Evidence

We find that observed measures of skills are highly correlated within an establishment. Employer fixed effects account for 27% of the cross-section variation in education and 23% of the variation in potential experience. Establishment dummy variables alone explain 28.6% of the cross-section variation in our index of worker quality, $X_{ik}\hat{\beta}$, and 31.3% of the variation in worker quality if X_{ik} includes tenure.

Fixed effects estimates of β are significantly different from the corresponding random effects estimates, which implies that the employer-specific component of log wages is significantly correlated with observed worker characteristics. In fact, high wage establishments employ higher quality workers. The correlation between the average index of worker quality at an employer, which we denote $\bar{X}_k\hat{\beta}$, and $\hat{\alpha}_k$ is approximately .40, whether or not tenure is included in $\bar{X}_k$. A one percentage point increase in an employer's conditional wage differential is associated with a .32% increase in the average quality of workers in the establishment (or .36 if $\bar{X}_k$ includes tenure). If α_k proxies for unobserved skills, our findings support the conjecture that observed and unobserved skills are positively correlated within an employer.[26]

C. Across-Employer Correlations in Wages and Skills by Occupation and Sex

There are substantial differences in worker characteristics by sex and occupation. The average female earns 62% of the average male wage, and

[26] Workers who are more likely to remain with their employer (i.e., with high values of $X_{ik}\theta$), sort into employers with lower turnover (i.e., with high values of τ_k). The correlation between $X_k\theta$ and τ_k is .221.

has 1.79 fewer years of education and 2.67 fewer years of tenure than the average male. We divide workers into two main occupation groups: professionals (including managers and administrators) and nonprofessionals (technical and clerical workers). Seventy-seven percent of men and only 40% of women are professionals. The average nonprofessional earns 51% of the mean professional wage, and has 2.82 fewer years of education and 2.05 fewer years of tenure than the average professional.

We compute average log wages and worker quality ($\bar{X}_k\hat{\beta}$) by sex and occupation, where $\hat{\beta}$ is obtained from estimates of (2), for each establishment. The across-employer correlation between average male and female log wages is .537, and the across-employer correlation between average male and female worker quality is .253 (.162 if X excludes tenure variables). Average pay and worker quality by occupation are also correlated across establishments. The across-employer correlation between average professional and nonprofessional log wages is .499, and the across-employer correlation between average worker quality by occupation is .221 (.168 if X excludes tenure variables).

We also estimate the log wage regression in (2) separately for men and women and obtain sex-specific estimates of β and α_k.[27] We correlate sex-specific $\hat{\alpha}_k$ and $\bar{X}_k\hat{\beta}$ across the 117 establishments that employ at least two workers of each sex. The correlation in sex-specific employer wage differentials is .575 (.569 if the log wage regression excludes tenure variables). The correlation in sex-specific indices of average worker quality is .330 (.224 if X excludes tenure variables).

These positive and significant correlations in pay and observed worker quality across employers are consistent with worker sorting and team production. The most skilled men tend to work with the most skilled women, and the most skilled professionals are typically teamed with the most skilled nonprofessionals. In addition, establishments that pay higher wages to men and professionals also pay women and nonprofessionals more.

VI. Employer Wage Growth Differentials

A. Literature Review

The recent empirical literature on wage growth has focused on decomposing wage changes in household panel data into components attributable to tenure and experience (Abraham and Farber 1987; Altonji and Shakotko 1987; and Topel 1991). These studies argue that cross-section

[27] We reject the hypothesis of pooling men and women at the .10 level, and estimate sex-specific wage regressions for 848 men in 162 establishments that employ at least two men and 735 women in 173 establishments that employ at least two women.

estimates of tenure returns are biased because good job matches are likely to last longer and higher anticipated on-the-job wage growth is likely to increase job tenure. Estimates of tenure returns based on wage changes in household panel data are also likely to be biased because of unobserved heterogeneity and endogenous turnover. Topel (1991) provides an approach that yields an underestimate of tenure returns in the absence of significant employer wage growth differentials. If a substantial component of within-job wage growth is employer specific, jobs with high anticipated wage growth may be more likely to survive. As Topel notes (p. 160), wage growth regressions using the selected sample of workers who do not change jobs will yield biased estimates of within-job wage growth.[28] Moreover, these selection effects would cause a corresponding overestimate of the anticipated returns to tenure, and Topel's methodology would no longer yield a conservative estimate of tenure returns.

There is no empirical evidence on wage growth differentials across U.S. employers. The only empirical study which investigates this issue is Abowd et al. (1994), who find significant differences in compensation-tenure profiles across French employers. Their standard deviation in firm-specific tenure slopes is .033; a firm one standard deviation above the mean has annual compensation growth that is 3.3% higher than the average firm. Starting pay differentials and compensation growth profiles are correlated $-.563$ across firms; employers offering greater opportunities for compensation growth offer lower starting pay.

The goal of this section is to determine whether wage growth rates vary significantly across employers, and whether jobs at high wage growth employers last longer in the WCP. We measure wage growth, that is, the returns to tenure and experience, for the portion of our cross-section sample that reports starting pay. We do not use Topel's (1991) methodology to calculate the returns to tenure holding constant experience because all workers are job stayers and all tenure spells are incomplete in our sample.

B. The Wage Growth Subsample

Starting pay is reported retrospectively for 46% of the workers in the WCP pilot survey. The low response rate suggests that it is difficult to obtain starting pay from the payroll and other records that are typically used by WCP respondents. When starting pay is not reported for one

[28] For example, if workers in fast food establishments have low mean tenure and within-job wage growth and lawyers have higher mean tenure and within-job wage growth, law firms will be overrepresented in long-tenure jobs. Estimates of returns to tenure and experience that are largely based on wage growth realizations at law firms are likely to overstate anticipated wage growth at fast food establishments.

worker it is typically not reported for all workers at an employer: over 86% of the workers without starting pay are in establishments that did not report starting pay for any worker. Our wage growth sample contains 736 workers with valid starting pay in 130 establishments that exhibit some within-employer variation in job tenure and employ at least two workers with no more than 30 years of tenure.[29]

Table 8 reports the means and standard deviations of wages, tenure, and worker characteristics for the wage growth sample. The average worker received 24.9% cumulative real wage growth over 6.9 years with their employer. The primary differences between the wage growth sample and the full WCP sample are that the average worker in the wage growth sample has 1.77 fewer years of tenure, 1.5 years less experience, 4.1% lower current pay, and has 2.5 fewer co-workers.

C. Regression Results

Consider employer wage differentials of the form $\alpha_{ks} + T_{ikt}\eta_k$, where α_{ks} is the starting log wage differential at employer k, T_{ikt} is the current tenure of worker i at employer k, and η_k is employer k's wage growth differential. The expressions α_{ks} and η_k are employer-specific parameters that influence an employer's wage profile. The wage growth of worker i at employer k is the difference between current and starting wages in (2):

$$\begin{aligned} &\ln W_{ikt} - \ln W_{iks} \\ &= T_{ikt}\eta_k + (X_{ikt} - X_{iks})\beta_s + (\beta_t - \beta_s)X_{ikt} + \varepsilon_{ikt} - \varepsilon_{iks}. \end{aligned} \tag{4}$$

The subscripts t and s denote the current and starting periods, respectively. Note that α_{ks} and time-invariant worker and employer specific components of the error term are differenced out of the wage growth regression. The vector X is the specification in (2) that includes tenure variables.

We estimate the wage difference regression in (4) and test the null hypothesis that $(\beta_t - \beta_s) = 0$. There is some evidence that demographic wage differentials vary over time; the p-value of this F-test is .064. However, the correlation between estimates of η_k, with and without the restriction that $(\beta_t - \beta_s) = 0$, exceeds .95. For ease of exposition, we report estimates of (4) based on the restricted model in Appendix D.

Table 9 presents predicted cumulative wage growth for men and women at the mean employer, for various combinations of education and experience. We find that wage growth declines as tenure increases, more experi-

[29] We deflated nominal starting pay by the average hourly earnings of workers in the United States to obtain real starting wages because the Employer Cost Index is not available for all starting years.

Table 8
Wage Growth Sample—736 Workers

	Mean	Standard Deviation
Real monthly wage	2,538.18	(1,170.08)
Log (real wage)	7.736	(.457)
Real starting monthly wage	2,004.79	(1,007.09)
Log (start wage)	7.487	(.486)
Tenure	6.902	(6.392)
Real wage change	.249	(.335)
Education	14.470	(2.193)
Starting experience	10.118	(8.587)
Experience	17.020	(9.827)
Female	.500	(.500)
Black	.076	(.265)
Other	.090	(.286)
Occupation:		
Professional	.321	(.467)
Administrative	.284	(.451)
Technical	.163	(.370)
Clerical	.232	(.423)
Industry:		
Durable goods manufacturing	.193	(.395)
Nondurable goods manufacturing	.490	(.500)
Services	.173	(.378)
Mining and construction	.045	(.207)
Other	.099	(.299)
MSA size:		
Not an MSA	.128	(.334)
Under 1 million	.220	(.415)
1–5 million	.443	(.497)
Over 5 million	.209	(.407)
Establishment size:		
Fewer than 500 employees	.451	(.498)
500–1,000 employees	.168	(.375)
over 1,000 employees	.380	(.486)
Northeast	.361	(.481)
Midwest	.308	(.462)
South	.245	(.430)
West	.086	(.280)
Number of co-workers	8.647	(5.123)

NOTE.—"Other" industry includes finance, insurance, real estate, wholesale and retail trade, transportation, communications, and utilities.

enced workers have slower wage growth, and women have substantially higher wage growth over the first 10 years of a job than men. Predicted wage growth rates for WCP men are quite similar to the growth rates for PSID men reported in Topel (1991). Over the first 10 years on the job, the average male at the mean employer in the WCP has cumulative wage growth of 40.1%, and the typical PSID male with 10 years of starting experience has cumulative wage growth of 42.1%. The WCP men experience slower wage growth in the first 5 years on the job and slightly faster wage growth over the next 5 years than PSID men.

For purposes of comparison, table 9 also presents predicted wage growth

Table 9
Predicted Cumulative Within-Job Wage Growth by Years of Job Tenure

	Years of Tenure		
	1	5	10
Starting Exp = 4; Ed = 12:			
Male:			
Cross-section fixed effect	.053	.234	.416
Wage growth fixed effect	.045	.211	.380
Female:			
Cross-section fixed effect	.059	.267	.467
Wage growth fixed effect	.069	.306	.505
Starting Exp = 15; Ed = 12:			
Male:			
Cross-section fixed effect	.042	.187	.337
Wage growth fixed effect	.043	.185	.296
Female:			
Cross-section fixed effect	.049	.219	.377
Wage growth fixed effect	.065	.280	.443
Starting Exp = 10.118; Ed = 14.470:			
Male:			
Cross-section fixed effect	.046	.192	.309
Wage growth fixed effect	.052	.234	.401
Female:			
Cross-section fixed effect	.048	.193	.284
Wage growth fixed effect	.060	.273	.467
Starting Exp = 4; Ed = 16:			
Male:			
Cross-section fixed effect	.062	.261	.421
Wage growth fixed effect	.052	.235	.408
Female:			
Cross-section fixed effect	.054	.216	.301
Wage growth fixed effect	.058	.272	.490
Starting Exp = 15; Ed = 16:			
Male:			
Cross-section fixed effect	.038	.148	.210
Wage growth fixed effect	.053	.226	.357
Female:			
Cross-section fixed effect	.046	.178	.231
Wage growth fixed effect	.054	.246	.428

NOTE.—Mean years of education is 14.470 and mean years of starting experience is 10.118 in the wage growth sample. The twenty-fifth and seventy-fifth percentiles of the education distribution are 12 and 16, and the twenty-fifth and seventy-fifth percentiles of the starting experience distribution are 4 and 15.

based on cross-section fixed effects estimates of (2). Cross-section regressions substantially underestimate women's wage growth. For men, cross-section regressions provide somewhat more accurate wage growth estimates but, on average, also underestimate wage growth. It is important to note from tables 6 and 9 that the estimated returns to experience and tenure for men are relatively insensitive to the estimation technique. Cross-section ordinary least squares, cross-section fixed effects, and wage growth regressions all yield roughly the same magnitudes of coefficient estimates. In contrast, women's returns to tenure and experience are substantially different across these estimation techniques. In particular, cross-section fixed effects estimates of returns to tenure substantially understate women's actual wage growth on the job. Recently hired (low tenure) women at high wage employers tend to have current wages that are substantially higher than the starting wages of high tenure women at the same employer. A hypothesis consistent with this empirical result is that recently hired women have more unobserved skills and sort into high wage employers.

Estimates of (4) imply substantial variation in wage growth across employers. We reject the null hypothesis that the η_k are equal across employers: the p-value of the test statistic is less than .001. The weighted standard deviation of $\hat{\eta}_k$ is .022: after 6.9 years of tenure (the sample average), cumulative wage growth is 15.2 percentage points higher at an establishment with $\hat{\eta}_k$ one standard deviation above the mean.[30] Although there is a significant pattern in wage growth rates across industries, there are substantial differences across employers within the same industry: two-digit SIC dummy variables explain 31.7% of the variation in $\hat{\eta}_k$.

We recover estimates of person-specific wage effects from (4), assuming that $(\beta_t - \beta_s) = 0$, which we denote as $\hat{\phi}_i$. The expression $\hat{\phi}_i$ includes the returns to time-invariant worker characteristics; racial dummy variables, third-order polynomials in education and starting experience, and interactions between these polynomials and a female dummy variable. The standard deviation of $\hat{\phi}_i$ is .451 across workers. Employer effects and time-invariant worker characteristics jointly account for 74.2% of the variation in $\hat{\phi}_i$. Employer dummy variables alone account for 43.5% and worker characteristics alone account for 55.8% of the variation in $\hat{\phi}_i$. Over half of the across-employer variation in $\hat{\phi}_i$ is due to differences in worker characteristics across establishments.[31] These results indicate substantial sorting across employers based on observed and unobserved time-invariant productivity characteristics.

We recover estimates of the conditional starting wage differential, $\hat{\alpha}_{ks}$, from a second stage wage regression with two observations per worker. The dependent variable is W_s for the first observation per worker and $W_t - \Delta W$ for the second observation, where ΔW is predicted from (4).[32] The explanatory variables in this second stage regression are time-

[30] When not weighted by the number of workers, the standard deviation of η_k is .027.

[31] Keane (1993) finds that 84% of the residual variance in log wages across industries is explained by individual fixed effects using the National Longitudinal Survey of Young Men. We are unable to replicate his methodology because workers in our WCP sample do not change employers or industries.

[32] Topel (1991) proposed a similar regression to estimate the returns to labor market experience. Less efficient estimates of α_{ks}, obtained from starting wages alone, are nearly identical.

invariant worker characteristics and a complete vector of employer dummy variables. The expression $\hat{\alpha}_{ks}$ is the estimated coefficient on employer k's dummy variable, and slope coefficients are used to generate an index of worker starting quality $X_{iks}\hat{\beta}$. The results of this second stage regression are reported in appendix E.

Conditional employer starting wage differentials are similar to current wage differentials. The standard deviation of $\hat{\alpha}_{ks}$ is .201, and the correlation between $\hat{\alpha}_{ks}$ and $\hat{\alpha}_{kt}$ (estimated from [2] using the wage growth sample) is .734. The estimated unweighted standard deviation of α_{ks} across employers, adjusted for sampling error, is .209. There is substantial variation in employer starting wage differentials within detailed industries; industry dummy variables account for 47.6% of the variation in $\hat{\alpha}_{ks}$. The correlation between $\hat{\alpha}_{ks}$ and $\hat{\eta}_k$ is $-.300$ and is significantly different than zero.[33] Current and starting wage differentials are highly correlated across employers, but establishments offering greater opportunities for wage growth appear to offer lower starting wages. The total employer wage differential $(\hat{\alpha}_{ks} + \hat{\eta}_k T_{ikt})$ depends on worker tenure, and has a standard deviation of .225 across workers.

Because of the substantial across-employer variation in $\hat{\eta}_k$, it is possible that jobs at high wage growth employers last longer, and longitudinal estimates of within-job wage growth and anticipated returns to tenure are upward biased. Note that we observe current and not completed tenure at an employer, so our analysis of the across-employer relationship between $\hat{\eta}_k$ and mean job duration is incomplete. Employer wage growth differentials are weakly positively correlated with average current tenure at an employer, conditional on worker characteristics: The correlation between $\hat{\tau}_k$, the employer tenure differential estimated from (3) using the wage growth sample, and $\hat{\eta}_k$ is .153.[34] A one standard deviation (.022) increase in $\hat{\eta}_k$ is associated with a 7.4% increase in $\hat{\tau}_k$. We find no significant correlation between $\hat{\alpha}_{ks}$ and $\hat{\tau}_k$. Jobs tend to last longer at employers with higher wage growth, but not at employers with higher starting pay.

Using $\hat{\alpha}_{ks}$ and $\hat{\eta}_k$, we calculate the log of the present value of pay at each employer for the first 10 years on the job assuming a 3% real discount rate.[35] The standard deviation of the log present value pay differential is .195 across workers. The present value of pay differential

[33] A portion of this relationship may occur because employers with a low starting wage differential, due to sampling variation, appear to have a higher than average wage growth differential. However, Abowd et al. (1994) find a stronger negative relationship in a much larger longitudinal sample.

[34] The test of the hypothesis that this correlation coefficient equals zero has a p-value of .084.

[35] Our results were insensitive to several alternative discount rates and years on the job.

is unrelated to differences in tenure across employers, conditional on worker characteristics. High present value establishments employ significantly higher quality female workers. For women, the correlation between the present value pay differential and $\bar{X}_{ks}\hat{\beta}$ is .192 and significant at the .05 level. This correlation is insignificantly different from zero for men.

VII. Conclusions

Many Bureau of Labor Statistics establishment surveys report the wages and detailed occupations of individual workers. In a pilot survey, establishments responding to the White Collar Pay Survey (WCP) were also asked to report the demographic characteristics of individual workers. Our empirical analysis of these data suggests that individual wage and worker demographic data in the WCP are at least as accurate as household reported data from the Current Population Survey.

The standard deviation of employer wage differentials, conditional on worker characteristics, is 18.3% of the mean wage in the WCP. One hypothesis for these large pay differentials is that average unobserved skills differ substantially across employers. If this were true, we might also expect a large within-establishment correlation in observed skills and high wage establishments to employ workers with more observed skills. We find empirical support for both of these conjectures.

Conditional employer pay differentials are not explained by occupational or sex segregation across establishments. The most skilled men tend to work in establishments with the most skilled women, and the most skilled professionals are typically employed in establishments with the most skilled nonprofessionals. This evidence is consistent with the team production models of Kremer and Rosen.

Our empirical results show that current wages and tenure are significantly positively correlated, both within and across establishments, but employers with higher starting wages do not have longer average tenure. Wage growth rates differ significantly across employers, and high wage growth establishments tend to have longer average tenure. If workers are aware of these substantial across-employer differences in wage growth rates, completed job durations are likely to be significantly longer at employers with higher anticipated wage growth. Thus wage growth regressions using household longitudinal data may yield biased estimates of within-job wage growth and overestimate the anticipated returns to tenure. Further insights about the across-employer relationship between wage growth and job durations require matched worker-employer panel data sets that report completed job durations.

Matched employer-worker data sets derived from establishment surveys could prove quite valuable in future research, especially if they are supplemented with employer-specific information that is difficult to obtain from households, such as the employer's cost of fringe benefits, profitability, or a firm's capital investments. These data could then be used to analyze important empirical issues, such as compensating wage differentials and rent sharing, that are difficult to address with household data.

Appendix A

Table A1
Log Wage Regressions for the WCP and CPS

	WCP	CPS
Experience	.598 (.546)	−.036 (.202)
Experience²	−.329 (.883)	−1.514** (.324)
Experience³	−.069 (.116)	.335** (.042)
Experience⁴	.004 (.008)	−.025** (.003)
Ed*Exp	−10.013 (9.556)	6.438* (3.652)
Ed*Exp²	.667 (.884)	.511 (.3298)
Ed²*Exp	5.612 (5.613)	−5.718** (2.228)
Ed³*Exp	−.972 (1.102)	1.372** (.458)
Ed²*Exp²	−.281 (.247)	.016 (.094)
Ed*Exp³	.022 (.047)	−.075** (.018)
Education	2.030 (5.520)	4.018 (2.879)
Education²	−23.070 (51.039)	−48.460 (29.613)
Education³	12.159 (20.980)	26.264* (13.525)
Education⁴	−2.355 (3.239)	−5.178** (2.310)
Female	11.415 (32.703)	7.592 (13.706)
Female*Experience	−.002 (.982)	.417 (.282)
Female*Experience²	−.711 (1.455)	.522 (.474)
Female*Experience³	.052 (.152)	−.276** (.059)
Female*Experience⁴	−.002 (.010)	.021** (.004)
Female*Ed*Exp	2.666 (17.696)	−11.734** (5.154)
Female*Ed*Exp²	.771 (1.723)	.516 (.507)
Female*Ed²*Exp	−3.604 (10.476)	8.325**
Female*Ed³*Exp	1.189 (2.049)	−1.710** (.664)
Female*Ed²*Exp²	−.225 (.540)	−.402** (.146)
Female*Ed*Exp³	−.019 (.066)	.078** (.027)
Female*Education	−4.164 (8.205)	−2.781 (3.789)
Female*Education²	49.865 (77.652)	37.292 (39.305)
Female*Education³	−24.286 (32.977)	−21.167 (18.098)
Female*Education⁴	4.126 (5.309)	4.279 (3.115)
Black	−47.060 (51.688)	−21.925 (27.487)
Black*Female	.112* (.064)	.180** (.025)
Black*Experience	2.309 (3.413)	.841 (.574)
Black*Experience²	−.924 (4.543)	−2.076** (.913)
Black*Experience³	−.048 (.254)	.294** (.136)
Black*Experience⁴	−.008 (.017)	.002 (.009)
Black*Ed*Exp	−49.710 (61.994)	−12.697 (10.914)
Black*Ed*Exp²	1.939 (6.157)	1.839* (.950)
Black*Ed²*Exp	34.072 (36.236)	6.552 (7.016)
Black*Ed³*Exp	−7.308 (6.865)	−1.366 (1.519)
Black*Ed²*Exp²	−.999 (2.026)	−.118 (.279)
Black*Ed*Exp³	.079 (.142)	−.258** (.059)
Black*Education	11.558 (13.694)	4.318 (7.588)
Black*Education²	−101.278 (139.243)	−29.382 (78.477)
Black*Education³	36.960 (63.217)	7.193 (35.997)

Table A1 (*Continued*)

	WCP	CPS
Black*Education^4	−4.686 (10.626)	−.227 (6.174)
Other	70.057 (57.329)	3.287 (39.938)
Other*Female	.088 (.058)	.006 (.028)
Other*Experience	−2.045* (1.220)	−.089 (.957)
Other*Experience^2	4.103* (2.222)	−.166 (1.412)
Other*Experience^3	−.509* (.294)	−.133 (.175)
Other*Experience^4	.018 (.024)	.010 (.013)
Other*Ed*Exp	31.383 (21.407)	3.018 (17.269)
Other*Ed*Exp^2	−3.789 (2.362)	.959 (1.462)
Other*Ed^2*Exp	−15.856 (12.696)	−3.777 (10.514)
Other*Ed^3*Exp	2.604* (2.578)	1.319 (2.153)
Other*Ed^2*Exp^2	.880 (.702)	−.424 (.403)
Other*Ed*Exp^3	.235 (.142)	.022 (.075)
Other*Education	−16.459 (14.343)	−3.022 (10.506)
Other*Education^2	144.741 (133.725)	50.960 (104.354)
Other*Education^3	−56.609 (55.126)	−31.063 (46.300)
Other*Education^4	18.328 (8.483)	6.388 (7.727)
Constant	−.314 (22.344)	−6.103 (10.515)
Number of observations	1,681	16,424
R^2	.6708	.5185
Adj. R^2	.6482	.5147
F-test for SIC	$F(41, 1{,}572) = 8.0$	$F(64, 16{,}292) = 19.6$
p-value	.000	.000
F-test for location	$F(6, 1{,}572) = 15.1$	$F(6,16{,}292) = 141.26$
p-value	.000	.000

NOTE.—For ease of exposition, second-order polynomial terms in education and experience have been divided by 100, third-order terms divided by 1,000, and fourth-order terms by 10,000.
* Indicates significant at the 10% level.
** Indicates significant at the 5% level.

Appendix B

Table B1
WCP Fixed Effects Regressions

	Log Wage Regressions		
	Excluding Tenure	Including Tenure	Log Tenure Regression
Experience	−.003 (.066)	−.022 (.071)	−.050 (.212)
Experience^2	.029 (.102)	.024 (.107)	−.131 (.328)
Experience^3	−.004 (.008)	.0002 (.008)	.007 (.025)
Ed*Exp	.346 (.811)	.644 (.779)	2.404 (2.346)
Ed*Exp^2	−.048 (.046)	−.057 (.048)	−.032 (.146)
Ed^2*Exp	−.185 (.219)	−.167 (.230)	−.846 (.702)
Education	−2.673** (.621)	−2.499** (.608)	−3.866 (.1990)
Education^2	18.034** (3.880)	17.010** (3.801)	23.913 (12.441)
Education^3	−3.824** (.806)	−3.628** (.789)	−4.801 (2.585)
Black	−.094** (.028)	−.088** (.027)	−.098 (.090)
Other	−.041 (.028)	−.047* (.027)	−.019 (.090)
Female	−17.573** (5.327)	−10.958** (5.436)	−48.582 (17.081)
Fem*Exp	.221** (.107)	.142 (.122)	.344 (.344)
Fem*Exp^2	−.135 (.138)	−.106 (.141)	−.535 (.444)
Fem*Exp^3	.011 (.011)	.003 (.011)	.059 (.034)
Fem*Ed*Exp	−3.011** (1.309)	−1.906 (1.532)	−3.609 (4.199)
Fem*Ed*Exp^2	.060 (.060)	.077 (.068)	.122 (.214)
Fem*Ed^2*Exp	.978** (.418)	.553 (.499)	1.048 (1.340)
Fem*Ed	3.228** (1.025)	1.910* (1.053)	9.281 (3.286)
Fem*Ed^2	−19.066** (6.538)	−10.396 (6.764)	−58.332 (20.966)

Table B1 (*Continued*)

	Log Wage Regressions		
	Excluding Tenure	Including Tenure	Log Tenure Regression
Fem*Ed^3	3.595** (1.387)	1.713 (1.443)	12.016 (4.447)
Tenure	...	.069 (.073)	...
Tenure^2	...	−.093 (.105)	...
Tenure^3	...	.0009 (.010)	...
Ed*Ten	...	−.426 (.917)	...
Ed*Ten^2	...	.043 (.052)	...
Ed^2*Ten	...	.048 (.292)	...
Fem*Ten	...	.168 (.164)	...
Fem*Ten^2	...	.218 (.176)	...
Fem*Ten^3	...	.009 (.015)	...
Fem*Ed*Ten	...	−2.710 (2.231)	...
*Fem*Ed*Ten^2*	...	*−.197* (.106)*	...
Fem*Ed^2*Ten	...	1.115 (.757)	...
Constant	19.832** (3.302)	18.849** (3.237)	20.964** (10.602)
R^2	.7559	.7794	.5382
Adj. R^2	.7110	.7366	.4532
F-test for establishment effects:			
$F(240, 1{,}419) =$	4.299	3.990	2.535
p-value	.000	.000	.000

NOTE.—For ease of exposition, second-order terms in education and experience (or tenure) have been divided by 100, and third-order terms have been divided by 1,000.
* Indicates significant at the 10% level.
** Indicates significant at the 5% level.

Appendix C

Table C1
OLS Regressions for the WCP

	Log Wage Regressions		
	Excluding Tenure	Including Tenure	Log Tenure Regression
Exp	.040 (.073)	.040 (.078)	−.040 (.214)
Exp^2	−.078 (.114)	−.138 (.117)	−.259 (.333)
Exp^3	.003 (.009)	.009 (.009)	.023 (.026)
Ed*Exp	.346 (.811)	.344 (.854)	2.733 (2.364)
Ed*Exp^2	−.012 (.051)	.008 (.053)	−.031 (.147)
Ed^2*Exp	−.184 (.244)	−.191 (.254)	−.968 (.712)
Ed	2.695** (.704)	2.386** (.680)	−2.637 (2.052)
Ed^2	18.147** (4.407)	16.407** (4.257)	16.277 (12.854)
Ed^3	−3.803** (.916)	−3.495** (.884)	−3.224 (2.672)
Black	−.129** (.029)	−.112** (.027)	−.203** (.084)
Other	.014** (.027)	.033 (.025)	−.185** (.078)
Female	−14.192 (5.833)	−5.174 (5.840)	−43.171** (17.012)
Fem*Exp	.180 (.119)	.071 (.132)	.338 (.346)
Fem*Exp^2	−.003 (.152)	.081 (.153)	−.422 (443)
Fem*Exp^3	−.002 (.012)	−.011 (.012)	.029 (.034)
Fem*Ed*Exp	−2.686* (1.453)	−1.397 (1.655)	−3.622 (4.238)
Fem*Ed*Exp^2	.024 (.074)	.012 (.075)	.172 (.216)
Fem*Exp*Ed^2	.886* (.465)	.452 (.537)	.941 (1.356)
Fem*Ed	2.515** (1.124)	.749 (1.133)	8.261** (3.278)
Fem*Ed^2	−14.332** (7.178)	−2.903 (7.286)	−52.272** (20.936)
Fem*Ed^3	2.611* (1.524)	.159 (1.557)	10.930** (4.445)

Table C1 (*Continued*)

	Log Wage Regressions		
	Excluding Tenure	Including Tenure	Log Tenure Regression
Tenure	...	.116 (.082)	...
Tenure^2	...	.032 (.118)	...
Tenure^3	...	−.006 (.011)	...
Ed*Ten	...	−1.437 (1.020)	...
Ed*Ten^2	...	−.013 (.058)	...
Ed^2*Ten	...	.483 (.326)	...
Fem*Ten	...	.117 (.181)	...
Fem*Ten^2	...	.180 (.196)	...
Fem*Ten^3	...	.019 (.017)	...
Fem*Ed*Ten	...	−1.734 (2.462)	...
Fem*Ed*Ten^2	...	−.230* (.118)	...
Fem*Ed^2*Ten	...	.778 (.834)	...
Constant	19.806** (3.731)	18.038** (3.606)	13.895 (10.880)
R^2	.5783	.6292	.3402
Adj. R^2	.5730	.6218	.3318

NOTE.—For ease of exposition, second-order terms in education and experience (or tenure) have been divided by 100, and third-order terms have been divided by 1,000.
* Indicates significant at the 10% level.
** Indicates significant at the 5% level.

Appendix D

Table D1
Wage Growth Fixed Effects Regression: Employer Effects Interacted with Tenure

	Coefficient	Standard Error
Tenure	−.090	(.095)
Tenure^2	.089	(.214)
Tenure^3	−.005	(.031)
Tenure*Education	1.804	(1.196)
Tenure*Education^2	−.586	(.384)
Tenure^2*Education	−.108	(.133)
Tenure*Stexp*(Tenure + Stexp)	−.058**	(.023)
Tenure*Education*Stexp	.077	(.055)
Female*Tenure	.192	(.203)
Female*Tenure^2	−.636	(.429)
Female*Tenure^3	−.004	(.066)
Female*Tenure*Education	−1.967	(2.729)
Female*Tenure*Education^2	.515	(.911)
Female*Tenure^2*Education	.404	(.261)
Female*Tenure*Education*Stexp	−.072	(.080)
Female*Tenure*Stexp*(Tenure + Stexp)	.037	(.029)
R^2	.729	
Adj. R^2	.662	
Number of observations	736	
F-test for establishment effects interacted with tenure:		
$F(129, 591) =$	2.716	
p-value	.000	

NOTE.—For ease of exposition, second-order terms in education and tenure have been divided by 100, and third-order terms have been divided by 1,000.
* Indicates significant at 10% level.
** Indicates significant at 5% level.

Appendix E

Table E1
Second Stage Log Starting Wage Regressions

	Coefficient	Standard Error
Experience	−.035	(.078)
Experience^2	−.224	(.144)
Experience^3	−.007	(.012)
Ed*Exp	1.388	(.892)
Ed*Exp^2	.150**	(.072)
Ed^2*Exp	−.651**	(.276)
Education	−1.725**	(.785)
Education^2	11.020**	(5.066)
Education^3	−2.114*	(1.082)
Black	−.057*	(.033)
Other	−.022	(.037)
Female	−13.613*	(7.940)
Female*Exp	.382**	(.179)
Female*Exp^2	−.299	(.197)
Female*Exp^3	.040**	(.016)
Female*Ed*Exp	−5.378**	(2.376)
Female*Ed*Exp^2	.118	(.112)
Female*Ed^2*Exp	1.841**	(.793)
Female*Ed	2.386	(1.559)
Female*Ed^2	−13.364	(10.060)
Female*Ed^3	2.326	(2.139)
Constant	15.611**	(4.017)
R^2	.6947	
Adj. R^2	.6600	
Number of observations	1,472	
F-test for establishment fixed effects:		
$F(129, 1{,}321)$ =	5.629	
p-value	.000	

NOTE.—For ease of exposition, second-order terms in education and experience have been divided by 100, and third-order terms have been divided by 1,000.
* Indicates significant at the 10% level.
** Indicates significant at the 5% level.

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