13 Employer-Provided Training, Wages, and Capital Investment

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13.1 Introduction

The returns to labor market skills have risen in the past two decades, prompting renewed interest in public and private sector training programs. Employer-provided training, which includes both formal training programs and informal on-the-job training, appears to be an important source of human capital acquisition. National Longitudinal Survey of Youth (NLSY) data indicate that 38 percent of young adults in the United States participated in formal training programs such as company training programs, courses in vocational and technical institutes, business school courses, seminars, or apprenticeship programs between 1986 and 1991 (Veum 1993). Despite the prevalence of these private sector formal training programs, few empirical studies have analyzed the employer characteristics or types of companies that are associated with the provision of employee training.

The existing empirical literature on formal training has focused on the relationship between worker characteristics, the likelihood of participating in a formal training program, and subsequent wage growth (see, e.g., Altonji and Spletzer 1991; Barron, Black, and Loewenstein 1993; Duncan and Hoffman 1978; Krueger and Rouse 1994; Lillard and Tan 1992; Lynch 1992; Veum 1994). In these empirical studies, establishment size and industry dummy variables are the employer characteristics that are typically related to the incidence and effectiveness of training programs (see Bishop 1982a, 1982b, 1985; Bar-

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ron, Black, and Loewenstein 1989). Research on private sector training has been limited by the availability of data sets that report firm characteristics, such as profitability and capital investment, as well as information about training programs and worker demographic characteristics. For example, Bartel's (1994) recent study of formal training programs uses an employer survey with extensive data on firm behavior and performance but no information about worker characteristics, such as education, experience, tenure, race, or sex. In contrast, many empirical studies of training have utilized the NLSY data set, which provides comprehensive information about worker characteristics, wage growth, and the type and duration of training programs but no information about employers' investment behavior or profitability.

It is widely accepted in the labor demand literature that skilled labor and capital are complements in production: more capital-intensive firms are expected to hire more skilled labor (Hamermesh 1993). The implied empirical relationship between a firm's capital or R&D investments and its provision of formal training is less clear. Firms that demand skilled workers may either provide their own training programs or hire workers who have been trained by previous employers or in school. The specificity of skills determines the substitution possibilities between workers trained on the current job and previously trained workers. In addition, we expect training to occur in firms where output and training tend to be complementary and the forgone output from training is lowest.

In this paper, we use a unique cross-sectional sample of white-collar workers from a Bureau of Labor Statistics (BLS) establishment survey to analyze the incidence of employer-provided training programs and their impact on wage-tenure profiles. In addition, we match a subset of these data on individual worker wages, tenure, and participation in a formal training program, with firm-level data on profitability and investment behavior from the Compustat database. Using these matched data, we provide evidence on the empirical relationship between firm profitability, firm investments in capital equipment and R&D, the provision of formal training programs, and the returns to training.

A second goal of this paper is to evaluate the feasibility of gathering worker-level wage, tenure, training, and demographic data in an establishment or employer survey. This data issue is important because there appears to be considerable demand for employer-employee matched data sets (in this volume, see Abowd and Kramarz, chap. 10; Prendergast, chap. 9; Troske, chap. 11). We examine establishments' responses to a pilot BLS survey, conducted in 1989 and 1990, which tested the feasibility of collecting worker demographic data from establishments. We analyze response rates to this pilot survey and compare our establishment-reported data to data for white-collar workers in two household surveys: the NLSY and the Current Population Survey (CPS). Although we find some significant differences in worker characteristics across all three surveys, we conclude that matched worker-employer data sets, based on

BLS establishment surveys, can provide useful information about internal and external labor market behavior.

A matched worker-employer data set has some advantages over household panel data sets, such as the NLSY, in analyzing employer-provided training programs. First, we observe multiple workers per establishment so that employer-specific effects can be included in models of the incidence of training and wage growth. Empirical models based on household data must ignore these employer-specific wage and training effects. Second, as noted above, our matched data set allows us to link individual worker wage, tenure, and training information with employer characteristics such as profitability, capital/labor ratio, and expenditures on R&D, for the subsample of workers employed by publicly traded firms.

There are also some caveats to our data set and empirical approach. First, our sample size is small by conventional labor economics standards, and we have retrospective data for starting wages rather than panel data. Second, the training variable we use is dichotomous—we do not observe the type or duration of the training that was provided. Third, our data set is not based on experimental data. The training programs we observe are endogenously determined, and we do not observe instrumental variables for the incidence of training programs. Unobserved heterogeneity in productivity growth across workers and firms may bias our estimates of the effects of training on wage growth.

13.2 Data

13.2.1 White Collar Pay Survey

The data set used in this study is derived from a subsample of the BLS White Collar Pay Survey (WCP), which is collected to determine the wages of private sector employees in white-collar occupations that match occupations in the federal government.[1] The WCP collects the straight-time salary and detailed occupation of full-time workers (who work between 37.5 and 40 hours per week) from a nationwide sample of private sector employers. The survey 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.

Our data set is based on a supplement to the WCP conducted in 1989 and

1. The WCP occupations are accountants, chief accountants, auditors, public accountants, personnel specialists, personnel supervisors/managers, directors of personnel, attorneys, buyers, computer programmers, computer systems analysts, computer systems analysts supervisor/manager, chemists, engineers, tax collectors, registered nurses, licensed practical nurses, nursing assistants, medical machine operating technicians, civil engineering technicians, engineering technicians, drafters, computer operators, photographers, accounting clerks, file clerks, key entry operators, messengers, secretaries, typists, personnel clerks/assistants, purchasing clerks/assistants, and general clerks.

1990. In this test survey, 354 establishments were asked questions about a random sample of their employees in "matched" white-collar occupations.[2] The employer was asked to report the worker's current and starting pay, age, race, sex, years of education, highest educational degree obtained, and tenure with the employer. In addition, the employer was asked whether the worker received "formal training (specific course work or a training program) within or outside the establishment which was paid for wholly or in part by the establishment."

Three hundred establishments provided information on current pay, tenure, and standard demographic characteristics for 1,727 workers between the ages of 18 and 64.[3] Employers were least likely to respond to questions about workers' starting pay and formal training.[4] Moreover, when either training or starting wage is not reported for one worker in an establishment, it tends to be missing for all workers in the establishment. Training is not reported for 28.6 percent of the 1,727 workers, and over 90 percent of the workers with missing values for training are employed in establishments that did not report training for any worker. Starting pay information is not reported for 55.7 percent of the workers in the 1,727 sample, and over 86 percent of the workers with missing values for starting pay are employed in establishments that did not report starting pay for any worker. There are 1,234 workers with valid responses to the training question in our sample, and starting wages are also reported for 601 of these 1,234 workers.

Our primary concern is that an employer's decision to report training may be correlated with unobserved variables that also influence wages and the costs and benefits of training. We check for possible patterns in nonresponse behavior across establishments by estimating a probit model where the dependent variable is one if the establishment did not report training for any worker and zero otherwise. Unfortunately, we do not observe any variables that are valid instruments for the incidence of training. Hence we do not attempt to correct for selection bias in our sample due to nonresponses but merely examine patterns of establishment nonresponses in the data.

Table 13.1 reports the estimated coefficients for a probit model of nonresponse to the training question. We find that nonreporting establishments hav[e] more employees and are more likely to be located in larger metropolitan area[s] in the Northeast or Midwest, on average, than the reporting establishment[s]. Relatively low wage employers are slightly less likely to respond to the trainin[g] question. The mean wage in nonresponding establishments is about 3 percen[t] lower, all else equal, than the mean wage in establishments that report training. There is no significant relationship between the probability of reporting training and the average education, experience, tenure, or the fraction of female o[r] black workers in an establishment.

As noted above, nonresponse problems are more substantial for a worker'[s]

2. Establishments were asked to report demographic data for a random sample of 2,386 workers. The mean wage and occupational distribution of these 2,386 workers is not significantly different from the mean wage and occupational distribution of the entire WCP sample from these 354 establishments. The sample sizes per establishment range from 1 to 33 workers, with more workers sampled in the larger establishments. Almost 80 percent of the sample was collected in 1990 when goods-producing industries were surveyed.

3. We excluded observations from the sample of 2,386 workers in 354 establishments for the following reasons: 362 for missing age, 25 because age was less than 18 or greater than 64, 17 for missing race, 17 for missing tenure, 208 for missing education, 16 because age minus tenure was less than 16 years, 1 because age minus education minus 6 was less than zero, and 13 because education was less than 12 years. This leaves a total of 1,727 workers in 300 establishments.

4. We had the least success in obtaining information about the duration of training programs from employers. Only 13 percent of our sample has valid information about the length of training programs. The mean duration across these 231 workers is 5.18 weeks, with a median duration of 1.4 weeks.

Table 13.1 Probit Models of Training and Starting Wage Nonresponse by Establishments

Independent Variable	Dependent Variable: Equals One if Training Not Reported (1)		Equals One if Starting Wage Not Reported (2)	
Education	.1153	(.1210)	−.0819	(.102
Experience	.0286	(.0227)	.0165	(.018
Tenure	.0168	(.0283)	.0057	(.024
Female	−.7035	(.5357)	−.2135	(.412
Black	−.0100	(.7798)	.0694	(.658
Log wage	−.9638*	(.5671)	.3012	(.472
Region				
Midwest	.3063	(.2645)	.4319*	(.230
South	−.4981*	(.2948)	.7616**	(.239
West	−.1810	(.3296)	.8719**	(.288
Industry				
Durable goods	−.4411*	(.2634)	.2502	(.213
Trade and finance	−.2327	(.4232)	−.4245	(.389
Services	−.3442	(.3949)	.1829	(.315
Mining and construction	.0504	(.3676)	.4564	(.322
MSA size				
Below 1 million	.1188	(.3246)	.0660	(.255
1–5 million	.5204*	(.3043)	.0433	(.253
Above 5 million	.5914	(.3779)	−.0330	(.317
Establishment size				
500–1,000 employees	1.0536**	(.2943)	.1354	(.239
Over 1,000 employees	1.2359**	(.2437)	.3061	(.189
Constant	3.9549	(3.8994)	−2.2987	(3.078
Sample size	300		300	

Notes: The omitted category is a nondurable-goods-manufacturing firm located in the Northea[st] outside of a metropolitan statistical area. Each observation is weighted by the number of surveye[d] workers in the establishment. Numbers in parentheses are standard errors.

*Significant at the 10 percent level.

**Significant at the 5 percent level.

starting wage. We check for possible patterns in nonresponse to the starting wage question across establishments by estimating a probit model where the dependent variable is one if the establishment did not report starting pay for any worker and zero otherwise. Column (2) of table 13.1 reports the estimated coefficients for this probit model. We find that reporting establishments are more likely to be located in the Northeast than the nonreporting establishments. No other establishment characteristic and no worker characteristics are significantly related to the probability of nonresponse.

Throughout the paper we focus our analysis on two samples of the WCP: a sample of 1,234 workers with nonmissing training data and a sample of 601 workers with nonmissing training and starting wage data. In our larger sample we impute starting wages, using starting experience and interactions of starting experience as instrumental variables.[5] In general, as demonstrated below, we find similar empirical results across samples. These findings, in addition to the absence of a significant relationship (except for regional dummy variables) between worker and employer characteristics and employer nonresponse to the starting wage question, suggest that restricting the sample to workers with nonmissing starting wages does not result in serious sample selection bias.

Table 13.2 reports means and standard deviations of the variables in our two samples. The key variables in our analysis are the formal training dummy variable, the logarithm of the current monthly wage (measured in 1989 dollars), the logarithm of the starting monthly wage (also measured in 1989 dollars), and job tenure.[6] Approximately 30 percent of the workers in each sample received formal training from their employers. Mean tenure is substantially shorter and the current real wage is somewhat lower for workers with reported starting pay.

13.2.2 Comparison with the Current Population Survey

We first compare our data set to a sample of private sector white-collar workers in the outgoing rotation groups of the 1989 CPS employed in occupations that match those in the WCP. The CPS sample contains 15,784 private sector, nonagricultural workers between the ages of 18 and 64 who typically work between 37.5 and 40 hours per week. Table 13.3 presents sample statistics by

5. The 601 sample is a subset of our 1,234 sample. We use imputed, rather than actual, starting wages for all 1,234 workers. Our starting wage regression includes starting experience and its square, education, an education and starting experience interaction, female, female interactions with starting experience and its square, and dummy variables for race, two-digit SIC industry, region, metropolitan statistical area (MSA) size, and establishment size.

6. We converted all current reported wages into 1989 dollars, using the December 1989 to December 1990 average change in the Employment Cost Index (ECI) for wages and salaries of workers in goods-producing industries. We deflated nominal starting pay by the average hourly earnings of workers in the United States to obtain real starting wages because the ECI is not available for all starting years. All workers with less than 18 months of tenure were assigned one year of tenure, and workers with at least 18 months of tenure were assigned the nearest integer year of tenure.

Table 13.2 Variable Means and Standard Deviations

Variable	Actual Starting Wage Sample		Predicted Starting Wage Sample	
Real monthly wage	2,469.71	(1,146.04)	2,587.46	(1,197.88)
Log real wage	7.710	(.452)	7.755	(.460
Real starting monthly wage	1,968.67	(965.80)		
Log real start wage	7.476	(.465)		
Predicted log real start wage			7.483	(.363
Wage growth	.234	(.302)		
Tenure	6.494	(6.208)	8.224	(7.784
Train	.280	(.449)	.303	(.460
Education	14.403	(2.140)	14.396	(2.118
Starting potential experience	10.311	(8.815)	9.983	(9.018
Female	.521	(.500)	.487	(.500
Black	.070	(.255)	.063	(.243
Industry				
Nondurable goods	.186	(.390)	.216	(.412
Durable goods	.509	(.500)	.496	(.500
Trade and finance	.078	(.269)	.064	(.245
Services	.163	(.370)	.132	(.339
Mining and construction	.063	(.244)	.092	(.289
MSA size				
Not an MSA	.165	(.371)	.212	(.409
Below 1 million	.255	(.436)	.253	(.435
1–5 million	.399	(.490)	.371	(.483
Above 5 million	.181	(.386)	.165	(.370
Region				
Northeast	.333	(.472)	.239	(.427
Midwest	.295	(.456)	.281	(.450
South	.271	(.445)	.355	(.479
West	.101	(.302)	.125	(.331
Establishment size				
Under 500 employees	.546	(.498)	.508	(.500
500–1,000 employees	.155	(.362)	.160	(.367
Over 1,000 employees	.300	(.458)	.331	(.471
Sample size	601		1,234	

Note: Numbers in parentheses are standard deviations.

broad industry group (manufacturing; trade, finance, and services; and minin and construction) for the CPS and WCP data sets. We focus on within-industr comparisons because of the rather large differences in industry compositio across data sets (the preponderance of the WCP data were collected from es tablishments in goods-producing industries).

Workers in the WCP earn higher pay than full-time white-collar workers i the CPS, especially in nonmanufacturing industries. Some of this large pa differential is due to the fact that workers in the WCP are more experiencec

Table 13.3 Comparison of Full-Time White-Collar Workers from the CPS and the WCP

Manufacturing	CPS	(*N* = 3,405)	WCP	(*N* = 879)
Monthly wage	2,340.04	(1,183.03)	2,583.25	(1,187.36)
Education	14.13	(2.02)	14.46	(2.10)
Experience	16.80	(11.07)	18.08	(10.22)
Female	.52	(.50)	.46	(.50)
Black	.05	(.22)	.04	(.21)
Northeast	.31	(.46)	.24	(.43)
Midwest	.17	(.37)	.27	(.44)
South	.26	(.44)	.39	(.49)
West	.26	(.44)	.10	(.30)
Not an MSA	.20	(.40)	.27	(.44)
Below 1 million	.26	(.44)	.31	(.46)
1–5 million	.31	(.46)	.28	(.45)
Above 5 million	.23	(.42)	.14	(.35)
Trade, Finance, and Services	**CPS**	**(*N* = 11,958)**	**WCP**	**(*N* = 242)**
Monthly wage	1,815.08	(970.42)	2,411.59	(1,163.67)
Education	13.77	(1.88)	14.21	(2.17)
Experience	15.77	(10.92)	17.85	(10.96)
Female	.79	(.41)	.61	(.49)
Black	.10	(.30)	.14	(.34)
Northeast	.27	(.44)	.31	(.47)
Midwest	.19	(.39)	.38	(.49)
South	.30	(.46)	.20	(.40)
West	.25	(.44)	.11	(.32)
Not an MSA	.22	(.42)	0	
Below 1 million	.26	(.44)	.03	(.16)
1–5 million	.31	(.46)	.75	(.44)
Above 5 million	.20	(.40)	.23	(.42)
Mining and Construction	**CPS**	**(*N* = 472)**	**WCP**	**(*N* = 113)**
Monthly wage	2,017.30	(1,323.72)	2,996.85	(1,262.90)
Education	13.73	(1.88)	14.33	(2.13)
Experience	17.49	(11.07)	19.98	(10.94)
Female	.72	(.45)	.47	(.50)
Black	.03	(.18)	.05	(.23)
Northeast	.18	(.38)	.07	(.26)
Midwest	.25	(.43)	.18	(.38)
South	.39	(.49)	.42	(.50)
West	.18	(.39)	.33	(.47)
Not an MSA	.31	(.46)	.20	(.40)
Below 1 million	.28	(.45)	.31	(.46)
1–5 million	.28	(.45)	.29	(.46)
Above 5 million	.14	(.34)	.19	(.40)

Note: Numbers in parentheses are standard deviations.

more educated, and less likely to be female than workers in the CPS. In addi tion, wages in the CPS are likely to be underreported; a recent study found tha 30 percent of CPS respondents report after-tax rather than gross pay (see Po livka and Rothgeb 1993). We also find that worker demographic characteristic account for 57 percent of the variation in log wages in the WCP; the sam worker demographic characteristics account for less than 36 percent of th variation in log wages in our CPS data. In Bronars and Famulari (1997) w present a more complete comparison of the CPS and WCP data sets and pro vide some evidence that the difference in unexplained variation in log wage across samples is due to greater measurement error in CPS reported wages.

13.2.3 Comparison with the National Longitudinal Survey of Youth

We also compare our data to a sample of full-time white-collar workers fron the NLSY in occupations that match the WCP. There are 779 white-colla workers in these occupations in the NLSY, for whom we observe wages i 1989, starting wages, and training. The oldest workers in the NLSY are age 32 in 1989. Table 13.4 compares means and standard deviations of variable in this NLSY data set to sample statistics for workers under age 33 in ou WCP data set and the CPS. Because of the substantial differences in industr composition across data sets, we again present comparisons of means withi broad industry groups.[7] First, note that only about one-third of our WC sample and 40 percent of the CPS sample are as young as the NLSY respon dents. In addition, less than one-fifth of the NLSY sample is employed in th manufacturing sector, where most of the WCP data were collected. Despit these caveats, all three samples are reasonably similar with respect to educa tion, experience, tenure, race, and sex in the manufacturing sector. In trade finance, and services, WCP workers are more educated and less likely to b female than either NLSY or CPS workers. Average current wages are signifi cantly higher in the NLSY in the manufacturing sector, and significantly highe in the WCP in trade, finance, and services. Wage growth appears to be substan tially higher in the NLSY than in the WCP subsample, primarily because start ing wages are much lower and have a much higher standard deviation in th NLSY.[8]

We find that 23 percent of white-collar NLSY workers and 28 percent o young WCP workers participated in training programs that were paid for b their employers. Note that we use information in the NLSY on participation i training programs that were explicitly paid for by the employer, which is onl available from 1986 to 1989. We therefore underestimate participation i

7. We present comparisons only for manufacturing industries and finance, trade, and service because sample sizes for both the NLSY and the WCP (age 32 and under) are quite small i mining and construction industries.

8. We also find that worker demographic characteristics account for 61 percent of the variatio in young workers' log wages in the WCP; the same worker demographic characteristics accoun for less than 35 percent of the variation in log wages in our NLSY data set.

Table 13.4 **Comparison of Full-Time White-Collar Workers under Age 33 from the NLSY, the WCP, and the CPS**

Manufacturing	NLSY	(N = 127)	WCP	(N = 283)	CPS	(N = 1,414)
Current monthly wage	2,207.23	(949.06)	2,022.75	(815.98)	2,030.17	(904.39)
Starting monthly wage[a]	1,476.92	(911.52)	1,678.17	(538.02)		
Training[b]	.30	(.46)	.23	(.42)		
Tenure	3.34	(2.62)	3.22	(2.49)		
Education	14.39	(2.08)	14.27	(1.94)	14.20	(1.92)
Experience	7.63	(3.15)	7.06	(3.06)	6.64	(3.82)
Female	.53	(.50)	.50	(.50)	.55	(.50)
Black	.05	(.21)	.04	(.20)	.05	(.22)
Northeast	.20	(.40)	.24	(.43)	.29	(.45)
Midwest	.35	(.48)	.28	(.45)	.17	(.37)
South	.31	(.46)	.37	(.48)	.28	(.45)
West	.14	(.35)	.11	(.32)	.27	(.44)
Under 500 employees	.45	(.50)	.55	(.50)		
500–1,000 employees	.11	(.31)	.19	(.40)		
Over 1,000 employees	.44	(.50)	.26	(.44)		
Not an MSA	.12	(.33)	.28	(.45)	.18	(.38)
Below 1 million	.27	(.45)	.31	(.46)	.25	(.43)
1–5 million	.36	(.48)	.28	(.45)	.32	(.47)
Above 5 million	.24	(.43)	.14	(.35)	.25	(.43)

Trade, Finance, and Services	NLSY	(N = 637)	WCP	(N = 88)	CPS	(N = 5,541)
Current monthly wage	1,620.88	(696.63)	1,996.37	(783.27)	1,626.32	(778.64)
Starting monthly wage[a]	1,180.89	(614.28)	1,682.83	(549.68)		
Training[b]	.23	(.42)	.36	(.48)		
Tenure	3.14	(2.51)	2.86	(2.27)		
Education	13.74	(1.94)	14.40	(2.10)	13.84	(1.83)
Experience	8.02	(3.00)	7.39	(3.26)	6.50	(3.81)
Female	.77	(.42)	.63	(.49)	.79	(.41)
Black	.13	(.34)	.07	(.25)	.10	(.30)
Northeast	.18	(.38)	.34	(.48)	.26	(.44)
Midwest	.28	(.45)	.38	(.49)	.17	(.40)
South	.37	(.48)	.23	(.42)	.30	(.46)
West	.16	(.37)	.06	(.23)	.26	(.44)
Under 500 employes	.74	(.44)	.74	(.44)		
500–1,000 employees	.08	(.27)	.02	(.15)		
Over 1,000 employees	.18	(.39)	.24	(.43)		
Not an MSA	.15	(.35)	0		.21	(.41)
Below 1 million	.33	(.47)	.02	(.15)	.27	(.44)
1–5 million	.30	(.46)	.83	(.38)	.32	(.47)
Above 5 million	.22	(.41)	.15	(.36)	.20	(.40)

Note: Numbers in parentheses are standard deviations.

[a]Predicted starting wage for the WCP sample.

[b]Training in the NLSY is employer-paid training since 1986 or beginning of job, whichever came last.

employer-provided training programs for workers with tenure of more than three years in the NLSY sample.[9]

The NLSY also contains information about the type and duration of training programs that can be used to augment the training information in our data set. Among workers in the NLSY who received employer-provided training, the median duration of their training is 2 weeks, with a mean of 7.33 weeks and standard deviation of 27.4 weeks. For workers age 32 and under in the WCP data set with nonmissing training duration data, the median duration of training is 1.7 weeks, with a mean of 8.03 weeks and standard deviation of 24.7 weeks. Despite the fact that responses to the training duration question are missing for a large portion of our sample, we are reassured by the remarkable similarity in the distribution of training episodes across the NLSY and WCP data sets.

Although we do not observe information about the type of training programs provided by employers in the WCP, this information is collected in the NLSY. Over 41 percent of the employer-provided training programs for white-collar workers (in matched WCP occupations) in the NLSY were classified as "formal company training programs run by the employer," over 25 percent were "seminars or training programs outside of work," and over 21 percent were classified as "seminars or training programs at work, not run by the employer." Given the other similarities in the two data sets, it is likely that workers in the WCP are also participating in the same types of training programs.

We conclude that our sample of WCP workers in manufacturing are reasonably representative of the population of white-collar workers in manufacturing. This is especially true for younger workers. The smaller sample of WCP workers in nonmanufacturing is less representative of the population: WCP workers are more likely to be male, highly educated, and highly paid. In empirical results not reported here, we find that standard demographic variables explain a much higher fraction of variation in pay across workers in the WCP than in either the CPS or the NLSY. These results are consistent with the hypothesis that wages in the WCP are measured with considerably less error than wages in the CPS or NLSY.

13.3 The Incidence of Training

13.3.1 Empirical Framework

We examine the relationship between participation in a formal training program and worker and employer characteristics by estimating the following regression:

9. We exclude the training information available in the NLSY prior to 1986 because it does not indicate whether the employer paid for the training program. Lynch (1992) shows that formal training programs are more likely to occur after the worker has completed one year on the job, which suggests that our conservative approach to measuring employer-provided training should underestimate actual training by a small amount: less than one-fourth of the NLSY sample has

$$(1)\qquad \Pr(\text{Train}_{ij} = 1) = X_{ij}\theta_0 + Z_j\lambda_0 + (X_{ij}\theta_1 + Z_j\lambda_1)T_{ij} + \varepsilon_{ij},$$

where i indexes workers and j indexes employers, $\text{Train}_{ij} = 1$ if the worker w
trained by her employer, X_{ij} is a vector of worker demographic characteristi
(including starting pay at the current employer), T_{ij} is job tenure, and Z_j is
vector of employer characteristics. Equation (1) includes interactions betwe
job tenure and worker and employer characteristics to account for variation i
the incidence of training due to differences in length of service with an en
ployer. The error term in equation (1) is assumed to have the following forn
$\varepsilon_{ij} = \mu_j + \nu_{ij}$, where μ_j is an employer-specific component of ε_{ij} and ν_{ij}
assumed to be identically independently distributed.

If workers share in the costs and benefits of formal training program
trained workers receive lower starting wages and experience higher wag
growth, ceteris paribus. Human capital models predict that workers face
trade-off between starting wages and training opportunities and the more ge
eral the training program, the higher the share of costs borne by the worke
Thus we expect the coefficient on starting wages in equation (1) to be negativ
and it should be the most negative for workers acquiring the most gener
skills.

Starting pay may also be related to the incidence of training in equation (1
because starting pay may proxy for unobserved productivity differences acro
workers. Starting pay is correlated with the amount of skills acquired by
worker prior to the current job and consequently with a worker's productivit
in human capital acquisition. Although it is plausible that workers with fewe
skills at the start of a job are more likely to receive training, all else equa
these workers may also be the least productive in acquiring human capital. I
the marginal productivity of human capital investment differs substantiall
across workers, relatively less productive workers may have lower startin
wages (due to fewer previous investments) and be less likely to receive trainin
from their current employers. In contrast, relatively more productive worke
may have both higher starting wages and be more likely to receive training o
the current job. Therefore, within-firm heterogeneity across workers implie
an ambiguous empirical relationship between a worker's starting wage and th
probability of training in equation (1).

13.3.2 Empirical Results

Comparisons to the National Longitudinal Survey of Youth

We first present estimates of equation (1) that ignore the employer-specifi
component of the error term. We consider this "pooled" specification becaus
training studies based on household surveys do not have multiple observation
per employer and therefore must ignore the employer-specific error compo
nent. We then compare our estimates to those obtained from the NLSY sub
sample in WCP-matched occupations. We use race, sex, education, tenure, an

ables for broad SIC industry group and establishment size as employer-specific characteristics, Z_j.

Column (1) of table 13.5 presents these pooled results for the 224 workers under age 33 in our WCP sample with reported starting pay. Few explanatory variables have a significant impact on the probability of receiving training. We find a significant positive coefficient on education and starting pay and a significant negative coefficient on the education and starting pay interaction. These results indicate that the workers most likely to receive training are relatively less educated workers with high starting wages and relatively more educated workers with low starting wages.

Column (2) presents regression results from the NLSY for the same specification of equation (1). The patterns of training incidence across NLSY workers and young workers in the WCP are reasonably similar. In both data sets we find that the workers most likely to receive training are relatively less educated workers with high starting wages and relatively more educated workers with low starting wages. Formal training programs appear to complement schooling for workers with low labor market experience and low starting wages, but employer-provided training programs may substitute for formal schooling for less educated workers with more labor market experience and higher starting wages. In the NLSY, we also find a significant relationship between tenure and the likelihood of receiving training, especially for workers with low starting wages, and significant differences in the incidence of training across establishment size categories and regions.

Random Effects Estimates of the Incidence of Training

In this section we use the WCP samples described in table 13.2 to estimate equation (1) and test for the presence of employer-specific effects in the error term.[10] In each case we strongly reject the null hypothesis that the variance of μ_j equals zero using a Breusch-Pagan Lagrange multiplier test. It is not surprising that we find an employer-specific component to the provision of training. In our sample of 1,234 workers with imputed starting pay, 148 establishments did not provide training to any of their 640 workers, 51 establishments provided training to all 197 of their workers, and 57 establishments with 397 workers exhibit some within-employer variation in the provision of training. A similar pattern is found in the sample of 601 workers with actual starting wages: 65 establishments did not provide training for any of their 297 employees, 25 establishments provided training for all 88 of their workers, and 34 establishments exhibit some within-employer variation in the provision of training to their 216 workers.

We test the hypothesis that μ_j is uncorrelated with the independent variables in our model using a Hausman specification test and fail to reject the null

10. We obtain similar results if we restrict the sample to the 224 workers under age 33 (comparable to the NLSY) in the WCP and use imputed starting wages.

Table 13.5 Training Incidence: Full-Time White-Collar Workers under Age 33

Variable	WCP (1)	(N = 224)	NLSY (2)	(N = 779
Education	.7362**	(.2990)	.3517**	(.1050)
Tenure	−.4002	(.3521)	.1621*	(.0869)
Female	−.1322	(.1232)	−.0093	(.0583)
Black	.1807	(.2371)	−.1386*	(.0752)
Log starting wage	1.1113*	(.6321)	.8275**	(.2187)
Education*Log starting wage	−.0944**	(.0406)	−.0490**	(.0144)
Tenure*Education	−.0106	(.0115)	−.0001	(.0039)
Tenure*Female	.0348	(.0337)	−.0129	(.0162)
Tenure*Black	−.0330	(.0763)	.0219	(.0203)
Tenure*Log starting wage	.0929	(.0596)	−.0203**	(.0099)
Durable goods	−.0136	(.1732)	.0044	(.1181)
Trade and finance	−.4315*	(.2407)	.0724	(.1120)
Services	−.1845	(.2230)	.0531	(.1009)
Mining and construction	−.1985	(.2826)	−.1126	(.2025)
500–1,000 employees	−.0740	(.1752)	.1480*	(.0882)
Over 1,000 employees	.0210	(.1343)	.1612**	(.0660)
Below 1 million	.1685	(.1786)	.0585	(.0760)
1–5 million	.3246	(.2004)	−.0003	(.0775)
Above 5 million	.1831	(.2278)	.0711	(.0934)
Midwest	.1788	(.1562)	.0542	(.0844)
South	.1563	(.1535)	.0220	(.0870)
West	.1576	(.2193)	−.0835	(.0884)
Tenure*Industry				
Durable goods	−.0513	(.0488)	−.0170	(.0285)
Trade and finance	−.0267	(.0631)	−.0358	(.0268)
Services	−.0032	(.0662)	−.0251	(.0235)
Mining and construction	−.1107	(.1033)	−.0256	(.0525)
Tenure*Establishment size				
500–1,000 employees	−.0611	(.0524)	−.0191	(.0226)
Over 1,000 employees	−.0267	(.0390)	−.0205	(.0154)
Tenure*MSA size				
Below 1 million	−.0733	(.0541)	.0111	(.0183)
1–5 million	−.0663	(.0608)	.0338*	(.0183)
Above 5 million	−.0759	(.0697)	.0158	(.0238)
Tenure*Region				
Midwest	−.0185	(.0442)	.0258	(.0201)
South	−.0561	(.0436)	.0351*	(.0205)
West	.0127	(.0618)	.0646**	(.0233)
Constant	−8.6385*	(4.4977)	−5.8703**	(1.5739)
R^2	.2235		.1173	

Note: Numbers in parentheses are standard errors.
*Significant at the 10 percent level.
**Significant at the 5 percent level.

hypothesis of zero correlation in each WCP data set. The significant differences in training propensities across employers documented above are insignificantly correlated with observed worker characteristics in these establishments. Therefore, we account for the employer-specific component of training incidence by estimating equation (1) using employer random effects and present these results in table 13.6. Column (1) presents estimates based on the sample of 601 workers with reported starting wages, and column (2) presents estimates based on the sample of 1,234 workers with imputed starting wages.

We find that a one-year increase in tenure, evaluated at sample means, significantly raises the likelihood of training by 0.46 to 0.80 percentage points. We find no evidence of significant differences in the incidence of training by race or sex, evaluated at mean tenure. In both samples, workers in MSAs with populations of 1 to 5 million and workers in the West are significantly more likely to receive training, evaluated at mean tenure. In the smaller sample with reported starting wages, workers in mining and construction industries are significantly less likely to receive training, and workers in the Midwest are significantly more likely to receive training, evaluated at mean tenure.

We include interactions between a worker's starting wage and demographic characteristics to account for differences in the relationship between starting wages and the incidence of company training across workers. As in the previous section, we find significant positive coefficients on both education and starting pay and a significant negative coefficient on their interaction term in equation (1) using either sample. Estimated coefficients on interactions between a worker's starting pay and other demographic characteristics were insignificantly different from zero in all model specifications.[11]

Table 13.7 presents differences in the probability of training across low starting wage (10th percentile), medium starting wage (median), and high starting wage (90th percentile) workers across four education groups: 12, 13 to 15, 16, and more than 16 years of education. The coefficients in table 13.7 are the differences between the estimated training probability for each type of worker and the estimated probability that a low-starting-wage high school graduate received company training, evaluated at sample means.[12] We find that the incidence of training is highest for a low-starting-wage worker with a college degree. Training is least likely for a high-starting-wage worker with a graduate degree and a low-starting-wage worker with a high school diploma.

11. Across the two samples in table 13.6, we find no evidence of significant coefficients on the interactions between starting pay and either tenure, starting experience, or female.

12. Table 13.7 compares workers across education groups at the same *relative position* in the starting wage distribution, and not with the same starting wage; e.g., a "high" starting wage is defined as the 90th percentile of the starting wage distribution for a particular education group. To put these relative comparisons in perspective, the 90th percentile of the log starting wage distribution for workers with a high school diploma equals the median log starting wage for workers with a college degree (7.68).

Table 13.6 Random Effects Estimates of Training Incidence among White-Collar Workers

Variable	Actual Starting Wage Sample (1)		Predicted Starting Wage Sample (2)	
Education	.2895**	(.1053)	.2195**	(.0940)
Tenure	.0277	(.0451)	.0232	(.0412)
Female	.0394	(.0448)	.0285	(.0340)
Black	−.0808	(.0739)	−1.075*	(.0552)
Log starting wage	.4950**	(.2158)	.4236**	(.2018)
Education*Log starting wage	−.0361**	(.0139)	−.0285**	(.0124)
Tenure*Education	−.0016	(.0013)	−.0003	(.0009)
Tenure*Female	−.0011	(.0056)	.0015	(.0029)
Tenure*Black	.0221	(.0085)	.0181	(.0053)
Tenure*Log starting wage	−.0002	(.0062)	−.0011	(.0068)
Industry				
Durable goods	−.0989	(.0942)	−.0099	(.0667)
Trade and finance	−.5038**	(.1834)	−.2257*	(.1304)
Services	−.0652	(.1326)	.1692*	(.0954)
Mining and construction	−.3847**	(.1549)	−.1188	(.1088)
MSA size				
Below 1 million	.1399	(.1126)	.0919	(.0804)
1–5 million	.2827**	(.1181)	.2328**	(.0814)
Above 5 million	.1292	(.1342)	.1251	(.0978)
Region				
Midwest	.1915**	(.0968)	.0846	(.0759)
South	.1015	(.1014)	.0952	(.0787)
West	.1861	(.1310)	−.2023**	(.0920)
Establishment size				
500–1,000 employees	−.1956*	(.1141)	−.0718	(.0829)
Over 1,000 employees	−.0774	(.0941)	−.0105	(.0667)
Tenure*Industry				
Durable goods	.0011	(.0066)	−.0039	(.0034)
Trade and finance	.0429**	(.0126)	.0232**	(.0060)
Services	−.0099	(.0110)	−.0100	(.1226)
Mining and construction	−.0092	(.0098)	−.0005	(.0045)
Tenure*MSA size				
Below 1 million	−.0039	(.0079)	−.0010	(.0038)
1–5 million	.0023	(.0081)	−.0030	(.0035)
Above 5 million	.0045	(.0093)	.0009	(.0049)
Tenure*Region				
Midwest	.0034	(.0068)	−.0052	(.0036)
South	−.0131*	(.0072)	−.0102**	(.0039)
West	.0075	(.0098)	.0014	(.0055)
Tenure*Establishment size				
500–1,000 employees	.0134*	(.0079)	.0004	(.0049)
Over 1,000 employees	.0051	(.0059)	.0009	(.0029)
Constant	−3.8238**	(1.5938)	−3.186**	(1.471)
Sample size		601		1,234

Notes: The omitted category is a nondurable-goods-manufacturing firm located in the Northeast outside of a metropolitan statistical area with less than 500 employees. Numbers in parentheses are standard errors.

Table 13.7 Training Probabilities by Education and Starting Wage Group

	Education			
Starting Wage	12 Years	13 to 15 Years	16 Years	More than 16 Years
Actual Starting Wage Sample (N = 601)				
Low (10th percentile)	.0000	.0745**	.1020**	.0962*
Median (50th percentile)	.0232	.0692**	.0662	.0229
High (90th percentile)	.0579	.0599	.0254	−.0413
Predicted Starting Wage Sample (N = 1,234)				
Low (10th percentile)	.0000	.0493**	.0643**	.0504
Median (50th percentile)	.0210	.0536	.0545	.0250
High (90th percentile)	.0433	.0583	.0407	−.0014

Note: Reported numbers are differences between estimated probability of training for a given worker and a low-starting-wage worker with a high school education.
*Significant at the 10 percent level.
**Significant at the 5 percent level.

13.4 Training and Wage Growth

13.4.1 Empirical Framework

Ideally, we would estimate the impact of training on wage growth in a panel data set by relating changes in workers' log wages over time to their investments in training. Our cross-sectional data set reports a worker's starting pay and training at an employer retrospectively. We therefore estimate a wage regression of the following form:

$$(2) \qquad \log W_{ij} = X_{ij}\beta_0 + Z_j\gamma_0 + (X_{ij}\beta_1 + Z_j\gamma_1)T_{ij} + \alpha_0 \text{Train}_{ij} + \alpha_1 \text{Train}_{ij} T_{ij} + \alpha_2 \text{Train}_{ij} \log(SW_{ij})T_{ij} + u_{ij},$$

where $\log W_{ij}$ is a worker's current wage and the vector of worker characteristics, X_{ij}, includes a worker's starting pay. The coefficients on X_{ij}, Z_j, T_{ij}, and Train_{ij} represent the impact of worker characteristics, employer characteristics, job tenure, and training on a worker's current pay, conditional on starting pay. Thus equation (2) models variation in wage growth across workers, and interactions between X_{ij} and Z_j and job tenure account for differences in rates of wage growth by worker and employer characteristics. We hypothesize that the error term in equation (2) has an employer-specific component: $u_{ij} = \eta_j + e_{ij}$, where η_j is the employer-specific effect and e_{ij} is an independently identically distributed error.

Differences across the wage profiles of trained and untrained workers in our specification are determined by the parameters α_0, α_1, and α_2. The human capital model predicts that the returns to training, that is, wage growth, should be highest for workers who bear the highest fraction of training costs. Workers

who receive more general company training and relatively lower starting pa are expected to experience more rapid wage growth. In other words, the huma capital model suggests that the coefficient α_1 should be significantly positiv and α_2 should be significantly negative in equation (2).[13]

13.4.2 Empirical Results

Comparison to the National Longitudinal Survey of Youth

Using the same subsamples of the WCP and NLSY as in table 13.5, w estimate the relationship between current wages, starting wages, and tenure i equation (2). We were unable to detect significant differences in the slope of wage-tenure profiles across trained and untrained workers in either sampl (estimates of α_1 and α_2 were insignificantly different from zero). We attribut this result to the small variation in job tenure across workers and our relativel small sample sizes. We therefore focus our attention on empirical models tha estimate a common training effect across all workers (i.e., that restrict α_1 an α_2 to be zero).

Table 13.8 presents coefficient estimates for the wage growth model in equa tion (2) for the WCP data set; results for the NLSY are presented in colum (2). We find large significant returns to tenure in both samples, but substan tially more regression toward the mean in wage growth in the NLSY. Female experience significantly slower wage growth in the NLSY, and more educate workers have significantly faster wage growth in the WCP. For most worke and employer characteristics, the pattern of regression coefficients are simila across samples. We find a significant positive relationship between training an wage growth in both samples, but the effects are significantly larger in th NLSY. The mean trained worker in the NLSY earns wages 8.8 percent highe than a similar untrained worker, while the mean trained worker in the WC earns wages that are 3.9 percent higher than a similar untrained worker, condi tional on starting pay.

Random Effects Estimates of Wage Growth

Using the WCP samples described in table 13.2, we test for the presence o employer-specific effects in equation (2) and reject the null hypothesis that th variance of η_j equals zero. We then test the hypothesis that η_j is uncorrelate with the independent variables in our model using a Hausman specificatio test. In each WCP data set we fail to reject the null hypothesis of zero correla tion. In other words, we find evidence of significant differences across employ ers in their average rates of wage growth, but these differences appear to b uncorrelated with observable worker characteristics. Therefore, we report ran-

13. Human capital models make few sharp predictions about the shape of wage profiles fo trained workers relative to untrained workers. The "predictions" we outline here are conditiona on the linear quadratic log(wage)-tenure relationship specified in eq. (2).

Table 13.8 OLS Wage Regressions: Full-Time White-Collar Workers under Age 33

Variable	WCP (1)		NLSY (2)	
Tenure	.5236**	(.1137)	.6057**	(.0655)
Tenure squared	−.0009	(.0016)	−.0118**	(.0018)
Log starting wage	.9590**	(.0663)	.5436**	(.0362)
(Log starting wage)*Tenure	−.0921**	(.0185)	−.0667**	(.0068)
Female	−.0350	(.0382)	.0150	(.0386)
Female*Tenure	.0005	(.0105)	−.0377**	(.0108)
Education	−.0085	(.0134)	.0564**	(.0090)
Education*Tenure	.0125**	(.0037)	.0036	(.0025)
Black	−.0300	(.0747)	−.0341	(.0500)
Black*Tenure	−.0158	(.0242)	−.0247*	(.0134)
Train	.0394*	(.0222)	.0880**	(.0241)
Industry				
Durable goods	.0322	(.0534)	.0560	(.0782)
Trade and finance	−.0004	(.0756)	−.0102	(.0744)
Services	.1500**	(.0712)	−.0398	(.0669)
Mining and construction	−.0090	(.0873)	.0793	(.1342)
MSA size				
Below 1 million	.0075	(.0556)	.0191	(.0504)
1–5 million	−.0311	(.0642)	.0635	(.0514)
Above 5 million	−.0503	(.0708)	.1444**	(.0619)
Region				
Midwest	−.1272**	(.0482)	−.0999*	(.0559)
South	−.0269	(.0473)	−.0406	(.0577)
West	−.0415	(.0673)	−.0484	(.0586)
Establishment size				
500–1,000 employees	.0739	(.0543)	.1134**	(.0586)
Over 1,000 employees	.0704	(.0427)	.0972**	(.0440)
Tenure*Industry				
Durable goods	−.0030	(.0151)	−.0165	(.0189)
Trade and finance	.0208	(.0198)	−.0304*	(.0179)
Services	−.0378*	(.0215)	−.0132	(.0156)
Mining and construction	.0247	(.0320)	−.0167	(.0348)
Tenure*MSA size				
Below 1 million	.0159	(.0169)	.0126	(.0121)
1–5 million	.0470**	(.0195)	.0230**	(.0121)
Above 5 million	.0549**	(.0216)	.0143	(.0157)
Tenure*Region				
Midwest	.0316**	(.0138)	.0108	(.0133)
South	.0122	(.0136)	−.0043	(.0136)
West	.0076	(.0189)	.0095	(.0155)
Tenure*Establishment size				
500–1,000 employees	−.0155	(.0164)	−.0123	(.0150)
Over 1,000 employees	−.0209	(.0128)	−.0047	(.0102)
Constant	.4198	(.3923)	2.3985**	(.2712)
Sample size	224		779	
R^2	.9046		.6289	

Notes: The omitted category is a nondurable-goods-manufacturing firm located in the Northeast outside of a metropolitan statistical area with less than 500 employees. Numbers in parentheses are standard errors.

*Significant at the 10 percent level.

dom effects estimates of equation (2) in table 13.9. Column (1) reports results for the 601 workers with reported starting wages, and column (2) reports results for the entire sample of 1,234 workers using imputed starting wages.[14]

The results in table 13.9 indicate that an additional year of tenure, holding constant starting wages, is associated with 4.3 percent higher current wages in column (1) and 3.5 percent higher current wages in column (2), evaluated at sample means. This difference in mean returns to tenure across samples is primarily due to the quadratic relationship between wages and tenure and the fact that the mean worker with nonmissing starting pay has about two years less tenure than the average worker with missing starting pay. The coefficient on the tenure–starting wage interaction is significantly negative, suggesting that wages exhibit moderate regression toward the mean over time.

Our estimates of α_1 and α_2 in table 13.9 are consistent with the predictions of the human capital model: low-starting-wage workers have the highest wage growth and therefore the highest returns to training. This result holds whether we use predicted or actual starting wages. We also find that wage growth is statistically significantly higher for whites, males, more educated workers, workers in trade and finance industries, and workers in the western region of the United States. Holding constant workers' starting wages in column (1), current wages are 7.9 percent lower for women, 6.8 percent lower for blacks, and 2.7 percent higher for workers with an additional year of education, evaluated at sample means. The race, gender, and education wage differentials in column (2) are similar in magnitude.

Table 13.10 presents estimates of average training effects for workers at the 10th, 50th, and the 90th percentiles of the starting wage distribution, evaluated at mean tenure. Female workers who received company training and earned low starting wages earn 5.5 to 10.2 percent higher wages than similar untrained workers in our samples. Trained female workers with the median starting wage receive 3.3 to 7.1 percent significantly higher current wages than similar untrained female workers. The current pay of trained female workers with high starting wages is insignificantly higher than the current wages of similar untrained female workers. The evidence of training effects for males is somewhat weaker; trained male workers with low starting wages currently earn 3.5 to 6.3 percent significantly higher wages than similar untrained male workers. The training effects for male workers with median and high starting wages are insignificantly different from zero in both samples.[15]

The evidence in table 13.10 suggests that employer-provided training has a

14. The specification differs from that in the previous section because it includes tenure squared, which is insignificant in eq. (1), and excludes the starting wage–education interaction, which is insignificant in eq. (2). Including tenure squared in eq. (1) or the starting wage–education interaction in eq. (2) does not substantially affect either set of results.

15. Note that we find larger and more significant effects for women than for men for the simple reason that women's average starting wage is lower than men's (there is no female–tenure–starting wage interaction in the regression). Thus, e.g., we would find a similar pattern for less educated compared to highly educated workers.

Table 13.9 Random Effects Wage Regressions

Variable	Actual Starting Wage Sample (1)		Predicted Starting Wage Sample (2)	
Tenure	.2413**	(.0274)	.1389**	(.0406)
Tenure squared	−.0011**	(.0002)	−.0009**	(.0001)
Log (starting wage)	.8413**	(.0341)	.6100**	(.0657)
(Log starting wage)*Tenure	−.0272**	(.0037)	−.0135**	(.0063)
Female	−.0054	(.0260)	−.0336	(.0302)
Female*Tenure	−.0126**	(.0033)	−.0079**	(.0028)
Education	.0196**	(.0070)	.0501**	(.0091)
Education*Tenure	.0011	(.0008)	.0002	(.0008)
Black	−.0219	(.0428)	−.0244	(.0475)
Black*Tenure	−.0068	(.0049)	−.0056	(.0046)
Train	.0373	(.0268)	.0528*	(.0278)
Train*Tenure	.0609*	(.0325)	.1104**	(.0332)
Train*Tenure*Log starting wage	−.0085*	(.0044)	−.0150**	(.0045)
Industry				
Durable goods	.0212	(.0309)	−.0168	(.0362)
Trade and finance	−.0140	(.0546)	−.0355	(.0675)
Services	.0467	(.0420)	−.0843*	(.0507)
Mining and construction	−.0039	(.0522)	−.0003	(.0575)
MSA size				
Below 1 million	.0174	(.0371)	.0739*	(.0424)
1–5 million	.0023	(.0395)	.1190**	(.0426)
Above 5 million	−.0053	(.0446)	.2065**	(.0519)
Region				
Midwest	−.0554*	(.0316)	−.0659*	(.0398)
South	−.0334	(.0329)	−.0247	(.0408)
West	−.0563	(.0413)	−.0555	(.0489)
Establishment size				
500–1,000 employees	−.0059	(.0349)	−.0098	(.0418)
Over 1,000 employees	−.0086	(.0276)	.0380	(.0339)
Tenure*Industry				
Durable goods	−.0099**	(.0035)	.0005	(.0028)
Trade and finance	.0162**	(.0069)	.0114**	(.0049)
Services	−.0111*	(.0058)	.0011	(.0051)
Mining and construction	−.0074	(.0055)	.0041	(.0038)
Tenure*MSA size				
Below 1 million	.0174	(.0371)	.0031	(.0032)
1–5 million	.0023	(.0395)	.0060*	(.0031)
Above 5 million	−.0053	(.0446)	−.0021	(.0041)
Tenure*Region				
Midwest	.0012	(.0037)	.0009	(.0029)
South	.0004	(.0039)	.0011	(.0032)
West	.0148	(.0056)	.0058	(.0047)
Tenure*Establishment size				
500–1,000 employees	−.0048	(.0043)	.0006	(.0032)
Over 1,000 employees	.0012	(.0031)	.0026	(.0025)
Constant	−.9032**	(.2217)	2.1627**	(.4074)
Sample size	601	1,234		

Notes: The omitted category is a nondurable-goods-manufacturing firm located in the Northeast outside of a metropolitan statistical area with less than 500 employees. Numbers in parentheses are standard errors.

Table 13.10 Predicted Wage Growth of Trained Workers by Starting Wage Group

	Actual Starting Wage Sample		Predicted Starting Wage Sample	
Starting Wage	Female	Male	Female	Male
Low (10th percentile)	.1018**	.0629**	.0545**	.0354*
	(.0270)	(.0221)	(.0250)	(.0209)
Median (50th percentile)	.0710**	.0094	.0331*	.0018
	(.0224)	(.0235)	(.0195)	(.0581)
High (90th percentile)	.0327	−.0464	.0064	−.0322
	(.0220)	(.0345)	(.0201)	(.0325)

Note: Numbers in parentheses are standard errors.
*Significant at the 10 percent level.
**Significant at the 5 percent level.

significant effect on wage growth for workers with relatively low starting wages. This effect is much less significant among workers with median to high starting wages. These results are consistent with human capital models that predict that workers receive returns to investments in training (experience more rapid wage growth) if they pay for the training through a lower starting wage. Workers who earned a relatively high starting wage and received training did not experience more rapid wage growth than untrained workers with relatively high starting wages in our sample. These differences may be due to differences in the specificity, duration, or intensity of training across workers with high and low starting wages.

13.5 Matching WCP Data with Firm Characteristics from Compustat and CRSP

One of the main contributions of this paper is to examine the relationship between company training and firm characteristics in greater detail than previous studies. In order to accomplish this, we matched establishments in our larger WCP sample to their publicly traded parent corporations in the Compustat database, which includes all firms traded on the New York Stock Exchange (NYSE), American Stock Exchange (AMSE), and NASDAQ exchange. (The Compustat data are compiled by Standard and Poor's from a firm's annual reports, financial statements, and 10K reports.) Many establishments in the WCP survey are not owned by these large publicly traded corporations, but there are 84 establishments owned by 69 different corporations that report valid current wage, demographic, and training data for 471 of their workers. We use this subsample of the WCP in our analysis of training and firm-specific characteristics. The Compustat database reports a firm's market value of equity, the value of its physical capital stock (plant and equipment) net of depreciation, R&D

expenditures, annual sales, and employment, in addition to a number of other financial variables. We were also able to match 61 firms and 420 workers to Center for Research in Security Prices (CRSP) data. CRSP data provide monthly (NYSE) or daily (AMSE and NASDAQ) stock market data for each of these firms. We determine each firm's annual stock market return in the year prior to the WCP survey.

The four firm characteristics that we use in our analysis are firm size (the logarithm of a firm's market value of equity), capital intensity (the logarithm of a firm's capital/labor ratio), R&D intensity (R&D/sales ratio),[16] and firm profitability (the firm's return on equity in the year prior to the WCP survey). Table 13.11 reports firm averages of the key variables in our analysis, and the number of corporations for which each variable is reported. Note that some variables, especially R&D, are not reported by some publicly traded corporations. Given our small sample sizes, we do not exclude these firms from our analysis. Instead, we replace all missing values with zeros and include a set of four "missing" dummy variables in our wage and training models. Each missing dummy variable equals one if the corresponding firm characteristic is not reported, and zero otherwise. As a result, we use all 69 firms and 471 workers throughout our analysis.

Table 13.11 presents means and standard deviations of worker characteristics for this subsample. Given our relatively small sample size we only report results for our sample of workers with imputed starting wages.[17] Note that the workers in the Compustat sample have 9.5 percent higher current wages, have 1.4 more years of tenure, and are less likely to be female than in our previous sample of workers with imputed starting wages. Employees in these large publicly traded firms are more likely to be employed in establishments in the South, more likely to have more than 1,000 employees, less likely to be in an MSA, and less likely to be in a service industry.

13.5.1 The Incidence of Training and Firm Characteristics

In estimating the probability of training in equation (1), we use the same explanatory variables as in table 13.6, with two exceptions. First, we measure employer size as the logarithm of a firm's market value of equity and exclude establishment size dummy variables from the regression. We also include the logarithm of a firm's capital/labor ratio, the ratio of a firm's R&D expenditures to its annual sales, and the firm's annual real stock market return (adjusted for dividends) in the previous year as employer characteristics, Z_j.

We find no evidence that worker characteristics are significantly related to the incidence of training across workers: we fail to reject the null hypothesis

16. All the Compustat variables we use in the analysis are real dollar averages compiled over the five-year period preceding the WCP survey. We do not use the logarithm of R&D as an explanatory variable, because R&D is zero for a number of firms, and instead consider the ratio of R&D to annual sales.

17. Of the 471 workers in Compustat firms, we have reported starting wages for 220 workers.

Table 13.11 Sample Statistics for Publicly Traded Firms and Their Employees

Variable	Observations	Mean (Standard Deviation	
I. Means by 69 Firms			
Capital stock (billion $)	69	1,807.9	(6.070.7)
Capital/labor (thousand $ per worker)	66	53.48	(102.96)
Log (capital/labor)	66	3.177	(1.13
Market value	67	2,635.8	(7,380.0)
Log (market value)	67	6.373	(1.89
Sales	69	4,551.6	(9,962.0)
R&D	45	125.12	(218.93)
R&D/sales	45	.0225	(.02
Real annual return, previous year	61	.0102	9.36
II. Means by 471 Workers			
Real monthly wage	471	2,822.85	(1,240.65)
Log (real wage)	471	7.8496	(.44
Predicted log start wage	471	7.5551	(.36
Tenure	471	9.5881	(8.22
Train	471	.3376	(.47
Education	471	14.5074	(2.14
Starting potential experience	471	8.9130	(8.34
Female	471	.4331	(.49
Black	471	.0552	(.22
Nondurable goods	471	.2696	(.44
Durable goods	471	.5520	(.49
Trade and finance	471	.0318	(.17
Services	471	.0149	(.12
Mining and construction	471	.1316	(.33
Not an MSA	471	.2994	(.45
Below 1 million	471	.2803	(.44
1–5 million	471	.3142	(.46
Above 5 million	471	.0162	(.30
Northeast	471	.1592	(.36
Midwest	471	.2760	(.44
South	471	.4713	(.49
West	471	.0934	(.29

that the coefficients on X_{ij}, $X_{ij}T_{ij}$, and Z_jT_{ij} are all equal to zero.[18] It is surprisi that we do not find a significant effect of years of tenure on the probability training. Employer characteristics are significantly related to the incidence training, but these regressors vary only across employers and not worke Therefore, we present estimates of equation (1) that rely only on firm avera data, where our dependent variable is the fraction of workers trained in t company.

18. We find similar coefficient estimates on worker characteristics in this smaller Compu sample when using the same Z_j vector as in table 13.3. The finding that coefficients on start wage, education, the starting wage–education interaction, and tenure are insignificant is attrit able to the smaller sample size and the inclusion of a firm's market value of equity, log capi labor ratio, R&D/sales ratio, and stock return in the Z_j vector.

Table 13.12 Training Incidence: Linear Probability Model Results across 69 Firms

Variable	Coefficient (1)	Coefficient (2)
Log (market value)		.0844**
		(.0382)
R&D/sales		−7.4675**
		(2.7944)
Log capital/labor		.0637
		(.0638)
Stock return		−.2264
		(.1713)
Industry		
Durable goods	−.1481	−.0674
	(.1122)	(.1157)
Trade and finance	−.4341	−.4051
	(.2956)	(.9085)
Services	.2249	.2235
	(.3897)	(.3637)
Mining and construction	.0481	−.2385
	(.1501)	(.1713)
MSA size		
Below 1 million	.5201**	.4302**
	(.1137)	(.1212)
1–5 million	.2515*	.2620
	(.1398)	(.1545)
Above 5 million	.2692	.0873
	(.1776)	(.1742)
Region		
Midwest	.1885	.0771
	(.1567)	(.1779)
South	−.1584	.4061**
	(.1514)	(.1217)
West	.0362	.3090
	(.1842)	(.1725)
Constant	.1494	.2281
	(.1650)	(.2565)

Notes: The omitted category is a nondurable-goods-manufacturing firm located in the Northeast outside of a metropolitan statistical area. We also include dummy variables in the model for missing R&D, capital/labor ratio, market value, and stock market return data. Numbers in parentheses are standard errors.

*Significant at the 10 percent level.

**Significant at the 5 percent level.

Column (1) of table 13.12 presents the results of a regression model weighted by the number of workers per firm including only industry, MSA size, and region dummy variables as explanatory variables. Column (2) includes these variables as well as the firm size, capital intensity, R&D intensity, and stock return variables calculated from Compustat and CRSP. We find that larger firms train a greater fraction of their workers. A 10 percent increase in the market value of equity, evaluated at sample means, increases the fraction of workers trained in a firm by 0.844 percentage points. Conditional on firm size, firms with higher R&D/sales ratios train a significantly smaller fraction of their workers. A 10 percent increase in the ratio of R&D to sales, evaluated at sample means (i.e., an increase of 0.00239) is associated with a 1.78 percentage point decline in the fraction of workers trained by a firm. Finally, we find that a firm's capital/labor ratio is unrelated to its likelihood of providing employee training.

Our empirical results that capital intensity and R&D intensity are not positively related to the incidence of formal training contrasts with the well-known empirical result that capital and skilled labor tend to be complements in production. Our results suggest that even though capital-intensive and R&D-intensive firms may employ more highly skilled labor, their workers are more likely to have obtained these skills in school, through previous employers, or through informal on-the-job training. Our results suggest that the costs of offering formal training programs are relatively lower in large corporations but appear relatively higher in companies that make large investments in R&D.

13.5.2 Wages, Training, and Firm Characteristics

We now consider the relationship between wage growth, training, and firm characteristics. We estimate equation (2) using ordinary least squares and cannot reject the null hypothesis of zero within-employer correlation in the error term u_{ij}. We therefore present OLS estimates of equation (2) in table 13.13. In table 13.9 above, we found strong evidence of an employer-specific component of the error term in equation (2). Much of the across-employer variation in wage growth appears to be accounted for by the inclusion of the capital intensity, stock market return, R&D intensity, and market value variables in the regression.

There have been few empirical studies of individual worker pay and firm profitability, capital intensity, and R&D intensity, other than studies of CEO and top executive pay (Troske 1993) is one of the few empirical studies that analyzes the relationship between individual worker pay and a plant's capital stock). Therefore, in column (1) of table 13.13 we present a standard wage regression that includes these firm characteristics but excludes training and starting wage variables. We find that capital intensity is much more important than firm size in explaining wage variation across employers.[19] A 10 percent increase in the capital/labor ratio is associated with 1.07 percent higher wages. Wages are also significantly higher in firms that spend relatively more on R&D; a 10 percent increase in the ratio of R&D to sales is associated with a

19. Troske (1993; chap. 11 in this volume) finds a similar result for wages and an establishment's capital stock. Conditional on capital intensity wages are insignificantly related to firm size measured by market value, employment, or sales.

Table 13.13 OLS Log Wage Regression: Workers in Publicly Traded Firms

Variable	Adding Compustat and CRSP to Standard OLS Wage Regression (1)		Wage Regression with CRSP, Compustat, and Starting Pay (2)	
Tenure	.0672**	(.0150)	.1740**	(.0857)
Tenure squared	−.0006**	(.0002)	−.0006**	(.0002)
Female	−.1141**	(.0416)	.0440	(.0537)
Female*Tenure	−.0046**	(.0036)	−.0114**	(.0047)
Black	−.0176	(.0932)	.0195	(.0923)
Black*Tenure	−.0047	(.0076)	−.0054	(.0076)
Education	.1273**	(.0100)	.0439**	(.0215)
Education*Tenure	−.0025**	(.0008)	−.0011	(.0018)
R&D/sales	1.6851**	(.7284)	1.0176	(.8244)
Log capital/labor	.1072**	(.0183)	.1014**	(.0244)
Log market value	.0103	(.0098)	−.0026	(.0119)
Stock return	.1144**	(.0475)	.1684**	(.0562)
Predicted starting wage			.6575**	(.1537)
Tenure*Log predicted starting wage			−.0208	(.0144)
Train			−.2940	(.1937)
Train*Tenure			.1271**	(.0488)
Train*(Log predicted starting wage) *Tenure			−.0168**	(.0065)
(Log capital/labor)*Train			.0722*	(.0413)
(R&D/sales)*Train			6.2008**	(2.7026)
(Log market value)*Train			−.0062	(.0025)
(Stock return)*Train			−.1377	(.1142)
Constant	5.3865**	(.1638)	1.7622**	(.9027)
R^2	.6991		.7248	

Notes: We also include dummy variables for SIC industry, region, and whether in an MSA, and these dummy variables interacted with tenure. We include dummy variables for missing R&D, capital/labor ratio, market value, and stock return data, and interactions between these four variables and Train. Numbers in parentheses are standard errors.

*Significant at the 10 percent level.

**Significant at the 5 percent level.

0.40 percent increase in wages. These empirical results suggest that capital-intensive and R&D-intensive firms employ workers with greater unobserved labor market skills, ceteris paribus. Thus our regression results support the hypothesis that skilled labor and capital, and skilled labor and R&D, are complements in production. Finally, note that a 10 percent increase in a firm's stock market return is associated with 1.14 percent higher wages.

In column (2) of table 13.13 we present estimates of the wage growth model in equation (2). We allow the returns to training to vary across companies by interacting training with capital intensity, stock market return, R&D intensity, and log market value. The average trained worker in our sample has 5.7 percent higher wages than the average untrained worker, though this difference is not

statistically significant. As in table 13.7, we find a significant training effect for workers with relatively low starting wages.

The results in table 13.13 indicate that wage growth for trained workers is significantly higher in more capital-intensive and R&D-intensive firms. A 10 percent increase in the ratio of R&D to sales significantly increases the return to training by 1.48 percentage points. A 10 percent increase in the capital/labor ratio raises the return to training by 0.72 percentage points. Given the large variation in log capital/labor and R&D/sales in our sample, it appears that much of the variation in returns to training across workers is attributable to differences in firms' investments in capital equipment and R&D.[20]

The combined results of tables 13.12 and 13.13 indicate that (i) large employers are significantly more likely to provide training to their workers, (ii) conditional on firm size, a firm's capital/labor ratio is unrelated to its propensity to provide formal training to its workers, (iii) conditional on firm size, R&D-intensive firms are significantly less likely to provide formal training to their workers, (iv) both R&D- and capital-intensive firms employ relatively more skilled workers, and (v) when training is provided by capital- and R&D-intensive firms, their trained workers exhibit significantly faster wage growth than similar untrained workers. These results suggest that skilled labor is complementary to capital and R&D but R&D- and capital-intensive firms face higher costs of providing these skills through formal training programs.

13.6 Conclusions

In this paper we use a unique microdata set of white-collar workers that (i) has multiple observations per employer and (ii) allows us to match workers to their publicly traded employers in the CRSP and Compustat databases. Our data set is representative of the population of white-collar workers in manufacturing, based on CPS and NLSY samples, but overrepresents highly educated, high-wage, male workers outside of manufacturing. Patterns in the incidence and duration of training programs between young workers in our sample and white-collar workers in the NLSY are remarkably similar. There appears to be substantially less measurement error in wages in our sample than in either the NLSY or the CPS. The human capital and demographic variables used in standard wage regressions account for a much higher fraction of the variation in establishment-reported wages than household-reported wages for similar workers. Thus our empirical results suggest that matched worker-employer data sets based on BLS establishment surveys, such as the one analyzed here, can provide useful information about labor market behavior.

Company-provided formal training has a substantial employer-specific com-

20. E.g., a one standard deviation increase in R&D/sales results in a 14.3 percentage point increase in the return to training. A one standard deviation increase in log capital/labor results in an 8.2 percentage point increase in the effect of training on wage growth.

ponent: most firms trained either all or none of their white-collar workers in our sample. We consistently find that college graduates with low starting wages and high school graduates with high starting wages are the most likely to receive employer-provided training. This suggests that employee training programs complement formal schooling for college graduates with little work experience but substitute for formal schooling for workers with substantial experience and high school diplomas.

We find significant returns to training, but these returns are somewhat smaller for young workers in the WCP than for similar white-collar workers in the NLSY. Low-starting-wage workers receive the highest returns to training, earning 3.5 to 10.2 percent higher current pay than untrained workers with the same starting pay. These results confirm the implication of human capital models. Workers who pay a greater share of their training costs through lower starting wages experience faster wage growth.

In our subsample of workers in publicly traded firms, employer-provided training occurs significantly more frequently in large companies. Conditional on firm size, training programs occur relatively more often in firms that invest less in R&D, but the propensity for training is unrelated to capital intensity (conditional on firm size). We find strong evidence that the returns to training are higher in companies that invest in either R&D or capital equipment. In conclusion, our empirical results provide mixed evidence on the complementarity between training and investment in either R&D or capital equipment. Although the returns to training appear highest in companies that make investments in R&D or capital equipment, the incidence of training is somewhat lower in R&D-intensive companies. Higher returns to employer-provided training in large, capital-intensive, and R&D-intensive firms may occur for several reasons: (i) the typical duration of training programs in these firms may exceed the mean duration in other firms, (ii) the content, intensity, and opportunity cost of training programs may differ across firms, and (iii) unobserved skill differences across trained and untrained workers may vary across firms and be related to firm size and capital intensity. Additional empirical work, using matched worker and employer data, can aid in distinguishing between these competing hypotheses for interfirm differences in the returns to training.

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