Do Workers Pay for On-the-Job Training?

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ABSTRACT

We examine the relationships among on-the-job training, starting wages, wage growth, and productivity growth. Our models suggest that training lowers starting wages, but the estimated magnitudes are small. When firms are asked directly, we find that they pay higher starting wages to workers requiring less training than is typical, but do not pay lower starting wages to workers who require more training than is typical. In contrast to the results for wage growth, we find a large, robust impact of training on productivity growth, suggesting that firms pay most of the cost and reap most of the returns to training.

I. Introduction

Since the seminal work of Becker (1962, 1964) and Mincer (1962, 1974), economists have recognized that investment in human capital while on the job may be a major determinant of wages. There have been numerous empirical and theoretical studies of on-the-job training. The early empirical work, however, suf-

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fered from a severe shortcoming. Data sets usually did not include direct measures of on-the-job training, so researchers had to rely on proxies to measure job training. Fortunately, in the last 15 years or so, numerous data sets have become available that contain better measures of on-the-job training.

The various theories of on-the-job training contain two common predictions: first, on-the-job training should increase wage growth, and second, on-the-job training should lower the starting wage. When training is general, the worker pays the full training costs by accepting a lower starting wage and receives higher future wages in return. When the training is specific to the firm, the worker and firm share the costs and the returns to training. Numerous papers using a variety of data sources have confirmed the prediction that training and wage growth are positively correlated.[1]

Although there is widespread support for the prediction that on-the-job training increases wage growth, the evidence is less clear when examining the impact of training on the starting wage. For instance, Barron, Black, and Loewenstein (1989), using the Employment Opportunity Pilot Program (EOPP) data set, find no statistically significant relationship between training and the starting wage. Bishop (1988) and Holzer (1990) also report similar results using the EOPP. Parsons (1989), using the National Longitudinal Survey Youth (NLSY) cohort, finds a positive relationship between starting wages and training, although the relationship is generally not statistically significant. Lynch (1992), using a sample of noncollege graduates from the NLSY data, reports that for the sample as a whole, uncompleted spells of training are positively associated with current wages, although there are some differences by education level.[2]

The lack of a negative correlation between the starting wage and on-the-job training represents a serious challenge to standard on-the-job training theory. Barron, Black, and Loewenstein (1989) argue that unobservable ability differences may explain the lack of a negative correlation between the starting wage and on-the-job training if "better" workers are matched to jobs that offer more human capital.[3] It may also be possible that workers do not pay for training immediately through a reduction in their wage but rather pay for it later in their careers.

This paper examines these issues using a new data set, a 1992 survey of firms funded by the Small Business Administration (SBA), that was based on the survey methodology of the EOPP. Given the similarities of the two data sets, where possible we present results from both the EOPP and the SBA data. An important feature of these two data sets, unlike others such as the NLSY, is that they contain rich measures of on-the-job training for newly hired workers.[4] In the next section of the paper, we

1. Studies finding that training is positively associated with wage growth include Altonji and Spletzer (1991); Barron, Black, and Loewenstein (1989, 1993); Booth (1993); Brown (1989); Lillard and Tan (1992); Levine (1993); Lynch (1992); and Parsons (1989). See Brown (1991) and Parsons (1986, 1990) for extensive reviews of the literature.

2. For workers with less than a high school education, uncompleted spells of training are negatively associated with current wages. For those with a high school degree or a college degree, there is a positive correlation between uncompleted spells of training and the current wage.

3. Kuhn (1993) also offers a theoretical model in which specific training may increase the starting wage.

4. The NLSY data that Lynch (1992) uses reports an incidence of only 4.2 percent for formal training spells that last over a month. Evidence from the EOPP survey, however, suggests that this substantially understates on-the-job training; Barron, Black, and Loewenstein (1987) report that 87 percent of all newly

briefly describe the data and provide some summary statistics. In Section III we present our major empirical findings, and in Section IV we offer some concluding remarks.

II. The Data

To test the predictions of human capital theory, we employ two data sets: the EOPP follow-up employer survey of 1982 and a 1992 survey of employers financed by the SBA.

A. The 1982 EOPP Survey

In 1980, the Department of Labor funded an extensive survey of employers to study the labor market effects of the EOPP. This 1980 EOPP survey interviewed employers at 23 sites across the country. Approximately 5,700 employers were involved in the original survey. In 1982, the follow-up survey successfully contacted about 70 percent of the original respondents. The 1982 EOPP data set provides more detailed information on the training activities of the most recently hired new employee than did the 1980 EOPP survey.

B. The 1992 SBA Survey

In 1992, the SBA funded a survey to examine training at large and small firms. Survey Sampling, Inc., of Fairfield, Conn., constructed the sample of businesses for this survey. Survey Sampling drew a stratified random sample of 3,600 businesses from the Comprehensive Business Database, oversampling large establishments to ensure statistically meaningful comparisons between large and small firms.[5] At the University of Kentucky, we designed the survey and the Survey Research Center (SRC) conducted the interviews in the summer of 1992. A letter was first sent to each business describing the survey. SRC attempted to track down firms with undeliverable letters using directory assistance and attempted to contact each of the 3,600 businesses for a telephone interview. Of the original sample of 3,600 establishments, 2,561 were eligible to complete an interview. The 1,039 ineligible establishments

hired workers received some amount of informal training provided by their manager. The NLSY data set is also less suited for examining the impact of training on starting wages because it samples the entire population of workers rather than just newly hired workers. More recent surveys in the NLSY include spells of formal training that are less than a month long. In addition, the most recent survey of the NLSY contains a measure of informal training, although Loewenstein and Spletzer (1994) suggest that this measure misses a significant amount of informal training. Using these more recent measures in the NLSY, Loewenstein and Spletzer (1996) find a training incidence rate of 9.9 percent in the first year of job tenure.

5. The sample was stratified by establishment size in the following manner: 1,250 businesses with 0–19 employees, 1,250 businesses with 20–99 employees, 550 businesses with 100–499 employees, and 550 businesses with 500 or more employees. Agriculture, Forestry, and Fisheries (SIC 0-99) and Public Administration (SIC 900 and above) were excluded. Except for these exclusions, we sampled businesses randomly within each size stratum, providing a representative distribution by industry and region. Thus, for example, unlike the EOPP data set, the SBA data set does not oversample low-income workers nor is it targeted only at sites where new government programs are planned.

were out of business, had disconnected phones, did not answer in any of 15 attempts, could not be reached because of Hurricane Andrew, had other miscellaneous problems, or had no employees. We had 1,288 establishments complete the survey. The 1,273 noncompletions consisted of refusals, those who reported that answering surveys was against company policy, those who stated that the appropriate person was repeatedly unavailable, and those who rescheduled the interview six or more times.

To get a feeling for how the sample of completions represents the stratified initial sample, we estimated a probit equation with the dependent variable equal to one if the establishment was in the sample and zero otherwise. Independent variables included a set of one-digit industry dummies, a dummy variable indicating whether the establishment was located in a metropolitan statistical area, and a vector of establishment-size variables.[6] Establishments from SIC code 7—a portion of the service industry—(10.2 percent in sample versus 16.6 percent universe) and SIC code 5—retail trade—(30.8 percent versus 33.0 percent) are somewhat underrepresented in our sample. Similarly, there are too few establishments from the Northeast census region (13.7 percent versus 17.4 percent) and too few urban establishments (77.6 percent versus 85.1 percent). In addition, the probability of being in our sample monotonically increases with the size of the establishment.

C. Means of Training Measures

Both the SBA and EOPP data sets focused on the last worker hired (in the case of the SBA survey, the last permanent worker hired). The employer gave detailed retrospective information about the training this worker received in the first three months of employment. In addition, the surveys asked limited questions concerning firm characteristics, demographic characteristics of the workers hired, recruiting activity required to fill the position, and information about their earnings. In addition, we know the number of months of experience in "jobs that have some application to the position" that each worker had. We refer to this measure as the worker's "relevant experience." In this section and the next section, we limit our samples for both the EOPP and SBA surveys to those respondents that provided complete information on all of the variables of interest and who were hired within seven years of the interview, which gives us a working sample of 756 workers for the 1992 SBA survey and 1,323 for the 1982 EOPP survey.[7]

6. The breakdowns for firm size were 1–4 employees, 5–9 employees, 10–19 employees, 20–49 employees, 50–99 employees, 100–199 employees, 200–499 employees, and 500 or more employees.

7. For the SBA data, we arrive at our working sample of 756 from the original 1,288 in the following manner: 31 observations have missing data on the year of hire or were hired prior to 1985, 149 additional observations are missing data on wages, 124 additional observations are missing training data, another 131 observations are missing data on one or both of the worker heterogeneity measures, another 49 respondents failed to report relevant experience, and an additional 48 observations are missing one or more of the other variables in the model. In the 1982 EOPP survey, 2,274 respondents reported that a permanent employee was their last worker hired. (We exclude temporary and seasonal new hires to make the EOPP data more comparable to the SBA data.) Of these, 65 are missing year of hire or were hired prior to 1975, 137 additional observations are missing wage data, 257 additional observations are missing training data, another 301 observations are missing one or both of the worker heterogeneity measures, 78 additional respondents failed to report relevant experience, and another 113 observations are missing one or more of the other variables in the model, giving a working sample of 1,323.

In both data sets, the mean characteristics of the working samples are only slightly different than the mean characteristics of the full sample. The mean proportion of time spent training in the SBA working sample is .362 and is .364 in the full sample. In the EOPP working sample, .295 is the mean proportion of time spent training while .280 is the mean for the full sample. In the SBA data, the mean establishment size in the working sample is smaller (185 versus 234) while in the EOPP the working sample mean is slightly larger (72 versus 70). For most other characteristics the relationship between the working sample means and the full sample means is similar in the two data sets. The working samples have slightly lower wages (SBA: \$8.72 versus \$8.88; EOPP: \$7.71 versus \$7.84), have slightly less years of experience (SBA: 3.36 versus 3.69; EOPP: 2.50 versus 2.81) and years of education (SBA: 13.45 versus 13.54; EOPP: 12.54 versus 12.58), are slightly younger (SBA: 29.27 versus 29.85 years; EOPP: 27.12 versus 28.02 years), and are less likely to be union members (SBA:.085 versus .106; EOPP: .095 versus .096) than are the full samples.

The SBA and EOPP surveys have four common measures of training: the time spent in formal training programs offered by the firm on site, the time spent in informal training by the worker's supervisor, the time spent in informal training by co-workers, and the time the worker spent watching others perform tasks during the first three months. Dividing these training measures by the total hours of employment during the first three months provides us with training measures in terms of the proportion of work-time devoted to each type of training. The SBA survey also contains a measure of the number of hours spent at off-site formal training programs during the first three months. This type of training was offered to only 10.3 percent of the workers. Its limited use and the fact that this measure of training is not available for the EOPP survey led us to treat off-site formal training as a separate training measure. Table 1 reports the magnitudes of the four common measures of training during the first three months for both the 1992 SBA survey and the 1982 EOPP survey.

Both surveys also asked a question similar to the Panel Survey of Income Dynamics measure of training:

> How many weeks does it take a new employee hired for (name's) type of position to become fully trained and qualified if he or she has no previous experience in this job, but has the necessary school-provided training?

Table 1 reports the mean answer to this question for each survey. Because the time it takes to become fully trained and qualified measures in part the difficulty of mastering the job, we refer to this measure as "job complexity."[8]

Panel A of Table 1 indicates remarkably similar responses to the training and job complexity questons across the EOPP and SBA surveys. For the EOPP measure, the median level of training in the first three months of employment is 16.3 percent of total work time. For the SBA measure, the median is 19.5 percent of total work time. Similarly, the measures of job complexity are quite similar. For the EOPP measure, the mean job complexity is 21.38 weeks with a median of 6.75 weeks,

8. Because workers differ in the length of work week, to make these measures comparable we calculate the time to become fully trained and qualified for a standard 40 hour work week using data on the worker's usual hours worked per week.

Table 1
Comparison of 1982 EOPP and 1992 SBA Training Measures

	EOPP		SBA	
Panel A	Proportion of Time in On-site Training[a] (1)	Job Complexity[b] (2)	Proportion of Time in On-site Training[a] (3)	Job Complexity[b] (4)
25th percentile	0.0625	2.4	0.085	2.5
Median	0.163	6.75	0.195	6.35
75th percentile	0.369	22.75	0.462	24.0
Mean	0.295	21.38	0.362	23.15
Standard deviation	0.387	41.5	0.512	49.0
N	1,323	1,323	756	756

Panel B	Mean Proportion of Time in On-Site Training EOPP[a] (1)	Training Incidence EOPP[c] (2)	Mean Proportion for Those Receiving Training EOPP[d] (3)	Mean Proportion of Time in On-Site Training SBA[a] (4)	Training Incidence SBA[c] (5)	Mean Proportion for Those Receiving Training SBA[d] (6)
Formal training	0.019	0.132	0.144	0.053	0.303	0.174
Informal management training	0.104	0.885	0.118	0.136	0.927	0.147
Informal coworker training	0.055	0.630	0.087	0.084	0.692	0.122
Watching others	0.117	0.818	0.143	0.088	0.693	0.127
Overall proportion/incidence	0.295	0.961	0.307	0.362	0.984	0.367

a. Proportion of work time spent in training during the first three months of employment.
b. Weeks until fully trained and qualified for the position, assuming no previous experience in the job, but having the necessary school-provided training.
c. Fraction reporting positive number of hours of each type of training.
d. Proportion of work time spent in each type of training for those receiving that type of training.

while for the SBA measure, the mean job complexity is 23.15 weeks with a median of 6.35 weeks. The second moments also appear similar, although the variances of training and job complexity are somewhat larger in the SBA data. Taken as a whole, these similarities in two surveys taken ten years apart are striking.

The use of a single measure of training does mask some differences between the EOPP data and the SBA data. In Panel B of Table 1, we look at the means and incidence rates of on-site formal training, informal management training, informal coworker training, and training by watching others from both data sets. The SBA data set has a greater incidence of on-site formal training and informal management training, while the EOPP data set has a greater incidence of informal coworker training and training by watching others. Among those receiving various types of training, workers in the SBA survey spent a greater fraction of work time receiving informal management and coworker training. In both data sets, over 96 percent of workers hired have some form of training.

III. The Impact of On-the-Job Training on the Starting Wage, Wage Growth, and Productivity Growth

A. *The Impact of Training on the Starting Wage*

To gauge the impact of on-the-job training on the starting wage, we specify a wage equation, augmented with measures of on-the-job training. Thus, let

$$\text{(1)} \quad \ln w = X\beta + T\gamma + \varepsilon,$$

where w is the wage rate, X is a vector of firm and worker characteristics, β is a vector of coefficients, T is a vector of on-the-job training measures with the corresponding vector of coefficients, and ε is an error term assumed to have the standard properties. For both the SBA and EOPP data sets, we use years of education, dummy variables to indicate a high school degree and a college degree, the logarithm of the size of the establishment, the logarithm of hours worked, a dummy variable indicating whether the worker is female, and a series of dummy variables representing one-digit industry and occupation categories.[9] In addition, we have a variable indicating the worker's union status. The union variable for the EOPP sample is the fraction of the establishment's workers who are union members. For the SBA sample, the union variable indicates the worker is a union member.

Both the SBA and EOPP data contain the relevant experience variable, which is a direct measure of this previously acquired on-the-job training. The exact wording of the question is: "How many months of experience in jobs that had some application to the position did (NAME) have before he/she started working for your company?" We convert this variable to years and refer to it as "relevant experience." While this is a measure of the relevant experience that workers have, they may also

9. The EOPP data set does not have a race variable, so to make the SBA and EOPP specifications as comparable as possible, we do not include race in the SBA regressions. However, the results for the SBA data are not affected by the inclusion of a race variable or race-gender interaction variables.

accumulate some general skills in jobs that are not relevant to their current employment. For such general experience, we have measures of the workers' ages to proxy for general experience. We therefore include relevant experience and its square and age and its square as controls well.

In Columns 1 and 4 of Table 2, we report the wage equation estimates for the SBA and EOPP data. There is a strong, concave relationship between wages and the relevant experience and between wages and age in both data sets. The first year of relevant experience increases starting wages about 4.2 percent in the SBA data and about 4.0 percent in the EOPP data.[10] Note, however, that only the EOPP estimated training effect is negative as predicted, and it is statistically insignificant. For the SBA data set, there are two training variables, the logarithm of the total proportion of work time spent in on-site training and the logarithm of the proportion of time spent in off-site formal training during the first three months of employment.[11] Earlier, we suggested a problem in estimating the negative effect of training on the starting wage arising from a matching of individuals with high ability to positions that require substantial training.[12] What we seek are variables that are correlated with such unobserved differences in worker ability. Two variables are used. First is the job complexity variable. We expect more-able individuals to match with positions with higher job complexity. In Columns 2 and 5 of Table 2, we add the measure of job complexity to the wage equation. With the inclusion of this control, the estimated parameter for the on-site training variables is now negative in both data sets, and for the EOPP sample the coefficient is just significant at the 5 percent confidence level.[13]

The second variable we introduce as a control for worker ability is derived from our analysis of employer search activities (see Barron, Berger, and Black, 1997). Employer search theory suggests that more-able workers will be hired by employers who spend more time screening each prospective job candidate. Columns 3 and 6 add the logarithm of the number of hours spent by the employer screening each job applicant for the position filled. We expect more-able individuals to be filling positions that involve a more intensive screening process. The results are encouraging. As we add this second "ability-control" variable, the predicted negative impact of

10. In results not reported here, we estimated similar equations using data from the Current Population Survey and 1990 census data. Using Mincer's (1962, 1974) potential experience as our measure of experience, we obtained somewhat smaller returns to experience.

11. Note that to avoid taking the logarithm of zero, we take the logarithm of the ratio of one plus total training hours during the first three months to total work hours during the first three months. We tested to see if we could combine the four measures of training; the F-statistic was 1.44 with a p-value of 0.23. In contrast, if we try to aggregate all five measures of training, the F-statistic is 7.01 with a p-value of 0.004.

12. Note that ability is interpreted broadly as any inherent worker characteristics that increase the value of the worker to the employer. For instance, higher-ability workers could be those who can produce more per hour, those who encourage coworkers to be more productive, or individuals who have a lower propensity to turnover.

13. Note that the estimated coefficient on the job complexity variable is about twice as large in the SBA results as in the EOPP results. One explanation for this is that the return to job complexity has been increasing over time, much like the return to formal education. Similarly, though not shown in the table, we find that the estimated coefficient on establishment size is higher in the SBA results than in the EOPP results. If large establishments hire unobservably better workers, there may be an increase in the return to such unobservable ability over time as well.

Table 2

Impact of Training on the Starting Wage, 1992 SBA and 1982 EOPP Data

	SBA			EOPP		
Independent Variables	(1)	(2)	(3)	(4)	(5)	(6)
Logarithm of proportion	0.0041	−0.011	−0.016	−0.0034	−0.012	−0.018
	(0.412)	(1.08)	(1.60)	(0.596)	(2.10)	(3.08)
Logarithm of proportion of time, off-site training	0.024	0.018	0.016	—	—	—
	(2.04)	(1.57)	(1.40)			
Logarithm of job complexity	—	0.068	0.064	—	0.037	0.035
		(5.61)	(5.33)		(5.07)	(4.84)
Log of hours spent per applicant interview	—	—	0.050	—	—	0.057
			(3.68)			(5.96)
Worker's relevant experience/10	0.429	0.392	0.386	0.412	0.396	0.376
	(6.73)	(6.25)	(6.21)	(9.57)	(9.24)	(8.85)
Worker's relevant experience squared/100	−0.084	−0.078	−0.078	−0.098	−0.095	−0.090
	(3.21)	(3.06)	(3.06)	(5.86)	(5.75)	(5.53)
Adjusted R^2	0.543	0.562	0.569	0.505	0.514	0.527
N	756	756	756	1,323	1,323	1,323

Note: The dependent variable in all regressions is the natural logarithm of the hourly wage. All regressions include the worker's age and age squared, gender, the number of years of schooling, dummy variables for high school and college degrees, the logarithm of the establishment size, the log of hours worked, a series of one-digit industry and occupation dummy variables, and a union variable. The union variable for the EOPP sample is the fraction of the establishment's workers who were union members. For the SBA sample, the union variable indicates the worker was a union member. Absolute values of t-statistics are given in the parentheses.

training on the starting wage becomes increasingly apparent. Now, the SBA estimated coefficient approaches significance at the 10 percent level and the EOPP estimated coefficient is significant at the 1 percent level.

We can draw three major conclusions from the estimated starting wage equations. First, contrary to the predictions of the human capital model, the coefficient estimates for off-site training (SBA data) are generally positive and statistically significant. Second, the coefficient estimates for on-site training in both the SBA and EOPP data sets do not offer robust support for the negative impact of training on the starting wage that is predicted by the standard human capital model. Even when the coefficient estimates are negative and statistically significant, their magnitudes are small; the largest elasticity we estimated reported in Table 2 is only −0.018. Finally, the inclusion of the job complexity and recruiting intensity variables increases any negative impact of training on the starting wage. To us, this last result suggests that cross-sectional estimates of the impact of training on starting wages may be biased because of a positive covariance between unobserved ability and on-the-job training.[14]

B. *Training Relative to the Typical Worker*

The evidence we presented in the last subsection, consistent with the findings of past research, suggests that there is little evidence in cross-sectional studies to support the basic human capital model. As noted above, Barron, Black, and Loewenstein (1989) suggest that unobservable ability differences could explain the lack of a negative correlation between the starting wage and on-the-job training if "better" workers are matched to jobs that offer more human capital. Because even well-specified wage equations explain only about half, or less, of the variation in wages, there is certainly a large role for unobservable factors to affect wages. When confronted with the potential for such unobservable differences, two strategies can be adopted. First, with panel data on individual workers, one could estimate fixed-effect models to control for heterogeneity across individuals, which is the approach of Loewenstein and Spletzer (1996). This approach ignores variation in (mean) training across individuals and identifies the impact of training on wages by the variation in training over time that individuals experience.[15] Second, one could estimate a "fixed-effect model" by looking at fluctuations in the training across workers for a given position, which is the approach we take in the next two subsections. This approach ignores (mean) variation in training across positions and identifies the impact of training on the starting wage by variations in training offered to workers within the position.

To assess how typical was the training experience of the last worker hired, respondents were asked whether the worker had received more, less, or the same level of training as the worker typically hired into this position. They were asked whether

14. Another explanation for the lack of a negative correlation between starting wages and training is contained in Mincer (1993). He finds that the wage gain in moving to a firm is smaller for trainees than for nontrainees, suggesting a higher previous wage for those selected into current training. We are unable to test this proposition directly because we do not observe the wage on the previous job. However, we do observe previous relevant experience and have included it in our estimated starting wage equations.
15. This requires that the heterogeneity across individuals be time invariant. This may be violated. For instance, if some individuals "mature" as they age, and if firms perceive this maturation, the time-varying heterogeneity may still be correlated with training.

Table 3
Training and Starting Wage, 1992 SBA Data

Panel A	More Training Than Typical	Same Training as Typical Worker	Less Training Than Typical
Higher wage than typical (N = 221)	12.2%	12.2%	47.6%
Same wage as typical worker (N = 788)	81.1%	86.2%	50.9%
Lower wage than typical (N = 20)	6.8%	1.6%	1.5%
Sample size (N = 1,029)	74	686	269

Panel B Ordered Probit Results[a]	(1)	(2)
Worker received more training than typical worker	−0.214	−0.236
	(1.25)	(1.36)
Worker received less training than typical worker	0.995	0.890
	(10.46)	(8.98)
Worker's experience/10	—	0.735
		(3.90)
Worker's experience squared/10^2	—	−0.209
		(2.75)
Logarithm of job complexity	—	0.089
		(2.61)
Chi-square statistic	122	155
Log likelihood function	−567.93	−551.63
N	1,029	1,029

a. The dependent variable is equal to zero if the worker is paid less than the typical worker, one if the worker is paid the same as the typical worker, and two if the worker is paid more than the typical worker. Absolute values of z-statistics given in the parentheses.

the starting wage was higher, lower, or the same as the typical starting wage for this position. In Panel A of Table 3, we examine the relationship between these two variables.[16] There are two striking findings. First, approximately 7 percent of the workers are trained more than the typical worker hired for this position, but over 26 percent of workers receive less training than the typical worker hired into the position. Second, only 1.9 percent of workers are given a wage below the wage

16. In this section, we use a sample of 1,029 from the SBA data set. This sample was reduced from the original 1,288 because 31 observations were missing data on the year hired or were hired prior to 1985, another 52 observations were missing data on the amount of pay or training relative to the typical worker, an additional 111 observations were missing data on relevant experience, and another 65 respondents failed to report job complexity. The relationships between the mean characteristics of this working sample and the full sample are similar to those discussed earlier for the working sample of 756 used in the analyses in Tables 1 and 2.

typically paid, but 21.5 percent of workers receive a wage above normal.[17] Among those receiving more training than the typical worker, only 6.8 percent of these workers receive wages below the typical worker, and 12.2 percent of these workers receive wages above the typical wage for this position. Of course some of this extra training may be the result of the workers being given added responsibilities not typically given to a worker hired in this position. Nevertheless, firms do not appear to make workers pay for this extra training. In contrast, firms do appear willing to adjust wages upward when the worker needs less training than the typical worker. Close to 48 percent of workers who receive less training than the typical worker are also paid a higher wage than the typical wage paid for newly hired workers in this position. Thus, the trade-off between the starting wage and the quantity of on-the-job training occurs asymmetrically—workers requiring less training are more likely to receive a higher starting wage, but when the workers receive more training than the typical worker, the trade-off is not apparent.

In Panel B of Table 3, we estimate an ordered probit model where the dependent variable is equal to zero if the worker is paid less than the typical worker, is equal to one if the worker is paid the same as the typical worker, and is equal to two if the worker is paid more than the typical worker. For independent variables we construct dummy variables to indicate that the worker receives more training than the typical worker and a dummy variable to indicate that the worker received less training than the typical worker. In Column 1 we report the estimates with just these two independent variables. The coefficient on more training than the typical worker, though negative as the theory predicts, is not statistically significant. The coefficient on less training than the typical worker, however, is positive as predicted, statistically significant, and more than four times the magnitude of the coefficient on less training. In Column 2, we add controls for the worker's relevant experience, experience squared, and the job complexity measure. These additional controls have little impact on the parameter estimates for the more and less training variables.

C. The Impact of Training on Wage and Productivity Growth

In this section, we compare the effects of training on productivity and wage growth. Under certain circumstances, this approach controls for worker heterogeneity. To see why, consider the following simple representation of on-the-job training.

Assume that workers hired into the same position have similar unobserved abilities. The productivity of a worker in a position with training level T depends on both the worker's type and the level of training. In particular, let $\alpha p_s(T)$ denote the starting productivity of a type α worker in a position with training level T. Increased training reduces the starting productivity of the worker, such that $dp_s/dT < 0$. In addition, employers offering training T incur direct costs $c(T)$ reflecting the time of other workers providing the training as well as other training expenses. Naturally, dc/dT is greater than or equal to zero. Let the productivity of a worker of type α

17. Some readers may be bothered by the asymmetry in these responses, especially if one wishes to interpret the typical worker as the mean worker. Given these responses, the respondents' frame of reference may be the median worker. Alternatively, firms may be reluctant to report that individuals are receiving a wage below that which is typical. This would also explain the asymmetry of responses.

after training be represented by $\alpha p_a(T)$. Increased training raises productivity, such that $dp_a/dT > 0$. Let w_s and w_a denote the starting wage paid to workers being trained and the wage paid after training is complete. For simplicity, assume a single period of training, N periods of subsequent employment, and a zero discount rate. Then the net present value of a worker hired for a position with training T is given by

$$(2) \quad PV = \alpha p_s(T) - c(T) - w_s + N(\alpha p_a(T) - w_a) = 0,$$

where competition among firms implies that the net present values of positions with varying levels of training equal zero. Human capital theory predicts that if training is general, then the starting wage and the wage paid to a fully trained worker will adjust such that the worker bears all the costs and reaps the entire return to such training. That is, when on-the-job training is general, we have

$$(3) \quad \alpha p_s(T) - c(T) = w_s$$

$$(4) \quad \alpha p_a(T) = w_a.$$

Equation 3 highlights the key claim of human capital theory that an increase in training T will lower the starting wage given $dc/dT \geq 0$ and $dp_s/dT < 0$. As we have discussed previously, if positions with increased training are filled with more-able individuals (that is, $d\alpha/dT > 0$) and we cannot fully control for this matching of more-able workers to positions with greater training, then our estimate of the negative effect of training on the starting wage will be biased upward. Equations 2 through 4 suggest, however, an alternative test for the prediction that workers will bear the entire costs of general training. Namely, dividing Equation 4 by Equation 3, taking logs, and differentiating with respect to the log of training, we obtain the following expression:

$$(5) \quad d\ln(p_a/p_s)/d\ln T = d\ln(w_a/w_s)/d\ln T + d\ln(1 - c/\alpha p_s)/d\ln T$$

It is straightforward to show that $d\ln(1 - c/\alpha p_s)/d\ln T \leq 0$ and thus that $d\ln(p_a/p_s)/d\ln T \leq d\ln(w_a/w_s)$.[18] In other words, the elasticity of wage growth with respect to training should be greater than or equal to the elasticity of productivity growth with respect to training when training is general. Therefore, Equation 5 provides another test of the standard human capital model with general training.

Both the EOPP data and the SBA data contain questions that provide us with measures of productivity and wage growth. For productivity, in the EOPP data, respondents were asked the following question:

> Please rate your employee on a productivity scale of zero to 100, where 100 equals the maximum productivity rating any of your employees [in this] position can attain and zero is absolutely no productivity by your employee. What is the productivity of [the last worker hired] during (his/her) first two weeks of employment?

18. The critical elements necessary to sign $d\ln(1 - c/\alpha p_s)/d\ln T$ are $c < \alpha p_s$, that one cannot incur costs of training greater than one's productivity, and that $dc/dT \geq 0$ and $dp_s/dT < 0$. If $c = 0$, then $\ln(1 - c/\alpha p_s) = 0$ and productivity growth equals wage growth.

We asked a slightly different version of this question to the SBA respondents:

> Please rate (name of last worker hired) on a productivity scale of zero to 100, where 100 equals (name's) productivity when (he/she) is fully trained and zero is absolutely no productivity by (name). . . . What was (name's) productivity on this scale during his/her first two weeks of employment?

Productivity growth from the start of employment until the worker is fully trained is then just 100/(reported starting productivity index). For wage growth, both surveys asked for the wage paid to workers after two years at the firm. If we assume that workers after two years of experience are fully trained and qualified, then the ratio of the wage after two years to the starting wage provides a wage growth measure that is roughly comparable to the productivity growth measure.[19]

In Table 4, we estimate the impact of training on the productivity and wage growth.[20] The dependent variables are expressed in natural logarithms as given by Equation 5.[21] The training variables are the logarithm of the total hours of training provided during the first three months. Other than the training variables, our independent variables are time invariant and therefore do not appear in the index equations, although there is very little change to the coefficients on the training measures if we use a specification similar to those used in Table 2.[22] In Column 1 we report the results for SBA productivity growth, and in Column 3 we report the results for productivity growth for the EOPP data. There is a remarkable degree of similarity of coefficients across the data sets: On-site training increases productivity growth with elasticity estimates of 0.246 for the SBA and 0.209 for the EOPP data. In Columns 2 and 4, we report the SBA and EOPP wage growth estimates. Again, there is a remarkable degree of consistency: On-site training in the first three months has a positive and significant effect on wage growth with elasticity estimates of 0.020 for the SBA data and 0.028 for the EOPP data. The impact of training on wage growth is much smaller than its impact on productivity. In both data sets, the impact of training on productiv-

19. We also estimated the wage growth models reported in Table 4 with the sample restricted to those with jobs in which the time to become fully trained and qualified was less than two years. The results are very similar to those reported in Table 4.

20. This analysis uses working samples of 860 from the SBA data and 1,683 from the EOPP data. The SBA sample drops from the original 1,288 to 860 because 31 observations have missing data on year hired or were hired prior to 1985, 331 observations were missing data on wage or productivity growth, and an additional 88 observations were missing data on training. The EOPP sample was reduced from 2,274 to 1,683 because 65 observations were missing the date of hire or were hired prior to 1975, 343 observations were missing data on wage or productivity growth, and an additional 183 observations were missing data on training. The mean characteristics of these working samples are similar to those used in the analyses reported in Tables 1 and 2.

21. Because a few of the productivity indices take on a zero value, we add one to each value of the index and then take the logarithm. If we estimate the models using ratios instead of log ratios as dependent variables, we obtain similar results to those reported in Table 4. The estimated effects of training on productivity growth, while smaller in these regressions than those reported in Table 4, are still several times larger than the estimated effects on wage growth.

22. In fact, when all of the controls are included, if our measures of worker ability (time to be fully trained and time spent screening job applicants) are adequate controls for job type, this regression of fully trained productivity relative to the productivity of a beginning worker is a regression of initial productivity.

Table 4
Impact of Training on Productivity and Wage Growth 1992 SBA and 1982 EOPP Data[a]

Independent Variables	Productivity Growth, SBA Data (1)[b]	Wage Growth, SBA Data (2)[c]	Productivity Growth, EOPP Data (3)[d]	Wage Growth, EOPP Data (4)[e]	Wage Growth Minus Productivity Growth, SBA Data (5)[f]	Wage Growth Minus Productivity Growth, EOPP Data (6)[g]
Logarithm of total on-site training in first three months of employment	0.246	0.020	0.209	0.028	−0.226	−0.181
	(9.66)	(4.20)	(14.4)	(8.98)	(8.84)	(12.59)
Logarithm of total off-site training in first three months of employment	0.046	−0.005	—	—	−0.051	—
	(1.37)	(0.76)			(1.50)	
Adjusted R^2	0.103	0.018	0.109	0.045	0.089	0.086
N	860	860	1,683	1,683	860	1,683

a. The absolute values of *t*-statistic are in parentheses.
b. The dependent variable is the natural logarithm of a fully trained and qualified worker relative to one plus the productivity of the newly hired worker.
c. The dependent variable is the natural logarithm of the wage paid after two years of experience relative to the wage of the newly hired worker in the same position.
d. The dependent variable is the natural logarithm of the maximum possible productivity on the job relative to one plus the productivity of the newly hired worker in the job.
e. The dependent variable is the natural logarithm of the wage paid to a worker after two years of experience relative to the wage of the newly hired worker hired into the same position.
f. The dependent variable is the difference between the dependent variables in Columns 1 and 2.
g. The dependent variable is the difference between the dependent variables in Columns 3 and 4.

ity growth is several times larger than its impact on wages.[23] Finally, we rearrange Equation 5 and provide estimates of the effect of training on the difference between wage growth and productivity growth in Columns 5 and 6 in Table 4. The coefficients on the training variables provide a test of the null hypothesis that the wage and productivity growth elasticities are equal. This hypothesis is soundly rejected in both data sets, implying that the differences between the wage and productivity growth training elasticities are statistically significant.

IV. Conclusion

Traditional human capital theory predicts that workers bear the full cost of general training and reap the full return. For specific training, the worker and the firm agree to share both the costs of and the returns to specific training. Although wages grow quickly in the first two years of employment, about 15.5 percent for the SBA data, the growth is weakly correlated with training. In contrast, productivity growth is highly correlated with training. It appears, therefore, that firms are bearing an overwhelming portion of the costs of training. Even when we use a fixed-effect model to control for unobserved abilities, the impact of training on wage growth is extremely small relative to the impact of training on the worker's productivity growth at the firm. Both data sets offer a very similar story: workers pay for very little of their training early in their careers.

There are several responses to the above finding. One, a response that follows the spirit of simple human capital theory, is to argue that most training is specific. The EOPP survey asked employers directly about how specific their training was. The survey asked whether almost all, most, some, or none of the skills learned by new employees in this job are useful outside of this company. Nearly 60 percent of the sample reported that the training is almost all general human capital. Only about 8 percent reported that almost none of the skills are of value outside the company. The responses of employers would also appear consistent with the large return to labor market experience. Bishop (1988) analyzes these data and concludes that many "employers are, in effect, induced to share the costs and benefits of general on-the-job training with their employees" (p. 1). Thus, it appears that employees pay only a small fraction of the training costs, and employers feel much of that training is general training.

Another response is to argue that informational asymmetries make much so-called "general" training in fact "specific" training. Katz and Ziderman (1990, 1147–8), for instance, observe that "Potential recruiters do not possess much information on the extent and type of workers' on-the-job training. . . . The informational asymmetry between a training and a recruiting firm thereby reduces the net benefits that a worker with general training can obtain by moving to another firm. We shall argue that this

23. Bishop (1988, 1996), using the EOPP, also finds that the impact of training is much larger in productivity growth equations than in wage growth equations.

implies that a firm may find it feasible to finance a part, or all, of a worker's general training.''[24]

A third response, suggested by efficiency wage theory, would be to argue that high training positions are positions where monitoring is difficult, or the costs of shirking are great, and thus are positions that pay a higher ''efficiency wage.''

Finally, it may be that while workers do not pay for training immediately early in their careers, they do pay for it at some later date, outside the range of our data. Sorting out the validity of these and other responses to our finding remains a topic of future research.

References

Altonji, Joseph, and James Spletzer. 1991. ''Worker Characteristics, Job Characteristics, and the Receipt of On-the-Job Training.'' *Industrial and Labor Relations Review* 45(1): 58–79.

Barron, John, Dan Black, and Mark Loewenstein. 1993. ''Gender Differences in Training, Capital, and Wages.'' *Journal of Human Resources* 28(2):343–64.

———. 1989. ''Job Matching and On-the-Job Training.'' *Journal of Labor Economics* 7(1):1–19.

———. 1987. ''Employer Size: The Implications for Search, Training, Capital Investment, Starting Wages, and Wage Growth.'' *Journal of Labor Economics* 5(1):76–89.

Barron, John, Mark Berger, and Dan Black. 1997. ''Employer Search, Training and Vacancy Duration.'' *Economic Inquiry* 35(1):167–92.

Becker, Gary. 1962. ''Investment in Human Beings.'' National Bureau of Economic Research, (NBER) Special Conference 15, *Journal of Political Economy,* 70(suppl.):9–49.

———. 1964. *Human Capital: A Theoretical and Empirical Analysis, with Special Reference to Education.* NBER: New York.

Bishop, John. 1988. ''Do Employers Share the Costs and Benefits of General Training?'' Working Paper #88-08, Cornell University Center for Advanced Human Resource Studies. Ithaca: Cornell University.

———. 1996. ''What We Know About Employer-Provided Training: A Review of the Literature.'' Working Paper #96-09, Cornell University Center for Advanced Human Resource Studies. New York: Cornell University.

Booth, Alison. 1993. ''Private Sector Training and Graduate Earnings.'' *Review of Economics and Statistics* 75(1):164–70.

Brown, Charles. 1991. ''Empirical Evidence on Private Training.'' *Research in Labor Economics* 11:97–113.

Brown, James. 1989. ''Why Do Wages Increase with Tenure?'' *American Economic Review* 79(5):971–91.

Holzer, Harry. 1990. ''The Determinants of Employee Productivity and Earnings: Some New Evidence.'' *Industrial Relations* 29(3):403–22.

Katz, Eliakim, and Adrian Ziderman. 1990. ''Investment in General Training: The Role of Information and Labour Mobility.'' *The Economic Journal* 100:1147–58.

Kuhn, Peter. 1993. ''Demographic Groups and Personnel Policy.'' *Labour Economics* 1(1): 49–70.

24. However, inconsistent with this idea, we find here that previous relevant experience is an important variable in explaining starting wages.

Levine, David. 1993. "Worth Waiting For? Delayed Compensation, Training, and Turnover in the United States and Japan." *Journal of Labor Economics* 11(4):724–52.

Lillard, Lee, and Hong Tan. 1992. "Private Sector Training: Who Gets It and What Are Its Effects?" *Research in Labor Economics* 13:1–62.

Loewenstein, Mark, and James Spletzer. 1994. "Informal Training: A Review of Existing Data and Some New Evidence." Bureau of Labor Statistics.

———. 1996. "Belated Training: The Relationship Between Training, Tenure, and Wages." Bureau of Labor Statistics.

Lynch, Lisa. 1992. "Private Sector Training and the Earnings of Young Workers." *American Economic Review* 82(1):299–312.

Mincer, Jacob. 1962. "On-the-Job Training: Costs, Returns, and Some Implications." *Journal of Political Economy* 70(suppl.)S50–S79.

———. 1974. *Schooling, Experience, and Earnings.* New York: National Bureau of Economic Research.

———. 1993. *Studies in Human Capital: Collected Essays of Jacob Mincer,* vol. 1. Aldershot, Hants, England: E. Elgar.

Parsons, Donald. 1986. "The Employment Relationship." In *Handbook of Labor Economics,* vol. 2, ed. Ashenfelter and Layard. Amsterdam: Elsevier Science Publishers.

———. 1989. "On-the-Job Learning and Wage Growth." Mimeo, Ohio State University.

———. 1990. "The Firm's Decision to Train" *Research in Labor Economics* 11:53–76.