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Volume 61 | Number 1 Article 4

October 2007

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Abstract
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Keywords
informal training

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THE ECONOMIC PAY-OFFS TO INFORMAL TRAINING: EVIDENCE FROM ROUTINE SERVICE WORK

XIANGMIN LIU and ROSEMARY BATT*

This study examines the relationship between informal training and job performance among 2,803 telephone operators in a large unionized U.S. telecommunications company. The authors analyze individual-level data on monthly training hours and job performance over a five-month period in 2001 as provided by the company's electronic monitoring system. The results indicate that the receipt of informal training was associated with higher productivity over time, when unobserved individual heterogeneity is taken into account. Workers with lower pre-training proficiency showed greater improvements over time than did those with higher pre-training proficiency. Finally, whether the trainer was a supervisor or a peer also mattered: workers with below-average pre-training proficiency achieved greater productivity gains through supervisor training, while workers with average pre-training proficiency achieved greater productivity gains through peer training.

In recent decades, skill requirements for many jobs have increased due to heightened international competition, technological change, and customer expectations. Employers who are investing in new work processes and technology expect workers to produce error-free output at higher levels of efficiency than in the past. Thus, the need for ongoing training has risen even though competitive pressures put constraints on training budgets.

Informal or on-the-job training provides an effective and efficient way to satisfy the demand for skill in organizations characterized by continuous change in technology and competition. It allows new employees to acquire firm-specific skills and knowledge that are hard to obtain in the market, while allowing incumbent employees to stay abreast of changes in technical systems and product offerings. Context-specific learning also reduces the losses associated with transferring learning from off-site to on-site applications. Moreover, compared to formal classroom training, informal training is less costly because it reduces productivity loss associated with time away from work and saves expenditures associated with training specialists and materials. Because it can be integrated into daily work schedules, it also provides greater flexibility than traditional, off-the-job training. In sum, informal training can yield substantial economic pay-offs to companies through the ongoing skill acquisition of employees. Yet, the overwhelming bulk of training research has focused on

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Industrial and Labor Relations Review, Vol. 61, No. 1 (October 2007). © by Cornell University.
0019-7939/00/6101 $01.00

formal training (Bishop 1997; Frazis and Loewenstein 2005).

The present study contributes to the training literature in several ways. First, we focus on an important but relatively neglected subject in the training literature—informal training rather than formal training, and incumbent workers rather than new hires. Second, we develop and test a model of productivity that includes the effects of training as well as its depreciation rate. The identification of depreciation rates allows us to estimate the payoff period of informal training and, therefore, the returns on human capital investments. Third, we use archival data from a firm-level computerized monitoring system to measure informal training hours and productivity for individual employees. Relatively few studies have examined rates of return to informal training, due in part to the difficulty of measuring it. The longitudinal nature of the data enables us to use first-difference models to control for unmeasured individual heterogeneity. Fourth, we integrate insights from organizational behavior to conceptualize how organizational contingencies and individual differences in employees and trainers affect training outcomes. That is, we examine how employees with different levels of capability respond to training in general and to supervisor versus peer trainers in particular. Finally, we focus on training in routine service jobs, specifically directory assistance telephone operators. If informal training has economic pay-offs in this context, it is likely to have even more benefits for jobs with greater skill requirements and opportunities for independent judgment.

Research on Training and Productivity

Prior research has defined two categories of firm-specific training: formal training and informal (on-the-job) training. Formal training typically includes a standardized curriculum provided by an instructor away from the job, although companies are increasingly delivering formal training through computer-based programs. Informal training occurs in the context of daily work and has been defined to include three types: a) time spent watching co-workers do the job; b) time spent in individualized training or feedback with supervisors at work; and c) time spent in individualized training or feedback with co-workers at work (Employment Opportunities Pilot Program 1979–80). The current study focuses on the latter two types of training.

Most empirical research on employer-provided training has focused on formal rather than informal training, despite the fact that an estimated two-thirds of the U.S. work force receives informal training at work (Altonji and Spletzer 1991; Frazis et al. 1998). Empirical studies of formal training are based on large sample surveys (Holzer et al. 1993; Bartel 1994; Black and Lynch 1996; Barrett and O'Connell 2001) and econometric case studies (Bartel 1995; Krueger and Rouse 1998). Studies using large sample survey data have shown positive effects of training, but suffer from measurement error that is substantially reduced in the econometric case studies (see Bartel 2000 for a review).

More relevant to the current study are analyses of informal training. Most are based on national-level surveys and examine workers in the first three months after hire (for example, Bishop 1991; Barron, Berger, and Black 1997b). Bishop's (1991) study analyzing the 1982 Employment Opportunity Pilot Projects (EOPP) included formal training and three types of informal training: learning by watching, informal training with supervisors, and informal training with co-workers. He found that the marginal rate of return for 100 hours of training ranged from 11% to 38%, depending on estimation techniques and type of training. Moreover, the amount of formal and informal training had very similar effects on productivity growth during the first year of employment. This implies that informal training, which is lower in cost than formal training, had higher marginal returns. In a second study, Bishop (1994) found that employer training raised both wages and productivity. Investments in training appeared profitable for employers because productivity gains were greater than wage growth. In these studies, job performance was measured on a 0–100 scale, as reported by employers.

Barron, Berger, and Black (1997b) investigated the effects of informal training on

wages, turnover, and productivity using three different data sources: the EOPP 1982 data, a 1992 Small Business Administration survey, and their own 1993 survey sponsored by the Upjohn Institute. Their findings were similar to those of Bishop regarding the value of informal training. They also demonstrated the extent of measurement error in national training surveys by comparing differences in training measures across surveys and by comparing matched-pairs of responses of workers and employers on the extent of training (Barron, Berger, and Black 1997a).

These studies based on national surveys provide the strongest evidence to date that informal training has economic benefits. However, they have several methodological problems. They use either job tenure as a proxy for informal training or estimates of training hours in national surveys; reports by employers and employees vary considerably; and productivity is reported by employers on a subjective scale.

In sum, while economic theory provides a general argument for why investments in informal training should lead to better performance via its effect on human capital, empirical studies are few and limited by measurement problems. Moreover, aside from the general proposition that investment in firm-specific training should improve performance, economic theory provides little guidance for theorizing about how, why, or under what conditions employer-provided training may have differentiated outcomes.

Informal Training as Information Processing and Continuous Learning

To improve our understanding of how informal training affects productivity, we examined variation in organizational contingencies that may shape the effectiveness of training. Two important factors are the levels of worker proficiency and task complexity. Ackerman (1987), for example, argued that the effectiveness of training for employees with different levels of ability depends importantly on the level of information processing that tasks require. For novel tasks requiring sophisticated information processing, he found that individuals with high levels of intellectual capability gained more from training than did those with lower capabilities. In this context, training will tend to accentuate the differences between employees with higher and lower capabilities. This line of argument is consistent with the economic studies showing that better-educated workers are more likely to receive formal training and to benefit from it (for example, Frazis, Hertz, and Horrigan 1995; Bartel 1995; Bishop 1997).

By contrast, for simple information-processing jobs, Ackerman found that the relationship between training and performance was influenced more by psychomotor differences (for example, speed of encoding or responding) than by general cognitive abilities. With sufficient training and practice, the less proficient trainees in his study learned specific task behaviors, and their performance approached that of more proficient employees. Thus, in the context of relatively simple information processing—like that found in this study and in most routine service work—the same amount of training should produce greater improvements in performance for less proficient workers than for the more proficient.

Beyond the issue of individual tasks and competencies is the question of how the interactions between different types of trainers and employees affect outcomes. Recent research on situated learning provides some direction here, as it views learning as influenced by the context in which it occurs, including social relationships and the way work is organized (Lave and Wenger 1991). By extension, informal training constitutes an example of situated learning in which the learner, the supervisor, and other workers influence the process and outcomes (Lave and Wenger 1991; Brown and Duguid 1991). In addition, because informal training occurs in the context of daily work routines and practices, it typically does not include the kind of pre-determined curriculum found in formal training. Its effectiveness depends importantly on the characteristics and capabilities of the learner and the trainer; differences in status or power between the trainer and trainee; and how these factors interact. An important distinction in this regard is whether trainers are supervisors or experienced co-workers.

Supervisors and workers differ in several respects—in the content of their knowledge, in their approach to training, in their ability to motivate learning—and these differences should make them more or less effective as trainers for different groups of workers.

Supervisors have knowledge of job-related rules, procedures, and performance requirements, but lack tacit knowledge of the job that workers perform. In the current environment of rapidly changing work processes and technologies, even supervisors promoted from production-level jobs experience rapid decay in their knowledge of day-to-day work processes. Given their knowledge base, they tend to transform informal training into a structured set of learning activities, using company manuals, standardized training materials, and follow-up observations. Swanson, O'Connor, and Cooney (1990) suggested that low-ability learners tend to gain more from highly structured learning environments than do high-ability learners. Supervisors also rely on their disciplinary authority to motivate effort; and less proficient workers are more vulnerable to reprimand for poor performance than are more proficient workers. For these reasons, supervisors are likely to be more effective than peers in training less proficient workers. In other words, supervisor-provided training should result in larger performance gains for less-proficient workers than for more-proficient workers.

Peer trainers, by contrast, are experienced workers, or "subject matter experts," who provide assistance and share knowledge with co-workers through informal instructional activities. They accumulate tacit knowledge of work processes and idiosyncratic job characteristics that supervisors do not have. This kind of knowledge does not lend itself to structured learning activities, but is more likely to be conveyed through knowledge-sharing or in the context of specific problems or tasks. In addition, as peers do not have any disciplinary authority over co-workers, they can draw on trust, persuasion, or social influence to intrinsically motivate learning (Bandura 1977). Trust facilitates cooperation, and where unions are present, solidaristic behavior among co-workers is likely to be stronger. Doeringer and Piore (1971) provided similar arguments in their analysis of internal labor markets and customary norms that shaped skill acquisition between more and less experienced workers. However, peer training is limited because it is incidental and emergent in nature, and may even be inconsistent across work shifts or trainers. Therefore, workers who already have a good command of the job are more likely to benefit from peer-provided training than are those with less job proficiency.

To summarize our arguments, we expect that informal training will be associated with better performance, and in the context of routine information-processing tasks, we expect that the relationship between informal training and performance will be stronger for workers with lower levels of proficiency than for workers with higher proficiency. Finally, we expect that the interactions between different types of trainers and trainees will produce differentiated results, with supervisor training more effective for less proficient workers and peer training more effective for more proficient workers.

Model Specification

A worker's human capital stock is affected by the amount of time devoted to training. As informal training encompasses a good amount of unstructured, context-specific knowledge, workers are likely to forget some acquired information over time; and some learning becomes obsolete with changes in technology and work processes. Therefore, worker i's stock of human capital at month t (as denoted by $STK_HC_{i,t}$) is given by the acquired informal training during month t (as denoted by $OJT_{i,t}$) plus the existing stock that a worker possessed in the previous period ($STK_HC_{i,t-1}$), minus what may have depreciated during the period, $\eta \cdot STK_HC_{i,t-1}$, η being the depreciation rate. Thus, the function of human capital stock ($STK_HC_{i,t}$) can be written as

$$(1) \qquad STK_HC_{i,t} = OJT_{i,t} + (1-\eta) * STK_HC_{i,t-1}.$$

By substituting recursively, equation (1) can be reduced to

$$(2) \qquad STK_HC_{i,t} = \sum_{k=1}^{t} OJT_{i,k} * (1-\eta)^{t-k}.$$

Following prior training studies (Frazis and Loewenstein 2005), we assume that a worker's job performance is a logarithmic function of past investments in human capital through informal training. Therefore, worker i's job performance at time t ($PERF_{i,t}$) can be expressed by the function

$$\ln(PERF_{i,t}) = \beta * \ln(STK_HC_{i,t}) + \mu_i + \nu_{i,t}, \tag{3}$$

where μ_i is a vector of person-specific characteristics assumed to have a time-invariant effect on performance and $\nu_{i,t}$ is a zero mean error term, independent of training variables.

By substituting equation (2) into equation (3), we obtain the function of a worker's job performance,

$$\ln(PERF_{i,t}) = \beta * \ln(\sum_{k=1}^{t} OJT_{i,k} * (1-\eta)^{t-k}) + \mu_i + \nu_{i,t}. \tag{4}$$

Because a large portion of μ_i are unobservable, we use a first-difference estimation of equation (4) to reduce errors due to omitted variables. In this formulation, all time-invariant effects drop out of the equation, leaving only time-varying factors. The first-difference transformation results in equation (5):

$$\ln(PERF_{i,t}) - \ln(PERF_{i,t-1}) = \beta * (\ln(\sum_{k=1}^{t} OJT_{i,k} * (1-\eta)^{t-k}) - \ln(\sum_{k=1}^{t-1} OJT_{i,k} * (1-\eta)^{t-k-1})) + (\nu_{i,t} - \nu_{i,t-1}). \tag{5}$$

Returns to training may vary among workers of different levels of job proficiency. To develop the test for individual differences prior to training, we sort workers into three groups according to their pre-training job competency (low, average, or high). Then we estimate equation (5) for each group to test the relationship between informal training and performance.

Next, we decompose training into training provided by supervisors ($OJT_SUP_{i,t}$) and by experienced peers ($OJT_PEER_{i,t}$) in order to examine the effects of different types of informal training. Therefore equation (5) can be extended to

$$\begin{aligned}\ln(PERF_{i,t}) - \ln(PERF_{i,t-1}) &= \beta_1 * \ln(\sum_{k=1}^{t} OJT_SUP_{i,k} * (1-\eta)^{t-k} - \sum_{k=1}^{t-1} OJT_SUP_{i,k} * (1-\eta)^{t-k-1}) \\ &+ \beta_2 * \ln(\sum_{k=1}^{t} OJT_PEER_{i,k} * (1-\eta)^{t-k} - \sum_{k=1}^{t-1} OJT_PEER_{i,k} * (1-\eta)^{t-k-1}) \\ &+ (\nu_{i,t} - \nu_{i,t-1}).\end{aligned} \tag{6}$$

Equations (5) and (6) can be estimated by non-linear least squares regressions. Our model specification has three advantages. First, the logarithmic specification captures the diminishing productivity returns of training. Second, first-difference models eliminate omitted variable bias due to unobserved person-specific effects. Finally, the use of non-linear least squares regression allows us to estimate the depreciation rate parameter from available data.

As suggested by Bartel (2000), accurate measures of return on investments (ROI) in employee training can guide employers' decisions regarding human capital investments. Because informal training incurs little expenditure associated with the purchase of training materials, we assume that costs only arise from the separation from production of a worker and a trainer. If the monthly wage of a worker is w_0 and that of a trainer is w_t and they work H hours each month, then the costs of t hours of training are

$$Costs = \frac{w_0 + w_t}{H} * t. \tag{7}$$

The benefits of training are the productivity gains that training produces. In the context of call centers in this study, productivity was measured in terms of seconds per call, or call handling time (CHT). Lower seconds per call equals higher productivity. Consider that call handling time is CHT_0 hours prior to training and that one hour's training is associated with a θ hour reduction in call length. After t hours of training, call handling time reduces to $CHT_0 - \theta * t$ in the present month, implying that a worker completes

$\frac{H}{CHT_0 - \theta * t}$ calls in this month, as compared to $\frac{H}{CHT_0}$ calls in the absence of training. Therefore, the productivity gains of t hours from training in this month are

$$\frac{w_0}{H} * \left(\frac{H}{CHT_0 - \theta * t} - \frac{H}{CHT_0} \right) * (CHT_0 - \theta * t),$$

which reduces to $\frac{w_0 * \theta * t}{CHT_0}$. As training effects depreciate at a monthly rate of η over time, productivity gains in the kth month are equal to $\frac{w_0 * \theta * t * (1-\eta)^k}{CHT_0}$. Assuming that the employee quit rate is q, the accumulated benefits due to t hours of training are

$$\text{(8)} \qquad Benefits = \frac{w_0 * \theta * t}{CHT_0} + \frac{w_0 * \theta * t * (1-\eta) * (1-q)}{CHT_0} + \ldots + \frac{w_0 * \theta * t * (1-\eta)^\infty * (1-q)^\infty}{CHT_0} = \frac{w_0 * \theta * t}{CHT_0 * (\eta + q - \eta * q)}.$$

Therefore, the return on investments is given by

$$\text{(9)} \qquad ROI = \frac{Benefits - Costs}{Costs} = \frac{\dfrac{w_0 * \theta * t}{CHT_0 * (\eta + q - \eta * q)}}{\dfrac{(w_0 + w_t) * t}{H}} - 1 = \frac{w_0 * \theta * H}{(w_0 + w_t) * CHT_0 * (\eta + q - \eta * q)} - 1.$$

Data

Research Strategy and Sample

The research site for this study is the telephone directory services division of a large unionized telecommunications company operating in a multi-state region of the United States. The focal occupational group (telephone operators) is the largest group of non-managerial employees in the business. By focusing on one occupational group in one company (Batt 1999) we reduce confounding error caused by factors such as business and human resource strategy, technology, selection criteria, and work processes. The presence of the union further standardizes such practices as pay rates, job posting and bidding, and grievance procedures across the multi-state area.

Our field research provided insights into business operations, competitive pressures, the skill requirements of jobs, and how and why informal training might be useful in this context. The business in this case handles directory assistance inquiries from anywhere in the United States. Calls do not vary dramatically in content, and individual operator centers do not specialize in any particular type of call. Government-mandated service levels require the company to answer each call within 6 seconds, with a compliance rate of at least 97.5%. In addition, cost competition is intense in this commodity market, and companies can save millions of dollars by reducing call handling time by fractions of a second. This can be accomplished either through new technologies (for example, voice recognition systems process portions of each call) or better work skills (for example, more efficient search strategies). The company also requires an 85% customer satisfaction rating, as measured by an outside vendor survey.

High levels of automation allow operators to handle over 1,000 calls per day, with an average call handling time (the average time to complete a call) of 21.37 seconds (based on our archival data). As soon as one call has ended, a second one enters the operator's headset, based on an automated call distribution system that assigns calls to the next available operator. Thus, the automated system should result in a random assignment of calls to workers; and managers we interviewed measured employee performance on the assumption that it did. These jobs are highly stressful, according to industry analysts and managers interviewed for this study.

The knowledge and skill requirements of the job are of four types: a) basic keyboarding, b) technical and procedural knowledge, c) social interaction skills, and d) substantive knowledge. According to our interview results, initial training focuses on the first two areas, ensuring that new hires have accurate and efficient keyboarding skills and know the procedures for retrieving information from a

variety of databases. The company provides an average of 2.1 weeks of initial training, and it takes employees about six months to become proficient on the job, according to our survey of a stratified random sample of 773 workers and their supervisors.

The company engages in several types of informal training activities. The most common form of training occurs through monthly performance reviews, as the company requires supervisors to provide individualized feedback to employees after listening remotely to their calls (typically 20 calls in a month). The employee is rated on efficiency standards such as initial start time of less than 4 seconds, number of searches per call less than 2.5, operator report time (scanning, giving options) less than 12 seconds, and release to audio at least 87% of the time (avoiding the need to read the number by having the system give it). Service quality is measured by such items as tone of voice, listening to questions carefully and answering them accurately, and degree of professionalism. Substantive knowledge is captured by the percentage of calls transferred to a more experienced operator (service assistant), which can be no more than 3%. In sum, these customized sessions provide specific guidance for improvement.

Beyond individualized performance reviews, the company uses work time to train workers in several areas: methods (new procedures for call handling or information processing), customer satisfaction (ways to improve service quality), district issues (business-specific information), performance improvement activities, and ergonomics. Both supervisors and peers provide these types of training.

Ongoing learning is important in this setting because changes regularly occur in service offerings, work processes, and information systems. For example, in our survey of supervisors, they reported that operators received an average of 6.7 emails per day on updates or new procedures. They also reported that service options, features, and pricing were updated "sometimes" to "often" (2.5 on a Likert scale of 1–5). Just prior to our fieldwork, the company had shifted to providing National 411 service (as opposed to regional service only), which was an important source of new revenues, but which required operators to learn an entire new database system. The efficient handling of calls depends not only on technical procedural knowledge but also on whether the operator has tacit knowledge of local terminology or names of businesses that diverge from how they are officially listed in information databases. In sum, in what is often considered a relatively low-skilled clerical job, there are ongoing changes in information systems and work processes that require regular attention to informal training.

Variation in training practices in this study derives largely from variation in managerial implementation of corporate policies. For example, the company set a policy that all supervisors must observe at least 70% of their employees each month, yet in one site we visited, the manager admitted that they were only observing 36%. Thus, managers varied substantially in whether they achieved that goal, depending on staffing levels, resources, or their own managerial competence. In addition, these managers had some discretion over their operational budgets: in our field interviews, for example, we found that managers differed in the amount of resources they decided to put into ongoing training.

The employee sample was drawn from the company's Human Resource Information (HRI) system, which contained data on demographics (age, race, gender, company tenure), job title, work group location, supervisor, work site location, and wage rate. We excluded 194 employees who had less than six months of employment because they were not rated using the same scale as employees beyond the six-month probation. We also excluded centers with fewer than 40 employees. The sample included 3,408 telephone operators, but randomly missing data reduced the sample used in the multivariate analyses to 2,803 workers at 45 service centers.

Operators in our sample are primarily white (71%) and female (86%), with an average age of 41 and company tenure of 11 years (as shown in Table 1). The company hires high school graduates and uses two rounds of systematic testing in its selection procedures. While the HRI system did not

Table 1. Descriptive Statistics.

	Total Sample			*Final Sample*			
Variables	*Obs.*	*Mean*	*Std. Dev.*	*Obs.*	*Mean*	*Std. Dev.*	*t-Value*
Call Handling Time (seconds per call)	2,929	21.67	4.46	2,803	21.67	4.24	0.02
Informal Training (hours per month)	17,040	1.25	1.43	11,701	1.34	1.40	–5.38
with Supervisors	17,040	0.98	1.17	11,701	1.03	1.10	–3.52
with Peers	17,040	0.27	0.80	11,701	0.31	0.86	–4.37
Age (years)	3,369	40.80	11.25	2,765	40.67	11.21	0.46
Company Tenure (years)	3,408	11.42	10.16	2,803	11.28	10.15	0.54
Sex, Dummy (1 = female)	3,408	0.87	0.34	2,803	0.86	0.35	0.70
Race, Dummy (1 = non-white)	3,408	0.28	0.45	2,803	0.29	0.45	–0.89

provide educational data, our survey of employees showed that most have had some post-secondary education, but only 8% have a four-year college degree. The average supervisor in the sample is 44 years old and has served the company for about 20 years; the average peer trainer is 50 years old and has served for 22 years. Seventy-six percent of supervisors are white and 83% of them are female, while 78% of peer trainers are white and 94% female.

Measures

Measures of training and productivity come from the computerized monitoring system in the call centers, which continuously records the work activities of each operator, including time on-line with customers and off-line for training or other activities. The monthly data in this study cover the period January 2001 through May 2001. Each time an employee logged off the computer for training, the minutes of training were recorded, along with whether the training was with a supervisor or peer trainer. Informal training is the length of time a worker spent in informal training each month. Average training per month ranged from 75 to 94 minutes. When the data are broken down by type of trainer, they show that workers received an average of 62 minutes of informal training with their supervisors and 19 minutes with peer trainers each month.

Recall that our measure of productivity is CHT, the average number of seconds an operator spends on a customer call; and lower call handling time equals higher productivity. To measure pre-training proficiency, we used an operator's percentage of objectives met (PCT_CHT) in the first month for which we had data (for example, January). Because the customer base varies geographically, each center specifies its own objectives, setting the minimum requirements expected from a worker performing at a normal pace. PCT_CHT is defined as the objective set by the center for call handling time divided by the actual time spent handling a call. Thus, an employee who handles a call in under the time that is set as the center's objective achieves a score higher than 100% on the "objectives met" criterion. The company set the range of acceptable performance between 94% and 107%. Any operators who fell below 94% were rated unsatisfactory, and above 107%, excellent. We chose this measure instead of CHT to eliminate the potential for error arising from unobserved, confounding establishment characteristics. Using the company's threshold criteria of 94% and 107%, we established three proficiency categories: low (506 workers, 29% of the total); average (674 workers, 39%); and high (555 workers, 32%).

Finally, we matched the training and productivity data to archival data from the company's HRI system. Through our first-difference model, we controlled for age, sex, race, company tenure, and other worker characteristics that are time-invariant.

Selection Bias

Prior literature suggests that non-random selection into training may seriously bias the estimation of returns to training (for example, Bartel 1995). In this study, we used longitudinal data and first-difference models that reduce the errors associated with self-selection into training. In addition, we performed a number of analyses to assess the extent of selection bias in the data. First, we found that the distribution of training is widespread: over the five months of data, only 2 workers out of 3,408 received no training. These cases were not part of our final sample of 2,803 workers. On a month-by-month basis, the percentage of workers who received some training ranged from 92.8% to 95.6%. We ran a random effects probit analysis to test whether performance in month 1 was a predictor of whether an employee received any training in a given month, and we found no statistically significant effect.

We then assessed variation in hours of training received and found statistically significant differences by proficiency level, thus confirming the need to take job proficiency into consideration. The lowest proficiency group received an average of 1 hour and 44 minutes (SD = 1.54) of informal training each month, while the average proficiency group received 1 hour and 28 minutes (SD = 1.53), and the high proficiency group, 1 hour and 19 minutes (SD = 1.33). In regressions controlling for supervisor and worker demographic characteristics, the average proficiency group received a total of 1.25 hours less training over five months (16 minutes per month) than did the low proficiency group, and the high proficiency group received a total of 1.55 hours less (18.6 minutes per month) (see Appendix 1). While these differences are statistically significant, they appear to be modest in magnitude. Histograms of the distribution of training hours within each proficiency group also showed a narrow range of variability. In addition, the relative proportion of training provided by peers versus supervisors was similar for each group: supervisor training represented 71% of all training for the low proficiency group, 78% for the average proficiency group, and 73% for the high proficiency group. In sum, these analyses show that there is a relatively even distribution of informal training in our sample, which is consistent with findings in national surveys (Altonji and Spletzer 1991).

Table 2. Relationship between Training and Job Performance: First-Difference Nonlinear Least Squares.

Independent Variable	*Dependent Variable: Call Handling Time*
Informal Training	–0.006***
	(–7.40)
Depreciation Rate	0.038**
	(2.08)
No. of Observations	8,898
No. of Persons	2,803

Notes:

T-statistics are in parentheses below the parameter estimates.

Informal training, as measured by hours per month, and call handling time, as measured by seconds per call, were transformed into logarithms.

The estimated depreciation rate was almost 0. Imposing this value, which allows fixed-effects estimates of a linear model, produced parameter estimates that were almost identical to those listed here.

**Statistically significant at the .05 level; ***at the .01 level (two-tailed tests).

Results

Training and Productivity

Table 2 presents the results of estimating equation (5)—the relationship between training and call handling time among all workers using first-difference non-linear least squares models.[1] Informal training has a strong negative effect on call handling time (a positive effect on productivity). For an average worker, a 10% increase in informal training (0.13 hours) is associated with a 0.06% reduction in call handling time (0.013 seconds) ($p < 0.01$), with a monthly depreciation rate of 3.8% ($p < 0.05$). In terms of absolute value,

[1]In Table 2 and subsequent analyses, we constrained the parameter space of the depreciation rate (η) to values between zero and one.

Table 3. Relationship between Training and Job Performance: Fixed Effects Estimation.

	Dependent Variable: Call Handling Time		
Independent Variable	*Workers of Low Pre-Training Proficiency*	*Workers of Average Pre-Training Proficiency*	*Workers of High Pre-Training Proficiency*
Informal Training	–0.016***	–0.006***	–0.003***
	(–15.47)	(–9.48)	(–3.80)
No. of Observations	3,225	4,651	3,825
No. of Persons	754	1,152	897

Notes:
T-statistics are in parentheses below the parameter estimates.
Informal training, as measured by hours per month, and call handling time, as measured by seconds per call, were transformed into logarithms.
The analyses included a total of 2,803 workers.
***Statistically significant at the .01 level (two-tailed test).

an additional hour of informal training is associated with a reduction of 0.10 seconds in call handling time in the current month. The results support the argument that the amount of time spent in informal training leads to productivity improvements in the contemporaneous period and that such an effect diminishes over time.

To provide a more accurate estimate of the returns to training, we took into account differences associated with pre-training proficiency. When we tested the relationship between informal training and productivity across low, average, and high pre-training proficiency groups, the estimated depreciation rate (η) we found was very close to zero. In this case, equation (5) is reduced to a fixed effects model that can be estimated by ordinary least squares.[2] As shown in Table 3, workers with lower proficiency demonstrated substantially higher performance gains related to training than did those with higher levels of proficiency. For workers in the low proficiency group, a 10% increase in informal training is associated with a 0.16% reduction in call handling time ($p < 0.01$). The same amount of change in training is associated with a 0.06% reduction in call handling time for workers in the average proficiency group ($p < 0.01$), and 0.03% reduction in the high proficiency group ($p < 0.01$). In other words, an additional hour of informal training leads to a reduction of 0.260 seconds in call handling time for the lowest-proficiency group, a reduction of 0.099 seconds for the average proficiency group, and a reduction of only 0.045 seconds for the highest proficiency group. Taken together, these analyses show the differential outcomes of training according to the proficiency level of the worker.

Supervisor versus Peer Training

Next we examine how variation in the type of training provider (supervisor versus peer) interacts with workers' proficiency levels. As we assume a logarithmic specification between training and performance, workers who received only supervisor-provided training or peer-provided training are regarded as missing and thus are dropped from the analyses. In other words, the following analyses only include the 1,735 workers who received both types of training. Table 4 reports these results.[3] For all workers who received training with a supervisor, call handling time is significantly reduced (–0.005, $p < 0.01$); and for those who received training with peers, call handling time is also significantly reduced (–0.003, $p < 0.01$). If we translate the logarithms into absolute values, the results indicate that a 10% reduction in call handling time is associated with either 2.12 hours of training provided by supervisors or 2.13 hours of training provided by peers.

[2]The reduced form:

$$\ln PERF_{i,t} = \beta * \ln(\sum_{k=1}^{t} OJT_{i,k}) + \mu_i + \nu_{i,t}.$$

Table 4. Relationship between Supervisor Training, Peer Training, and Job Performance: Fixed Effects Estimation.

	Dependent Variable: Call Handling Time			
Independent Variable	*All Workers*	*Workers of Low Pre-Training Proficiency*	*Workers of Average Pre-Training Proficiency*	*Workers of High Pre-Training Proficiency*
Supervisor Informal Training	–0.005***	–0.010***	–0.004***	–0.003*
	(–4.83)	(–4.75)	(–2.64)	(–1.77)
Peer Informal Training	–0.003***	–0.006***	–0.004**	0.005**
	(–2.44)	(–2.83)	(–2.12)	(2.06)
No. of Observations	5,708	1,695	2,261	1,752
No. of Persons	1,735	506	674	555

Notes:
T-statistics are in parentheses below the parameter estimates.
Informal training, as measured by hours per month, and call handling time, as measured by seconds per call, were transformed into logarithms.
*Statistically significant at the .10 level; **at the .05 level; ***at the .01 level (two-tailed tests).

However, this level of aggregation masks differences by level of proficiency. For workers in the low proficiency group, a 10% increase in supervisor training is associated with a 0.1% reduction in call handling time ($p < 0.01$), and a 10% increase in peer training is associated with a 0.06 reduction in call handling time ($p < 0.01$). In other words, the call handling time of a less proficient worker who receives 1.12 hours of supervisor training or 1.36 hours of peer training will fall by 10% (0.024 seconds). The results support the idea that less proficient workers realize greater performance improvements from supervisor training than from peer training, presumably because it is more structured and extrinsically motivated than peer training.

We also found that supervisor training and peer-provided training reduced the call handling time for workers in the average proficiency group. Although the estimates of the coefficients are close in value (both are –0.004, $p < 0.01$ and $p < 0.05$ respectively), we need to take into account that supervisor training and peer-provided training differ in magnitude. In particular, a typical worker in this group received 1.03 hours of supervisor-provided training and 0.27 hours of peer-provided training every month. In order to reduce call handling time by 10% (0.021 seconds), a worker in this group would have needed to receive 2.7 hours of supervisor training, but only 1.4 hours of peer-provided training. Therefore, workers in the average proficiency group gained more from peer trainers than they did from supervisors because they reached the same productivity gains from learning with peers in less time. Moreover, the company gained added economic benefits from using peer trainers because their labor costs (wages) were lower than those of supervisors.

Finally, while investments in training generate the least benefits to workers with high levels of competence, as suggested by the interaction term in Table 3, we find that supervisor training is beneficial for these workers at a marginal level of significance (–0.003, $p < 0.10$); but training delivered by peers is negatively related to productivity (0.005, $p < 0.05$). These results are contrary to our expectations, and we discuss them below.

Calculating the Returns on Investments in Training

Shaving fractions of seconds off phone calls may appear to have a very modest effect on productivity. However, in call centers that manage millions of transactions in a typical year, these small efficiency improvements translate into millions of dollars in savings. To assess the costs and benefits of training in

Table 5. Rates of Return to Training.

Description	*All Workers*	*Workers of Low Pre-Training Proficiency*	*Workers of Average Pre-Training Proficiency*	*Workers of High Pre-Training Proficiency*
Call Handling Time Prior to Training (seconds)	21.67	24.36	21.56	18.49
Informal Training Received (hours)	1.34	1.50	1.31	1.24
Reduction in Call Handling Time Associated with One Additional Hour of Training (seconds)	0.097	0.260	0.099	0.045
ROI	489.8%	1,305.1%	503.3%	218.7%

Note: A monthly loss rate (skill depreciation and turnover) of 4.3% is assumed in ROI calculations.

this case, we calculated the return on investment by using employee wage records and the estimated coefficients of training on call handling time, as shown in Tables 2 and 3. Unlike Bishop (1991) who only accounted for the training time of trainers, we also take into account the training time of workers. Average monthly earnings for telephone operators, service assistants, and supervisors were $2,764, $3,318, and $4,944, respectively. As supervisors provided 78% of total training, the weighted monthly wages of trainers were $4,580. Total work time was 150.5 hours each month. Our analysis suggested that a one-hour change in informal training was associated with a 0.097-second reduction in time per call for an average worker. When we take pre-training job competency into account, this translates to a reduction of 0.260 seconds for workers with low initial competency, 0.099 seconds for those with average proficiency, and 0.045 seconds for those with high competency.

In addition to skill depreciation, it would be more accurate to take into account, as well, the effects of employee turnover, which is likely to lead to a loss of human capital. Company archives indicated that the quit rate was less than 5% each year. The estimated depreciation rate in the data is 3.8% each month. To be conservative, we assume a monthly quit rate of 0.5%, or 6% per year. This results in a loss rate of 4.3% each month. We calculated rates of return for workers in each group of initial competency based on the above information. The results are shown in Table 5. The first column reports the ROI for all workers in the sample. The returns to company investments for informal training are quite high—489.8%. To illustrate the nonlinearity between training and productivity, columns (2), (3), and (4) report the returns of a worker whose initial job competency was low, average, and high, respectively, and who received the average amount of training in her proficiency group.

Discussion

This study focused on the relationship between informal training and productivity among incumbent telephone operators in a large unionized telecommunications company. Using objective data from company archives and a first-difference model to control for worker heterogeneity, our analyses produced three major findings. First, we found a statistically significant positive relationship between investments in informal training and productivity; and the benefits of training were sustained over several months. Because we use objective data and our specification takes into account the stock and flow of training investments, as well as the depreciation of learning, we have been able to provide an estimation of the returns to training that is more fine-grained than similar estimates in prior studies.

Second, our results indicate that individual differences, as measured by pre-training proficiency, need to be incorporated into evaluations of training effectiveness, both because they affect the returns to training and because they interact with the type of training offered. The relationship between training and performance was strongest for workers in the less

proficient group, less pronounced for those in the average proficiency group, and weakest for those in the high proficiency group, suggesting that information processing and self-regulatory mechanisms are different among workers with different levels of initial job competence. In addition, workers in the less proficient group who received training benefited more from training with supervisors than with peers. The opposite was true for workers in the average proficiency group. This difference is understandable, as supervisors tend to provide structured training on basic procedures while peer trainers draw on their tacit knowledge of idiosyncratic work processes to enhance the existing knowledge of experienced workers. These findings are consistent with the literature on situated learning, which suggests that learning on the job depends not only on the attributes of individuals, but also on the interactions among employees at work.

Contrary to expectations, however, we found that for the high proficiency group, supervisor training was marginally effective, but peer-provided training lowered productivity. One possible explanation is that the high proficiency peers simply used the "training" time to socialize. Alternatively, they may have used the time to experiment with new work methods that, while lowering productivity, improved other outcomes, such as customer satisfaction or quality, which are not measured in this study.

Finally, this quantitative case study demonstrates that companies may recoup their investments in training, even in settings characterized by highly routinized work. The return on training investment for this sample of telephone operators was 489.8% for all workers. As Kusterer (1978) noted, no job is literally unskilled, and all jobs require the acquisition of a substantial amount of working knowledge in job-specific domains. Informal training is an effective tool for upgrading the skills and job competence of high-school-educated workers. Moreover, in contrast to formal training, which tends to be concentrated among young, well-educated, professional or managerial employees, or those in large establishments, informal training is widespread, and the likelihood of its receipt seems to be little influenced by worker characteristics such as sex, race, or even formal education (Altonji and Spletzer 1991). Therefore, it provides a valuable learning opportunity for workers who do not go on to college or who cannot afford to devote a lengthy amount of time to certificated programs.

This study does have several limitations. First, to deal with the issue of selection bias, we examined the association between worker characteristics and informal training, and found that workers who received lower performance ratings received greater amounts of informal training. To reduce the magnitude of this problem, we disaggregated the data and estimated separate models for workers with different pre-training proficiency levels. We also used first-difference models of estimation. These strategies alleviate, but do not completely solve, the selection problem. Second, we do not allow for time-variant individual heterogeneity in this study. Nevertheless, the results suggest that our models explain more than 94% of total variance. Third, we examine only proximal productivity outcomes. While labor efficiency is clearly a high priority in this commodity production setting, managers were also concerned about customer satisfaction ratings and employee behaviors such as absenteeism. In such routinized jobs, time off the phone for training is viewed as a benefit, with motivational results that may reduce emotional exhaustion or burnout and absenteeism, and in turn generate better service by employees or additional cost savings.

Finally, the important policy question is, "So what?" The present study examines a setting in which work tasks have been increasingly automated and employment levels have fallen steadily over the past 50 years. However, employers still need to maximize the productivity of existing processes even as they continue to seek new levels of efficiency through automation; and with ongoing changes in software technology and information systems, employees need ongoing training to adjust to those changes. In addition, as Levy and Murnane (2004) and others have demonstrated, the jobs left behind are typically more complex than

those that have been automated, requiring higher skills and job-specific training. If this study is viewed as a critical test—focusing on a setting in which the pay-offs to training are not likely to be found—then we believe the findings may generalize to a broader set of employees whose skills require regular on-the-job upgrading due to ongoing changes in products, marketing, work processes, and technologies. A large proportion of U.S. workplaces fall into this category; and compared to directory assistance services, they involve jobs that offer employees greater opportunity and discretion to use their skills and knowledge. In these contexts, the pay-off to systematic informal training should be greater than that found in our study.

Appendix 1
Total Training Hours Received in Five Months as a Function of Worker Characteristics

Variable	*Coefficient*	$P > \|t\|$
Pre-Training Proficiency, Dummy (1 = average)	–1.248	0.00
Pre-Training Proficiency, Dummy (1 = high)	–1.550	0.00
Age (years)	–0.003	0.68
Organizational Tenure (years)	–0.017	0.04
Sex, Dummy (1 = female)	–0.067	0.68
Race, Dummy (1 = non-white)	0.341	0.04
Constant	7.688	
R-Squared	0.4835	
Adjusted R-Squared	0.4723	

Note: Work units (39 in total) were considered as dummy variables in the regression.

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