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# The Economic Pay-Offs To On-The-Job Training In Routine Service Work

Xiangmin Liu  
*Cornell University*

Rosemary Batt  
*Cornell University, rb41@cornell.edu*

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## **Keywords**

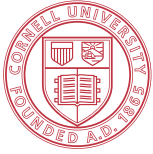
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**Cornell University**  
School of Industrial and Labor Relations  
Center for Advanced Human Resource Studies

CAHRS at Cornell University  
187 Ives Hall  
Ithaca, NY 14853-3901 USA  
Tel. 607 255-9358  
[www.ilr.cornell.edu/CAHRS](http://www.ilr.cornell.edu/CAHRS)

## WORKING PAPER SERIES

# The Economic Pay-Offs To On-The-Job Training In Routine Service Work

Xiangmin Liu  
Rosemary Batt

**Working Paper 05 – 11**



# **The Economic Pay-Offs To On-The-Job Training In Routine Service Work**

**Xiangmin Liu**

and

**Rosemary Batt\***

**July 2005**

<http://www.ilr.cornell.edu/cahrs>

This paper has not undergone formal review or approval of the faculty of the ILR School. It is intended to make results of Center research available to others interested in preliminary form to encourage discussion and suggestions.

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**Abstract**

This study examines the relationship between on-the-job training and job performance among 3,408 telephone operators in a large unionized telecommunications company. We utilize individual data on monthly training hours and job performance over a five-month period as provided by the company's electronic monitoring system. Results indicate that the receipt of on-the-job training is associated with significantly higher productivity over time, when unobserved individual heterogeneity is taken into account. Moreover, workers with lower pre-training proficiency show greater improvements over time than those with higher pre-training proficiency. Finally, whether the training is provided by a supervisor or a peer also matters. Workers with lower proficiency achieve greater productivity gains through supervisor training, while workers with higher proficiency achieve greater productivity gains through peer training.

\*Xiangmin Liu is a Ph.D. student in Human Resource Studies at the ILR School, Cornell University. Rosemary Batt is the Alice H. Cook Professor of Women and Work, ILR School, 387 Ives Hall, Cornell University, Ithaca, NY 14853, 607-254-4437 (phone), 607-255-1836 (fax), rb41@cornell.edu. This study was funded by the Russell Sage Foundation. Copies of the computer programs used to generate the results in this paper are available through Rosemary Batt at the address above.

**Introduction**

In recent decades, skill requirements for many jobs have increased due to heightened international competition, technological change, and customer expectations (Osterman 1995; Cappelli et al. 1997). 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 on-going training has risen even though competitive pressures put constraints on training budgets.

On-the-job training (OJT) provides an effective and efficient way to satisfy the demand for skill in organizations characterized by continuous change in technology and competition. First, 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. Second, it may be more effective than classroom training because employees learn through continuous, context-situated learning initiatives, rather than via infrequent or isolated training activities (Sugrue 2003). Context-specific learning also reduces the losses associated with transferring learning from off-site to on-site applications. Third, compared to formal classroom training, on-the-job training is less costly because it reduces productivity loss associated with time away from work and it 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, on-the-job training can yield substantial economic pay-offs to companies through the on-going skill acquisition of employees. Yet, the overwhelming bulk of training research has focused on formal classroom training (Bishop 1997; Frazis and Loewenstein 2003).

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 -- on-the-job training rather than formal training, and incumbent workers rather than new hires. Second, we develop and test a model of productivity that disaggregates the effects of prior training (the accumulated

'stock' of training) from those of current training (what we refer to as the 'flow' of training). Most prior studies have failed take into account the effects of skill accumulation; and some researchers have emphasized the need for longitudinal studies that differentiate the returns to prior and current training (e.g., Black and Lynch 1996).

Third, we use archival data from a firm-level computerized monitoring system to measure on-the-job training hours and productivity for individual employees. Relatively few studies have estimated rates of return to on-the-job training due in part to the difficulty of measuring it. The longitudinal nature of the data enables us to use fixed effects models to control for unmeasured individual heterogeneity and to disaggregate the effects of accumulated versus current training. 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. While automation has increasingly eliminated clerical jobs like these (Levy and Murnane 2004), routine service work is still abundant in the economy. More importantly, we chose this context as a critical case. Conventional wisdom is that such routinized and technology-driven work requires little skill, and investments in training are unlikely to have meaningful productivity effects. If on-the-job training has economic pay-offs in this context, it is likely to have more benefits for jobs with greater skill requirements and opportunities for independent judgment.

The organization of this paper is as follows. In Section 2, we review prior literature on the relationship between training and productivity, and we develop our hypotheses. After discussing the data set and econometric specifications in Section 3, we present empirical results in Section 4 and calculate return on investment. The final section discusses the implications of our findings.

### **Research on Training and Productivity**

The theoretical argument linking employer-provided training to performance is well established. Human capital theory distinguishes between general training and firm-specific training, with the former focused on improving human capital that is portable across firms and the latter designed to increase the skills of employees in a particular firm (Becker 1962). The theory predicts that employers will invest in firm-specific training because it increases marginal benefits and reduces the probability of inter-firm mobility. Moreover, it assumes that investments in workers' capacities are comparable to those for other resources in the production process, with investments in an initial period assumed to generate returns in subsequent periods. Firms decide how much to invest in training by calculating the net present value of the costs and benefits of such a decision (Stevens 1994; Loewenstein and Spletzer 1999b).

Prior research has categorized firm-specific training into two types: formal training and informal or 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. On-the-job 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 to date has focused on formal rather than on-the-job training. While an estimated two-thirds of the U.S. workforce receives on-the-job training (Altonji and Spletzer 1991; Frazis et al. 1998), much prior research has focused on employer-sponsored formal training for managers and professionals (e.g., Mathieu and Leonard 1987; Bartel 1995) or on public training programs for the unemployed and disadvantaged (e.g., Courty and Marschke 1997; Greenberg, Michalopoulos, and Robins 2003). Moreover, many studies have



relied on wage growth, mobility, or self reports of productivity to estimate the outcomes of training (e.g., Mincer 1988; Lynch 1992; Parent 1999; Loewenstein and Spletzer 1999).

Here, we review studies of training and actual performance, which are of two types: large-sample surveys and econometric case studies (Bartel 2000). Studies of formal training using large sample survey data have yielded positive, but inconclusive results (Holzer et al. 1993; Bartel 1994; Black and Lynch 1996; and Barrett and O'Connell 2001). Holzer et al. (1993), for example, used a three-year panel of data from the Michigan Job Opportunities Bank Upgrade project (MJOB), a state-financed training grant program for small manufacturing firms in the process of implementing new technology. Holzer and his colleagues found that a doubling of the amount of formal training per employee reduced the output scrap rate by about 7 percent, but lasting effects of training were not significant and there was little effect of training on sales or wages. Bartel (1994) examined productivity gains from formal training in large manufacturing companies. She found that some businesses that were operating below their expected productivity levels in 1983 implemented training programs after 1983. Higher productivity growth rates due to training programs brought these businesses up to the productivity levels of comparable businesses by 1986.

Black and Lynch (1996, 2001) utilized data from the National Center on the Educational Quality of the Workforce National Employers Survey (EQW-NES). They found that the percentage of training that occurred off-the-job was significantly positively associated with productivity in manufacturing companies, and computer training had a positive impact in non-manufacturing companies. However, neither the total number of employees trained in a prior period nor the number trained in the current period had a significant relationship to sales, based on cross-sectional estimations (Black and Lynch 1996). Finally, the authors suggested that it was not so much whether the employer trained workers, but rather how training was actually implemented, that affected productivity (Black and Lynch 2001). Barrett and O'Connell (2001) also reached mixed conclusions in their survey of formal vocational training among 215 Irish

companies. Results were sensitive to how training was measured as well as the type of training offered. General training had positive effects while specific training did not.

The second approach to research on employer-provided training, which is applied in this paper, is to conduct a detailed firm-level study of training and its effectiveness. This strategy, which substantially reduces measurement error and bias caused by unobserved heterogeneity, is exemplified in recent work by Bartel (1995) and Krueger and Rouse (1998). Among professional employees in a large manufacturing company, Bartel (1995) found that one-day participation in formal training programs increased wages by 1.8 percent, and employees who received training also experienced significant increases in their subjective performance ratings. Krueger and Rouse (1998) examined a workplace education program at two mid-sized companies in manufacturing and services. On-site classroom courses, designed to improve basic skills for low skilled workers, produced mixed results. In the manufacturing setting, trained workers were more likely to bid for new jobs and to receive upgrades than comparable non-participants. In the service company, however, training participants were not different from non-participants except on the measure of self-reported job performance. These findings were particularly robust because biases due to non-random selection into training were controlled for. As suggested by Bartel (1995), for example, training can be either “career advancement” or “remedial.” In a career advancement situation, workers selected to receive more training are likely to be more capable workers than their peers, irrespective of the amount of training they receive. Estimation of training effects is therefore upward biased as it may simply reflect selection into training, rather than human capital accumulation and utilization. By contrast, less capable workers are likely to receive remedial training so that estimates of the returns to training should be downward biased. .

In contrast to the research on formal training, only a handful of studies have examined on-the-job training, and these have used national level surveys (Bishop 1991; Barron, Berger, and Black 1997a, 1997b). Most prior studies have used either job tenure as a proxy for informal

training or self-reported estimates of training hours in national surveys, both of which are subject to serious measurement error (Loewenstein and Spletzer 1999a; Barron, Berger and Black 1997a). Moreover, while on-the-job training for incumbent workers has grown in response to changing technologies and work processes, existing studies of on-the-job training have tended to examine workers in the first three months of being hired (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 on-the-job training: learning by watching, informal training with supervisors, and informal training with co-workers. Bishop found that the marginal rate of return for 100 hours of training ranged from 11 to 38 percent, 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.

Barron, Berger, and Black (1997b) also investigated the effects of on-the-job 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 are similar to those of Bishop regarding the value of on-the-job 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 survey data provide the strongest evidence to date that on-the-job training has economic benefits. However, they have several methodological

problems. First, they rely on retrospective data; but as Loewenstein and Spletzer (1999) note, measurement error increases with the span of time between the training spell and the interview. Second, the survey reports by employers and employees vary considerably. Barron, Berger, and Black (1997a), for example, found that the correlation between worker and establishment measures of training was less than 0.5, with employers usually reporting 25 percent more hours of training on average than workers. Third, productivity is reported by employers on a subjective scale. Fourth, training and job performance are almost inherently heterogeneous, so that it is inappropriate to aggregate between firms and industries (Bartel 1995).

In sum, human capital theory provides a general argument for why investments in training should lead to better performance via its effect on human capital. However, empirical studies provide inconsistent results, in part due to the measurement limitations of national survey data. 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 on-the-job training may have differentiated outcomes.

### **On-the-Job Training as Information Processing and Continuous Learning**

To improve our understanding and empirical estimation of how on-the-job training affects productivity, we go beyond the model of discrete, isolated investments in human capital. We believe it is more useful to conceptualize on-the-job training as a process of continuous learning, or the on-going accumulation of human capital at work. The returns to on-the-job training, in this view, include two dimensions: the 'stock' of training benefits that accumulates over time and the 'flow' of current training benefits that may be immediately applied to work activities. This approach provides a more precise estimate of how training affects productivity over time. We present this conceptualization mathematically in the model specifications below.

In addition, we examine variation in organizational contingencies that may shape the effectiveness of training. Two important factors concern the level of proficiency of workers and the level of complexity of tasks. According to Ackerman (1987), 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. Training in these circumstances will tend to accentuate the differences between employees with higher and lower intellectual capabilities. This line of argument is consistent with the findings in much of the economics literature that higher educated workers are more likely to receive formal training and are more likely to benefit from such training (e.g., Frazis, Hertz, and Horrigan 1995; Bartel 1995; Bishop 1997).

By contrast, for tasks requiring simple and consistent information processing, Ackerman found that the relationship between training and performance was influenced more by psychomotor differences (e.g., speed of encoding or responding) than by general cognitive abilities. With sufficient training and practice, trainees in his study internalized task behaviors and the performance levels of the less proficient and more proficient gradually converged. Thus, in the context of relatively simple information processing – as that found in this study and in most routine service work -- on-the-job training should lead to a convergence of individual performance differences, with less proficient workers should show greater improvement than the more proficient for the same amount of training.

Beyond the issue of individual tasks and competencies is the question of how the interactions between different types of trainers and employees affect outcomes. The recent research on situated learning provides some direction here, as it conceptualizes learning as a social process (Lave and Wenger 1991; McLelland 1995). From this perspective, learning is contextually bounded and influenced by the activity, context, and social relationships in which it is situated. By extension, on-the-job 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). More specifically, because on-the-job 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, choices, and capabilities of the learner and the trainer; differences in status or power between the trainer and trainee; and how these factors interact. A common and important distinction in this regard is whether trainers are supervisors or experienced co-workers.

Prior research shows that supervisors typically take a quite different approach to training than do peer trainers. Supervisors usually take a relatively structured approach to training, using company manuals, standardized training materials, and follow-up observations. They transform on-the-job training into a more standardized set of learning activities. Swanson, O'Connor, and Cooney (1990) suggested that low-ability learners tend to gain more from high-structured learning environments than do high-ability learners. Also, the supervisor influences a worker's effort through disciplinary authority as less proficient workers are more likely to be subject to reprimand and corrective feedback than the more proficient. As a result, they are likely to increase their effort to avoid punishment. This line of reasoning suggests that supervisors are likely to be more effective than peer trainers 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 who provide assistance and share knowledge with co-workers through informal instructional activities. They are the 'subject experts' in the workplace. They accumulate tacit knowledge of work processes through day-to-day practices, and therefore possess significant knowledge of idiosyncratic job characteristics, which supervisors often do not have. Particularly in the current environment of rapidly changing work processes and technologies, even supervisors who have been promoted from production level jobs experience rapid decay in the relevance of their accumulated tacit knowledge.

In addition, training with peers is a social influence process through which workers learn to conform to the norms and customs of the social group (Bandura 1977). Workers are likely to be

open to learning from experienced peers, whose expertise can be clearly observed and whose position does not carry any disciplinary authority. 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. This line of reasoning also echoes Sisson's (2001) argument that peer trainers are competent to the extent that they rely on their own job experience while supervisor trainers are competent to the extent that they rely on company manuals.

However, there are limitations to the effectiveness of peer training because it is incidental and emergent in nature, and may even be inconsistent across work shifts or trainers.

Therefore, those workers who already have a good command of job-related knowledge and skills are more likely to benefit from peer-provided training than those with less job proficiency.

To summarize our arguments, we expect that on-the-job training will be associated with better performance, both through the immediate effects on the flow of human capital as well as the cumulative effects on the stock of human capital. In addition, because this study focuses on routine information processing tasks, we expect that the benefits of on-the-job 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

We begin by assuming that job performance is a function of human capital and worker characteristics. The performance equation for worker  $i$  at time period  $t$  is

$$PERF_{it} = \alpha + \beta \cdot HC_{it} + \delta \cdot X_i + \varepsilon_{it} \quad (1)$$

where  $PERF_{it}$  is worker  $i$ 's job performance at time  $t$ , as measured by CHT and PCT\_CHT,  $HC_{it}$  is the accumulation of human capital of worker  $i$  at time  $t$ ,  $\beta$  represents the effects of  $HC_i$  on

performance, and  $X_i$  is a vector of control variables assumed to affect performance with the current employer;  $\varepsilon_{it}$  is the error term that is assumed to be normal. This specification highlights the key argument of human capital theory that more investment in human capital leads to better performance.

We incorporate several modifications to address some neglected characteristics of on-the-job training. Because on-the-job training is not the only way that workers acquire human capital to adequately perform their job, we take into account the amount of human capital accumulated prior to training. Initial human capital stock ( $HC_0$ ) represents the stock of human capital that a worker accumulates prior to the period of observation. Moreover, conventional econometric models consider the investment in human capital and its returns as a discrete, two-stage model. These models do not allow for the simultaneity of learning and production, as is the case in on-the-job training. Therefore, we decompose investments in on-the-job training into two components: on-the-job training accumulated prior to time period  $t$  and on-the-job training accumulated during time period  $t$ . Investment in on-the-job training thus contributes to worker productivity through two mechanisms: either as a portion of accumulated human capital stock (as estimated by  $\beta$ ) or as an incremental flow to human capital (as estimated by  $\gamma$ ). In addition, often a readjustment period is required before a worker fully applies his or her newly learned skills on the job. To allow for these adjustments and the possible lag between investments and benefits, we expect that the effect of existing stock of human capital ( $\beta$ ) will outweigh that of  $OJT_{it}$  ( $\gamma$ ). The presence of a union in the company, as well as skill specificity through on-the-job training, considerably reduces the propensity to quit. We assume that workers do not leave their jobs (in fact, turnover in the real company was two percent annually) and that the stock of human capital is non-decreasing in the model. Thus, we extend the specification of a worker's job performance as follows:

$$PERF_{it} = \alpha + \beta \cdot HC_{i0} + \beta \cdot STK\_OJT_{it} + \gamma \cdot FLW\_OJT_{it} + \delta \cdot X_i + \varepsilon_{it} \quad (2)$$



$$\text{where } STK\_OJT_{it} = \beta \sum_{k=0}^{t-1} FLW\_OJT_{ik} \quad (3)$$

$$\gamma = \beta \cdot \theta \quad (4)$$

Furthermore, we use a fixed effects model to correct for time-invariant unobserved individual heterogeneity. Consider

$$\varepsilon_{it} = \mu_i + v_{it} \quad (5)$$

where,  $\mu_i$  represents unobservable person-specific characteristics affecting performance, and  $v_{it}$  is a zero mean error term, independent of training variables.

Equation (2) is thus equivalently transformed as

$$PERF_{it} = \alpha + \beta \cdot HC_{io} + \beta \cdot STK\_OJT_{it} + \gamma \cdot FLW\_OJT_{it} + \delta \cdot X_i + \mu_i + v_{it} \quad (6)$$

## Data

### Research Strategy and Sample

The research site for this study is the telephone operator 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. The strategy of focusing on one occupational group in one company (Batt 2002) reduces 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 on-the-job training might be useful in this context. The business in this case handles directory assistance inquiries from anywhere in the United States. Government-mandated service levels require the company to answer 97.5 percent of calls in 6 seconds. In addition, cost competition is intense in this commodity business, and companies can save millions of dollars by reducing call handling time by fractions of seconds.

This can be accomplished either through new technologies (for example, voice recognition systems now process portions of each call) or better work skills (e.g., more efficient search strategies). The company also requires an 85 percent 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. 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 interviews, 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 on-the-job training activities, including training in methods (new procedures), customer satisfaction (better ways to improve service quality), district issues (business-specific information), ergonomics, and performance feedback. The majority of the training is devoted to monthly performance feedback, with a supervisor or peer trainer providing individualized instruction after listening remotely to several of the employee's calls (typically 20 calls for business, residential, and government sectors). 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; release to audio at least 87 percent of time (having the system give the number rather than the operator reading it). Service quality is measured by such items as tone of voice,

listening and answering questions 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 percent. In sum, these customized sessions provide specific guidance for improvement.

A second type of on-the-job training is methods training, which focuses on new procedures for call handling, information processing, or updates in the information database: these types of changes are not uncommon as companies continually search for ways to improve work processes. 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). For example, prior our fieldwork, the company had recently moved 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 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 routine clerical job, there are on-going changes in information systems and work processes that require regular attention to on-the-job 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 percent of their employees each month, yet in one site we visited, the manager admitted that they were only observing 36 percent. 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 some managers had decided to put more resources into on-going training than others.

The employee sample was drawn from the company's Human Resource Information System (HRIS), 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 new employees with 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 less than 40 employees. The final sample includes 3,408 telephone operators at 48 service centers.

Operators in our sample are primarily white (73 percent) and female (86 percent), with an average age of 41 and company tenure of 11 years. The company hires high school graduates and uses two rounds of systematic testing in its selection procedures. While the HRIS system did not provide educational data, our survey of employees showed that most have had some post-secondary education, but only eight percent 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 percent of them are female, while 78 percent of peer trainers are white and 94 percent of them are 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 of January 2001 to 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. On-the-job training is the length of time that a worker spent in on-the-job training each month. The percentage of operators who received training each month ranged from 92.8 percent to 95.6 percent, with an average training time that ranged from 75 to 94 minutes. All employees except for 2 out of 3,408 received some training in this period.

When broken down by type of trainer, workers received an average of 59 minutes of on-the-job training with their supervisors and 17 minutes with peer trainers each month.

We used two measures of productivity. The first measure, call handling time (CHT), is the average number of seconds an operator spends on a customer call. Lower call handling time equals higher productivity. The second measure is the percentage of local official objectives met (PCT\_CHT). 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, if an employee handles a call in less time than the center's objective, the employee scores higher than 100 percent of objectives met. The company set the range of acceptable performance between 94 and 107 percent. Any operators who fell below 94 percent were rated unsatisfactory, and above 107 percent, excellent.

To measure pre-training proficiency, we used an operator's percentage of objectives met in the first month for which we had data (e.g., January). We chose this measure instead of CHT to eliminate potential error confounded by establishment characteristics. Using the company's threshold criteria of 94 percent and 107 percent, we established three proficiency categories: low (761 workers, 22%); average (1,142 workers, 34%); and high (916 workers, 27%).

Finally, we matched the training and productivity data to archival data from the company's Human Resource Information System (HRIS). Through our fixed-effects model, we controlled for age, sex, race, company tenure, and other time-invariant workers characteristics.

### **Selection Bias**

Prior literature suggests that non-random selection into training may seriously bias the estimation of returns to training. Drawing upon prior research and company information, we did a number of analyses to assess the extent of selection bias in this study. 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. On a month-by-month basis, the percentage of workers who received some training ranged from 92.8% to 95.6% of workers. We ran a random effects probit analysis to test whether performance in month 1 was a significant predictor of whether an employee received any training in a given month, and we found no significant effect.

We then assessed variation in hours of training received (see Appendix 1). Controlling for supervisor and worker demographic characteristics, we found that workers with lower performance ratings in month 1 received significantly longer hours of total training. This confirmed the need to run separate analyses by proficiency group (low, average, and high) as describe above. The lowest proficiency group received an average of 1 hour and 44 minutes (1.54 SD) of OJT each month, while the average proficiency group received 1 hour and 28 minutes (1.53 SD), and the high proficiency group, 1 hour and 19 minutes (1.33 SD). Thus, the lowest proficiency group received an average of 16 minutes more training each month than the average group, and 25 minutes more than the high proficiency group. While these differences are statistically significant, they would 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 sum, these analyses show that there is a relatively even distribution of on-the-job training in our sample, which is consistent with findings in national surveys (Altonji and Spletzer 1991). In addition, there is negative selection into training in this sample, but it appears that the magnitude of variation in receipt of on-the-job training is small. Nonetheless, our estimates of training benefits are biased downwards so that we present a conservative estimate of the returns to training.

## **Results**

Table 1 reports the means, standard deviations, and correlation matrix for the major variables in the study. Contrary to expectations, measures of accumulated and contemporaneous investments in on-the-job training are not significantly related to call handling

time. In fact, the relationship between on-the-job training and the percentage of objectives met is significant and negative, which contradicts our expectations and suggests that further analyses are needed. Some control variables have a statistically significant relationship with training outcomes. White workers and younger workers are likely to be more productive, but sex is not statistically significant.

**Table 1:  
Means, Standard Deviations, and Correlation Matrix**

		Mean	Std. Dev.	1	2	3	4	5	6	7	8	9
1	Call handling time	21.371	4.312									
2	Percentage of local objective met	1.025	0.140	-0.766*								
3	On-the-job training as stock	3.104	2.957	-0.023	-0.073*							
4	On-the-job training as flow	1.248	1.434	0.011	-0.066*	0.133*						
5	Sex	0.868	0.339	0.010	-0.013	-0.044*	-0.025					
6	Race	0.279	0.449	0.164*	-0.087*	0.088*	0.078*	0.033*				
7	Age	40.799	11.252	0.282*	-0.289*	-0.083*	-0.038*	0.164*	0.037*			
8	Tenure	11.425	10.156	0.300*	-0.254*	-0.090*	-0.035*	0.174*	0.195*	0.6720*	0.6720*	

Note:

1. Sex: dummy variable for sex with male=0 and female=1.
2. Race: dummy variable for race with white=0 and nonwhite=1.
3. Pairwise correlation with Bonferroni adjustment.

### Training and Productivity

Next, we provide a fixed effects estimation of the model by drawing on the longitudinal data. A set of Hausman tests supports the use of fixed effects models over random effects models in this study. In Tables 2 and 3, the first column presents the estimated relationship between on-the-job training and productivity from fixed effects analyses. The results support the argument that the amount of time spent in on-the-job training leads to productivity improvements both in the current month and the following months. A positive and sustained return to training is line with some studies using fixed effects to control for individual heterogeneity (Bishop 1994; Bartel

1995). The results show that one hour's training is associated with a 0.06 second reduction ( $p < .01$ ) in call handling time and a 0.07 percent improvement in the percentage of objectives met ( $p < .10$ ) in the current month. It is also related to a 0.05 second time reduction ( $p < .01$ ) and a 0.11 percent objective improvement ( $p < .01$ ) in the subsequent months. Moreover, the pattern of standardized coefficients of *STK\_OJT* and *FLW\_OJT* is consistent with our expectation that a readjustment lag exists. Lagged effects probably occur because as workers need time to transform what they have learned into automatic or unconscious behavior. As a result, the standardized coefficient for productivity of on-the-job training is larger in subsequent months than in the current month. The pattern is particularly dramatic for the percentage of objectives met, where the lagged on-the-job training coefficient is approximately triple the magnitude of the coefficient for contemporaneous effects.



**Table 2:**  
**Relationship between On-the-Job training and Call Handling Time (t-statistics included)**

	All Workers				Workers of low pre-training proficiency				Workers of average pre-training proficiency				Workers of high pre-training proficiency			
	Coef.		Std. Beta		Coef.		Std. Beta		Coef.		Std. Beta		Coef.		Std. Beta	
On-the-job training as stock	-0.051	***	-0.035	***	-0.093	***	-0.064	***	-0.023	***	-0.016	***	-0.018	**	-0.013	**
	(-7.04)				(-5.95)				(-3.28)				(-2.48)			
On-the-job training as flow	-0.061	***	-0.020	***	-0.096	***	-0.032	***	-0.019	*	-0.006	*	-0.001		0.000	
	(-4.99)				(-3.47)				(-1.78)				(-0.05)			
Constant	21.523				24.570				21.633				18.502			
No. of obs.	11,788				2,824				4,120				3,417			
No. of persons	3,298				761				1,142				916			
F	31.58				20.78				6.15				3.23			

Note: \* Significant at 0.10, \*\* at 0.05, \*\*\* at 0.01.

**Table 3:**  
**Relationship Between On-the-Job training and Percentage of Objectives Met**  
**(t-statistics included)**

	All workers		Workers of low pre-training proficiency		Workers of average pre-training proficiency		Workers of high pre-training proficiency	
	Coef.	Std. Beta	Coef.	Std. Beta	Coef.	Std. Beta	Coef.	Std. Beta
On-the-job training as stock	0.001 <sup>***</sup> (-5.23)	0.024 <sup>**</sup>	0.002 <sup>***</sup> (6.22)	0.04 8 <sup>***</sup>	0.001 (1.61)	0.011	-0.000 (-0.58)	-0.006
On-the-job training as flow	0.001 <sup>*</sup> (-1.90)	0.007	0.002 <sup>***</sup> (2.53)	0.01 7 <sup>***</sup>	0.000 (0.85)	0.004	-0.001 (-1.46)	-0.013
Constant	1.022		0.886		1.006		1.170	
No. of obs.		11,788		2,824		4,120		3,417
No. of persons		3,298		761		1,142		916
F		14.10		20.47		1.48		1.09

Note: \* Significant at 0.10, \*\* at 0.05, \*\*\* at 0.01.

To test for differences associated with pre-training proficiency, we performed a fixed effects estimation for each group of workers with different proficiency. The analysis (columns 2-4 of Tables 2 and 3) shows that workers with lower proficiency showed substantially higher performance gains related to training than did those with higher levels of proficiency. For an average worker of low proficiency, one additional hour of on-the-job training is associated with a 0.096 second reduction in call handling time ( $p < .01$ ) in the current month, and a 0.093 second reduction ( $p < .01$ ) in the subsequent months. By contrast, for a typical worker of average proficiency, the same amount of training is associated with a reduction of only 0.02 seconds, either contemporaneously ( $p < .10$ ) or subsequently ( $p < .01$ ). For workers with high proficiency, the relationships are weaker still. One hour of training is associated with a 0.02 reduction in seconds per call ( $p < .05$ ) in the months after training, and has no significant immediate effects. In other words, performance gains through training are primarily driven by the less proficient workers. This pattern is more pronounced for the estimation of percentage of objectives met. Only the less proficient group shows significant productivity gains associated with training. The coefficients on training for the other two groups are negligible and insignificant.

These results raise the question of whether differences in effect sizes are partly due to regression to the mean. However, our results reveal something more than that. Descriptive statistics for each group showed different patterns of productivity improvements in each group over the five months. While the productivity of the least proficient group increased over time, its variability became lower in the same time period.

### **Supervisor Versus Peer Training**

Next we examine how variation in the training provider (supervisor versus peer) interacts with the level of proficiency of workers. Tables 4 and 5 report these results. For workers with lower levels of proficiency, training with the supervisor is associated with significantly higher productivity, as measured by call handling time and by percent of official objectives met. By contrast, training with peer trainers is not significant. For a typical worker in the less proficient

group, the receipt of one-hour's training with a supervisor is associated with a 0.19 second reduction in call length ( $p < .01$ ) in the current month and 0.13 seconds ( $p < .01$ ) in the following months. It is also associated with a 0.28% ( $p < .01$ ) increase in the percentage of objectives met in the current and subsequent months. The results support the idea that less proficient workers realize significant performance improvements from supervisor training, presumably because it is consistent, individualized, and extrinsically motivated. Except for a small and significant lagged effect for highly proficient workers (-0.02,  $p < .01$ ), supervisor training has no significant relationship with the performance of average and high proficiency workers.

For workers with average levels of proficiency, it is the training with experienced peers that is significantly related to higher productivity, not training with supervisors. Every a one-hour increase in peer training for this group is associated with a 0.04 seconds ( $p < .01$ ) reduction call handling time in the current month and 0.06 seconds in the following months ( $p < .01$ ). The amount of training is also related to a higher percentage of objectives met (by 0.28% in subsequent months,  $p < .01$ ). These findings indicate that workers of average pre-training proficiency are more likely to benefit from peer training than supervisor training. Finally, probably because investments in training generate the least benefits to workers with high levels of competence, it does not seem to matter much whether training is delivered by supervisors or peers.

**Table 4:**  
**Relationship between Supervisor Training, Peer Training, and Call Handling Time (t-statistics included)**

	All workers		Workers of low pre-training proficiency		Workers of average pre-training proficiency		Workers of high pre-training proficiency	
	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.
Supervisor on-the-job training as stock	-0.048*** (-4.45)	0.011	-0.135*** (-4.97)	0.027	-0.012 (-1.24)	0.009	-0.022*** (-2.06)	0.011
Supervisor on-the-job training as flow	-0.083*** (-5.08)	0.016	-0.191*** (-3.96)	0.048	-0.011 (-0.93)	0.012	-0.012 (-0.68)	0.018
Peer on-the-job training as stock	-0.065*** (-3.10)	0.021	-0.035 (-0.88)	0.040	-0.057*** (-2.60)	0.022	-0.013 (-0.52)	0.025
Peer on-the-job training as flow	-0.034* (-1.68)	0.020	-0.035 (-0.98)	0.036	-0.045*** (-2.04)	0.022	0.017 (0.75)	0.023
Constant	21.538	0.033	24.695	0.092	21.628	0.028	18.513	0.032
Number of obs	11,788		2,824		4,120		3,417	
Number of groups	3,274		761		1142		916	

Note: \* Significant at 0.10, \*\* at 0.05, \*\*\* at 0.01.

**Table 5:  
Relationship between Supervisor Training, Peer Training, and the Percentage of Objectives Met  
(t-statistics included)**

	All workers		Workers of low pre-training proficiency		Workers of average pre-training proficiency		Workers of high pre-training proficiency	
	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.
Supervisor on-the-job training as stock	0.001*** (2.38)	0.0003	0.0028*** (4.41)	0.0006	-0.0002 (-0.49)	0.0004	-0.0002 (-0.36)	0.0007
Supervisor on-the-job training as flow	0.001*** (2.32)	0.0005	0.0028*** (2.52)	0.0011	0.0004 (0.65)	0.0006	-0.0004 (-0.36)	0.0011
Peer on-the-job training as stock	0.002*** (3.52)	0.0006	0.0016 (1.67)	0.0009	0.0028*** (2.85)	0.0010	0.0001 (0.03)	0.0016
Peer on-the-job training as flow	0.001 (0.47)	0.0006	0.0009 (1.03)	0.0008	0.0009 (0.91)	0.0010	-0.0024 (-1.65)	0.0015
Constant	1.021	0.0010	0.8847	0.0022	1.0062	0.0013	1.1692	0.0021
Number of obs.	11,788		2,824		4,120		3,417	
Number of groups	3,274		761		1,142		916	

Note: \* Significant at 0.10, \*\* at 0.05, \*\*\* at 0.01.

**Calculating Returns on Investment (ROI)**

Shaving fractions of seconds off of 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, shaving off these fractions translates into millions of dollars in savings. To assess the costs and benefits of training in this case, we calculated the return on investment by using employee wage records and the estimated coefficients of OJT\_STK on call handling time, as shown in Tables 2 and 4. Unlike Bishop (1991) who only accounts for the training time of trainers, we also take into account the training time of workers. For a typical worker in our study, the average call handling time was 21.67 seconds per call prior to training. Each additional hour of on-the-job training was associated with a 0.05 second reduction in time per call. The average annual earnings for telephone operators, service assistants, and supervisors were \$33,171, \$39,811, and \$59,328, respectively. Viewing the dollar value of operator labor savings as benefits and the dollar value of trainees' and trainers' time devoted to instructive activities as costs, the company's investments in training have economic pay offs when the monthly rate of human capital loss of the workforce, including skill depreciation, worker turnover, and retirement, is less than 20%. We also used three alternative conditions to estimate ROI: (1) human capital does not decrease; (2) human capital decreases at the rate of 5% per month; and (3) human capital decreases at the rate of 10 % per month. The results (and formula used to calculate these results) are shown in Table 6. Assuming that operators work seven hours per workday and 4.3 weeks per month, ROI is 318% at a monthly human capital loss rate of 5%. Thus, the returns to company investment in on-the-job training are quite high.

**Table 6**  
**Rates of Return to Training**

Monthly rate of human capital loss	All Workers		Low proficiency	Average proficiency	High proficiency
	$ROI_{firstyear}$	$ROI_{total}$	$ROI_{total}$	$ROI_{total}$	$ROI_{total}$
0%	250.6%	Very large	Very large	Very large	Very large
5%	192.0%	317.8%	545.3%	92.2%	75.7%
10%	149.9%	108.9%	222.7%	-3.9%	-12.2%

Notes: Calculation of returns on investments are based on

$$ROI = \frac{Benefits - costs}{costs} = \frac{\frac{W_0}{H} \cdot S - \frac{W_t + W_0}{H}}{\frac{W_t}{H}} = \frac{W_0}{W_t} \cdot (S_0 \times \sum_{t=0}^{\infty} (1 - \eta)^t - 1) - 1$$

where  $W_o$  is the average wage of operators,  $W_t$  is the average wage of trainers,  $S_0$  refers to labor savings due to one-hour training in the first month, and  $\eta$  is the month rate of human capital loss.

### Discussion

This study focused on the relationship between on-the-job training and productivity among incumbent telephone operators in a large unionized telecommunications company. Using objective data from company archives and a fixed effects model to control for worker heterogeneity, our analyses produced three major findings. First, we found a significant positive relationship between investments in on-the-job training and productivity; and the benefits of training were sustained over several months. Because our specification takes into account both the stock and flow of training investments, and the lag between investments and benefits, we were able to provide a more fine-grained estimation of the returns to training.

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. Given amount of training, less proficient employees made greater performance gains than did more proficient workers, suggesting that information processing and self-regulatory mechanisms are different among workers with different levels of initial job competence. In addition, less proficient workers benefited more from training with supervisors than with peers, while the opposite was true for more able workers. 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 on-the-job learning depends not only on the attributes of individuals, but on the interactions among employees at work.

Finally, this quantitative case study demonstrates that companies may recoup their investments in training, even in settings characterized by highly routinized work. Based on this sample of telephone operators, we estimated a 318% return on investment, under the assumption that human capital decreases 5% per month. 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. On-the-job training is an effective tool for high-school educated workers to upgrade skills and enhance job competence. Moreover, in contrast to formal training, which tends to be concentrated among young, well-educated, professional or managerial employees, or those in large establishments, on-the-job training is widespread and worker characteristics (such as sex, race, and even formal education) do not appear to have a significant influence on the receipt of on-the-job training (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.

There are several limitations to this study, however. First, to deal with the issue of selection bias, we examined the association between worker characteristics and on-the-job

training, which demonstrates a pattern of negative selection into training. Workers who received low performance ratings appeared to receive greater amounts of on-the-job training. That suggests that our estimation of training effects is downward biased and tends to be conservative. Moreover, we included pre-training proficiency levels in our models and used fixed effects estimation. These strategies alleviate, although do not completely solve, this problem. Second, we do not allow for time-variant individual heterogeneity in this study. Nevertheless, the results suggest that our models explain more than 93% 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 very 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 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 last 50 years. If employer strategies emphasize investment in labor-saving technology, why bother with training? Moreover, the current study also takes place in a unionized setting, in which turnover rates are low, so the employer can be certain to reclaim investments in training. What about the typical service workplace in which turnover rates are 30 to 100 percent annually?

We believe that the answer to the first question is that firms need to maximize the productivity of existing processes even as they continue to seek new levels of efficiency through automation; and with on-going changes in software technology and information systems, employees need on-going training to adjust to those changes. In addition, as Levy and Murnane 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 – 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 on-going changes in products, marketing, work processes, and technologies. A large proportion of U.S. workplaces falls into this category; and compared to directory assistance services, involve jobs that offer employees greater opportunity and discretion to use their skills and knowledge. In these contexts, the pay-off to systematic on-the-job training should be greater than that found in our study.

The second question is more problematic. Over the last decade, employers have increasingly embraced market-mediated contracts, with low commitment to long term employment relations. To the extent that they continue to rely on a high turnover model of employment, then they may have little incentive to invest in job-related training, even among relatively high skilled employees. In this sense, the decision to invest in training is part of a broader set of policy decisions regarding which type of work and employment system employers choose to embrace. Particularly for employers in price conscious service and sales markets, the incentives to compete on the basis of high turnover employment models may continue to dominate the landscape. However, given that U.S. employers actually do invest substantially in on-the-job training, this research suggests that paying attention to how it is actually carried out may yield positive benefits that outweigh the costs.

## References

- Acemoglu, Darren, and Jorn-Steffen Pischke. 1999. "Beyond Becker: Training in Imperfect Labour Markets." *Economic Journal*, Vol. 109 (February), pp.112-42.
- Ackerman, Phillip L. 1987. "Individual Differences in Skill Learning: An Integration of Psychometric and Information Processing Perspectives." *Psychological Bulletin*, Vol. 102, No. 1, pp.3-27.
- Altonji, Joseph G. and James R. Spletzer -1991-. "Worker Characteristics, Job Characteristics, and the Receipt of on-the-Job Training. " *Industrial and Labor Relations Review*, Vol. 45, No. 1 (October), pp. 58-79.
- Bandura, Albert. 1977. *Social Learning Theory*. New York: General Learning Press.
- Barret, Alan, and Philip J. O'Connell. 2001 "Does Training Generally Work? The Returns to In-company Training." *Industrial and Labor Relations Review*, Vol. 54, No. 3 (April), pp. 647-62.
- Barron, John M., Mark C. Berger and Dan A. Black. 1997a. "How Well Do We Measure Training?" *Journal of Labor Economics*, Vol. 13, No. 3 (July), pp.507-28.
- Barron, John M., Mark C. Berger and Dan A. Black. 1997b. *On-the-Job Training*. Kalamazoo, M.I.: W.E. UpJohn Institute for Employment Research.
- Bartel, Ann. 1994. "Productivity Gains from the Implementation of Employee Training Programs." *Industrial Relations*, Vol. 33, No. 4 (October), pp. 411-25.
- Bartel, Ann P. 1995. "Training, Wage Growth, and Job Performance: Evidence from a Company Database." *Journal of Labor Economics*, Vol. 13, No. 3 (July), pp. 401-25.
- Bartel, Ann P. 2000. "Measuring the Employer's Return on Investments in Training: Evidence from the Literature." *Industrial Relations*, Vol. 39, No. 3, pp. 502-24
- Batt, Rosemary. 2002. "Managing Customer Services: Human Resource Practices, Quit Rates, and Sales Growth." *Academy of Management Journal*, Vol. 45, No.3, 587-97.
- Becker, Gary. S. -1962- *Human Capital: A theoretical and empirical analysis, with special reference to education*. Chicago, I.L.: The University of Chicago Press.
- Bishop, John. H. 1991. "On-the-Job Training of New Hires. " In David Stern and Jozef M.M. Ritzen ed., *Market Failure in Training? New Economic Analysis and Evidence on Training of Adult Employees*. New York: Springer-Verlag, pp. 61-98.
- Bishop, John. H. 1994. "The Impact of Previous Training on Productivity and Wages. " In Lisa M. Lynch, ed., *Training and the Private Sector: International Comparisons*. Chicago, I.L.: The University of Chicago Press.
- Bishop, John. H. 1997. "What We Know about Employer-Provided Training: A Review of the Literature. " In Soloman W. Polacheck ed., *Research in Labor Economics*, Vol. 16. Greenwich, C.T.: JAI, pp. 19-87.

Black, Sandra, and Lisa Lynch. 1996. "Human Capital Investments and Productivity." *American Economic Review*, Vol. 86, No. 2, pp. 263-67.

Black, Sandra, and Lisa Lynch. 2001. "How to Compete: the Impact of Workplace Practices and Information Technology on Productivity." *The Review of Economics and Statistics*. Vol. 83, No. 3 (August), pp.434-45.

Brown, John Seely. and Paul Duguid. -1991. "Organizational Learning and Communities-of-Practice: Toward a Unified View of Working, Learning and Innovation." *Organization Science*, Vol. 12, No. 1-, pp. 40-57.

Cappelli, Peter, Laurie Bassi, Harry C. Katz, David Knoke, Paul Osterman, and Michael Useem. 1997 *Change at Work*. New York: Oxford University Press.

Courty, Pascal, and Gerald Marschke. 1997. "Measuring Government Performance: Lessons from a Federal Job-Training Program." *American Economic Review*, Vol. 87, No. 2, pp. 383-88.

Doeringer, Peter, and Michael J. Piore. 1971. *Internal Labor Markets and Manpower Analysis*. Lexington, M.A.: Heath and Company.

Frazis, Harley, Maury Gittleman, Michael Horrigan, and Mary Joyce. 1998. "Results from the 1995 Survey of Employer-Provided Training." *Monthly Labor Review*, Vol. 121, No. 6, pp.3-13.

Frazis, Harley, Diane Herz, and Michael Horrigan. 1995. "Employer-Provided Training: Results from a New Survey." *Monthly Labor Review*, Vol. 118, No.-5-, pp. 3-17.

Frazis, Harley-, and Mark Loewenstein. 2003. "Reexamining the Returns to Training: Functional Form, Magnitude, and Interpretation." Working Paper 367, U.S. Bureau of Labor Statistics.

Greenberg, David H., Charles Michalopoulos, and Philip K. Robins. 2003. "A Meta-Analysis of Government-Sponsored Training Programs." *Industrial and Labor Relations Review*, Vol. 57, No. 1 (October), pp.31-53.

Holzer, Harry J., Richard N. Block, Marcus Cheatham, and Jack H. Knott. 1993. "Are Training Subsidies for Firms Effective? The Michigan Experience." *Industrial and Labor Relations Review*, Vol. 46, No. 4 (July), pp. 625-36.

Krueger, Alan and Cecilia Rouse. 1998. "The Effect of Workplace Education on Earnings, Turnover, and Job Performance." *Journal of Labor Economics*. Vol. 16, No. 1 (Jan.), pp. 61-94.

Kusterer, Kenneth. -1978-. *Know-How on the Job: The Important Working Knowledge of "Unskilled" Workers*. Boulder, C.O.: Westview Press.

Lave, Jean, and Etienne Wenger. 1991. *Situated Learning: Legitimate Peripheral Participation*. New York: Cambridge University Press.

Levy, Frank, and Richard Murnane. 2004. *The New Division of Labor: How Computers are Creating the Next Job Market*. Princeton, N.J.: Princeton University Press.

- Loewenstein, Mark A., and James R. Spletzer. 1999a. "Formal and Informal Training: Evidence from the NLSY. " In Solomon W. Polacheck and John Robst, ed., *Research in Labor Economics*, Vol. 18. Greenwich, CT: JAI, pp. 403-38.
- Loewenstein, Mark A., and James R. Spletzer. 1999b. "General and Specific Training: Evidence and Implications." *Journal of Human Resources*, Vol. 34, No. 4, pp. 710-33.
- Lynch, Lisa M. 1991. "The Role of Off-the-Job vs. On-the-Job Training for the Mobility of Women Workers. " *American Economic Review*, Vol. 81, No. 2(May), pp. 151-56.
- Lynch, Lisa. 1992. "Private-Sector Training and the Earnings of Young Workers." *American Economic Review*, Vol. 82, No. 1 (March), pp. 299-312.
- Mathieu, John. E. and Russell L. Leonard. 1987. "Applying Utility Concepts to a Training Program in Supervisory Skills: a Time-Based Approach. " *Academy of Management Journal*. Vol. 30, No. 2 (April), pp. 316-35.
- Mincer, Jacob. 1988. "Job training, wage growth, and labor turnover. " Discussion paper no. 2690. National Bureau of Economic Research.
- Parent, Daniel. (1999). "Wages and mobility: The impact of employer-provided training." *Journal of Labor Economics*, Vol. 17, No. 2(April), pp. 298-317.
- Osterman, Paul. 1995. "Skill, training, and work organization in American establishments." *Industrial Relations*. Vol. 34, No. 2 (April), pp. 125-46.
- Sisson, Gary R. 2001. *Hands-On training: A Simple and Effective Method for On-the-Job Training*, San Francisco, C.A.: Berrett-Koehler.
- Swanson, H. Lee, James E. O'Connor, J.E., and John B. Cooney. 1990. "An Information Processing Analysis of Expert and Novice Teachers' Problem Solving. " *American Educational Research Journal*, Vol. 27, No. 3 (Fall), pp. 533-56.
- Stevens, Margaret. 1994. "An Investment Model for the Supply of Training by Employers." *Economic Journal*, Vol. 104, No. 424, pp. 556-70.
- Sugrue, Brenda. 2003. *American Society for Training and Development: 2003 State of the Industry Report*. Alexandria, V.A.: ASTD.

### Appendix 1

#### Worker Characteristics and Total Training Hours Received in Five Months

	Coef.	P> t
Performance ratings prior to training	-0.8849	0.00
Age	0.0023	0.75
Organizational tenure	-0.0058	0.49
Sex	-0.2963	0.09
Race	0.3399	0.05
Constant	7.6623	0.00
R-squared	57.71%	
Adjusted R-Squared	54.90%	

Note: 1. \* Significant at 0.10, \*\* at 0.05, \*\*\* at 0.01.

2. Number of observations =2360

3. Sex: dummy variable for male=0, female=1.

4. Race: dummy variable for race with white=0 and nonwhite=1

5. Supervisors (143 in total) were considered as dummy variables in the regression.