**The Influence of Employment Practices on Manufacturing Performance
In the Semiconductor Industry**

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Melissa M. Appleyard
The Darden Graduate School of Business Administration
University of Virginia
P.O. Box 6550, Charlottesville, VA 22906-6550, USA
Tel: (804) 924-4030
Fax: (804) 243-7681
e-mail: appleyard@virginia.edu

Clair Brown
Department of Economics
University of California at Berkeley
Center for Work, Technology, and Society, MC5555
Berkeley, CA 94720
Tel: (510) 843-6227
Fax: (510) 843-6280
e-mail: cbrown@uclink4.berkeley.edu

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The Influence of Employment Practices on Manufacturing Performance In the Semiconductor Industry

This paper analyzes the factors contributing to superior manufacturing performance in the semiconductor industry. Through an analysis of firm-level data from the United States, Asia, and Europe, we explore the relationship between firm performance along quality and quantity dimensions and three components of the employment system: skill development, employee participation in problem solving, and employee collaboration. We find that manufacturing success is related to the introduction of new production technology and the involvement of all occupations in problem solving under the leadership of engineers, who play a key (and growing) role in this high-tech industry. We find that the operators and technicians play a smaller role in creating high-performing semiconductor factories than has been found in studies of more traditional factories, such as autos and steel.

Key Words: Problem solving, Teams, Employment system, Semiconductors, Human Resources

Through an analysis of both quantitative and qualitative firm-level data from Asia, Europe and the United States, this paper demonstrates how semiconductor companies have structured their employment system to solve the technically demanding problems that arise daily on the shop floor. Although the employment system includes all aspects of the employment relationship, in this article we focus on a subset of practices: skill development, employee participation in problem solving, and employee collaboration. To adjust for the influence of technological change on performance, we analyze data that span two generations of manufacturing equipment. This study asks to what extent employment practices affect manufacturing performance in the technology-intensive semiconductor industry.

Two characteristics distinguish the semiconductor industry as a “high-tech” industry: labor costs run less than 10% of annual manufacturing costs and expenditures on research and development generally run more than 10% of sales. The semiconductor manufacturing environment also is quite distinctive with strict specifications governing the manufacturing process flow. Semiconductor operations rely on engineering talent to fine-tune production processes. Engineers guide the process of problem solving and innovation, and they cooperate with technicians, and operators to a lesser extent, to monitor and calibrate the equipment. The question of whether technicians and operators play a substantial role on the shop floor in this technology-intensive industry, as has been found to be the case in less technology-intensive industries such as automobiles and steel, has not been answered. In contrast to the findings in studies on the automobile (MacDuffie, 1995) and steel (Ichniowski, *et al.*, 1997) industries, our results indicate that operators and technicians do *not* play a dominant role in determining manufacturing performance in the semiconductor industry. Instead, engineers and technological change play critical roles in this high-tech industry.

Our findings suggest that a semiconductor manufacturer’s need to solve problems quickly and permanently requires that operators and technicians identify problems immediately and then work with engineers to uncover root causes and implement lasting solutions. We believe that the findings from this research have important implications for the evolution of employment practices as companies increasingly adopt information technology (IT) and automation systems similar to those found in the semiconductor industry.

This paper begins with a discussion of how the employment system affects manufacturing performance in the semiconductor industry (Section I). In Section II we characterize the work environment in a semiconductor fabrication facility (fab), and present specific examples of advanced problem solving undertaken at fabs in Japan, Korea, and the United States. In Section III, using fieldwork and survey data from twenty-three fabs, we analyze the relationship between fab performance and three major components of the employment system—skill development, participation in problem solving by occupation, and collaboration. Semiconductor fabs routinely provide training for their employees, and we base our skill development variables on this company-provided training. To understand the role of each occupation in problem solving and innovation on the shopfloor, we examine the participation of operators, technicians and engineers in two primary problem-solving activities—equipment maintenance and statistical process control (SPC). Because of the highly integrated production process, fabs generally encourage collaboration both across occupations and across functions, and we examine how firms structure group problem solving. The final section presents our conclusions.

I. The Relationship between Employment Systems and Manufacturing Performance

Past theoretical and empirical studies have developed frameworks for thinking about the interplay between systems of HR practices and firm performance. Milgrom and Roberts (1995), Baker, Gibbons and Murphy (1994), Holmstrom and Milgrom (1994), and Kandel and Lazear (1992) have emphasized the importance of complementarities among the components of the work organization in affecting organizational performance. These models reflect free-rider problems, imperfect information, agency problems, multiple complex work tasks, and the interdependency of the component parts.

To further examine the importance of interdependencies, empirical studies of the steel and automobile industries have linked complementary components of employments systems to performance. A comprehensive study of steel finishing lines in the United States showed that groups of complementary innovative work practices (incentive pay, teams, flexible job assignments, employment security, and training) have large effects on productivity, while changes in individual work practices had little or no effect on productivity (Ichniowski, *et al.*, 1997). Arthur (1994) found that specific combinations of policies and practices that created a system based on commitment (not control) predict higher productivity and lower turnover for steel minimills. In automobile assembly plants, MacDuffie (1995) found that innovative

HR practices, which function as interrelated elements in an internally consistent HR system, positively affect performance. High performance HR systems contribute most to assembly plant productivity and quality when they are integrated with flexible production manufacturing systems.

Researchers also have used national surveys to study the relationship between HR systems and firm performance. Huselid (1995) found that systems of high-performance work practices have an impact on both intermediate employee outcomes (turnover and productivity or sales per employee) and short- and long-run measures of corporate financial performance. Youndt, *et al.* (1996) found that the HR system can substantially influence performance when aligned with appropriate manufacturing strategies. They found that a human-capital-enhancement HR system was directly related to performance (employee productivity, machine efficiency, and customer alignment) when the firm had a quality manufacturing strategy. Other manufacturing strategies also moderated the HR-performance link. Examining the use of technology in the manufacturing environment and its influence on the employment system, Brynjolfsson and Hitt (1997) found that firms that use a decentralized work system have greater demand for information technology and have greater output from their IT investment.

A few studies have looked specifically at the relationship between HR practices and qualitative and quantitative measure of manufacturing performance in the semiconductor industry. These studies include analyses of participative management practices and team structures. Sattler and Sohoni (1999), using fab-level data from the Berkeley semiconductor industry program,[1] found that participative management practices have a significant positive correlation with manufacturing quality, but the positive correlation with quantity measures was not significant. Sattler and Sohoni argue that quality (yield) problems can be linked to specific causes, and electrical engineers can improve quality by diagnosing the problems. In contrast, scheduling and product demand affect throughput and therefore the causes of problems associated with output quantities cannot be traced to specific work activities. For a selected group of employment system variables in our study, however, we found that the employment system is positively associated with both quality and quantity measures.

Bailey (1998) examined a cognitive model of participation by comparing the productivity of various types of teams in semiconductor fabs that use different employment practices.[2] Contrary to expectations, she found that continuous improvement teams had higher productivity measures than self-directed work teams, even though the former had relatively more task and less team training, fewer problem-solving or maintenance tasks, and lower levels of cross training than the latter.

Our study departs from the previous work in two ways. First this study incorporates all levels of employees into the analysis. Second we examine detailed work practices and their interplay. Specifically we study how manufacturing workers, including engineers, operators and technicians, engage in problem-solving and training activities in order to understand empirically how the various components of the employment system function together. This paper focuses on three important parts of the employment system that drive innovation activities on the shopfloor:

- training for production workers that develops the skills used in their tasks (*e.g.*, problem solving and maintenance) and continuous education for engineers;
- the participation of the trained personnel in work activities that target efficient problem solving and manufacturing improvements;
- collaboration that facilitates interaction and sharing of knowledge across all job categories.

We expected that world-class manufacturing performance in the semiconductor industry would depend on these three components—training and skill development, participation in problem solving, and collaboration.

II. Work and Technology in Semiconductor Fabs

Before turning to the methodology and findings of this study, we highlight the characteristics of work and technology in the semiconductor industry. The success of a semiconductor process flow depends critically on engineering talent—both of the design, development, and integration engineers who craft the production process and of the manufacturing engineers who run the process in a high-volume setting. Engineering expertise guides the complex problem-solving activities during the introduction of a new process as well as continuous improvement projects for mature processes. Because of the technical complexity associated with circuit design and the integration of process steps, operators and technicians are constrained in their ability to solve technical problems without extensive training in engineering and science.

Consequently, operators and technicians have limited involvement in new process development, but they participate in solving both one-time and recurring problems with installed manufacturing processes usually by operating in teams with engineers. Rapid and effective problem solving is a critical activity for short-run competitiveness in the semiconductor industry where companies compete fiercely not only on the basis of price but also quality, *e.g.*, reliability of the semiconductor device. While most pronounced in the engineering ranks, the challenge of encouraging creativity in problem solving while maintaining control over the production process extends through all levels of the organization. Because of the demanding technical requirements of semiconductor process flows, maintaining control over the production flow receives considerable attention.

As in many manufacturing settings, precise specifications govern each process step and process steps are grouped together into production modules. Unlike other production settings, however, the allowable margin for error is extremely narrow. The circuitry on leading-edge semiconductor devices cannot be seen with the naked eye. For example, process recipes contain processing rules calibrated in nanometers (10^{-9} of a meter), so even a slight deviation from an equipment setting can ruin a whole production lot. Furthermore, the semiconductor process flow does not proceed linearly. The wafers of silicon upon which the circuitry is deposited loop through the factory making repeated trips through the primary production modules. Managing these production loops demands sophisticated integration skills during new process development to guarantee that later loops do not compromise the functional integrity of the earlier layers of circuitry.[3] Once in manufacturing, this complicated looping process requires sophisticated scheduling systems.

The industry's migration to new generations of manufacturing technology has influenced the scope of responsibilities assumed by the three job categories. For example, when companies install equipment that processes silicon wafers of a larger diameter in order to increase the number of semiconductor devices per wafer, a number of the work activities become automated. In the transition from silicon wafers measuring 6" in diameter to 8" wafers, work activities such as the movement of wafer lots between process steps, data collection, data analysis (*e.g.*, statistical process control), scheduling, and the entry of production recipes into the equipment have been increasingly automated.[4] As discussed below, our sample of fabs comprises both 6" and 8" fabs, permitting us to take into account technological change.

The proliferation of computer-based production systems in the fab has changed the work activities for each occupation. As computer systems have became more self-contained in terms of collecting and analyzing data and then acting upon the information, the role of operators in statistical process control has diminished. Similarly, operators now play a passive role in scheduling, replaced by systems that adjust in real-time by incorporating more data than readily available to the operators—for example, from customers or in-line manufacturing monitoring devices. In the 8" fabs, operators oversee the automated information technology and control systems as well as monitor the equipment to make sure everything is functioning properly.

The migration to 8" fabs has also modified the roles of technicians and engineers. The skills and knowledge required of technicians to maintain the 8" equipment are similar to what is required for 6" equipment maintenance, with the addition of more automated features and computer integration as discussed above. In addition to performing scheduled maintenance activities, technicians often assist engineers with tool installation, cleans, and troubleshooting. The need for engineering input, especially regarding software, into the fabrication process has risen with the increased use of automation. Engineers develop, implement, and monitor the automated manufacturing and IT systems, and this requires the skills of software engineers as well as process and equipment engineers. In addition, the engineers have more data readily available to them for SPC activities. In 8" fabs, it appears that the role of the engineer has become increasingly central in the smooth running of the fab and in problem solving and innovation activities, while much of the support role of the operators has been taken over by the computerized systems.

Examples of Problem Solving.

To capture the nature of advanced problem solving and innovation on the shopfloor, we present examples from Japan, Korea, and the United States. Teams of engineers and experienced technicians shoulder much of the responsibility for advanced problem solving with only marginal input from operators, whose main contribution may be monitoring the process, collecting data, and running basic statistical analyses. While conducting our field research, we also observed lower-level problem solving by operators and technicians addressing issues directly related to their jobs, such as routine maintenance for technicians and material-handling and machine operation for operators. These activities were especially useful in reducing equipment maintenance time, operator mistakes, and bottlenecks.

Example from Japan: In one company, the equipment maintenance department expects its personnel to reach specific *kaizen* (improvement) goals, which tend to be "last year's result plus alpha." The example here is from the department's photolithography (photo) group, which set the goal of improving the up-time on their machines from 93.5%, achieved the previous year, to 95%. Their machines, called steppers, project the patterns for the circuitry onto the silicon wafers.[5] To reach their department's improvement goal, teams in the photo equipment area identified and solved a number of problems. One of the teams was composed of a senior engineer from the equipment maintenance department and two maintenance technicians. The maintenance technicians at this fab are required to have degrees from a technical high school.

This photo team analyzed the source of defects in the photo area and identified a primary cause. They determined that defects were caused by faulty nozzles used to apply a developer solution onto the exposed wafers.[6] While the standard developer nozzles generally spray a uniform distribution of the developer solution over the wafer surface, in this case, defect-causing bubbles formed. The group altered the configuration of the developer nozzles, allowing them to reduce the force and aeration of the spray. This modification eliminated the presence of bubbles and allowed for a 30% reduction in the consumption of developer. The team constructed and implemented the modification independently from the equipment supplier and believed that this modification distinguished their fab's manufacturing performance from other fabs using the same equipment. When asked if they showed this modification to the equipment maker, the engineer group leader replied, "Hell no!," as they wished to prevent the spread of this defect-improving to their competitors via the supplier.

Example from South Korea: A Korean company in our sample conducts in-line monitoring of machines and process parameters and closely monitors yields at the end of the production line. Statistical analysis correlating yield losses with individual machines revealed a problem in the etch equipment area. The etch machines, which remove unwanted material from the wafer's surface, were found to be underetching.[7] For a previous production process, these machines had been used to perform a deep etch (a trench etch) that resulted in hardware damage. Although long etches like the trench etch had been discontinued, the machines had poor "endpoint detection," *i.e.*, the etch stops prematurely, and this led to the underetching problem.

Two etch engineers formed the “yield improvement team” to analyze the etchers and collected data from across production modules. On a weekly basis, they combined data from the Poly Etch engineer, the Oxide Etch engineer, and one of the Metal Etch engineers to track the trend. Their short-term solution was to add an inspection operation that measured the remaining oxide after etch. They discussed the problem with the equipment vendor, who added a special operating instruction to the on-line manufacturing execution system, but this did not help and the vendor gave up. As in the previous example, the engineers were left to devise their own solution without assistance from the equipment vendor. For the long term, they embarked on a new recipe involving a fixed-time etch to replace the end-point based etch. They estimated that it would take about one month to finish the new recipe.

Example from the United States: At one U.S. fab, yield improvement procedures are split into three cases: (1) reacting to a yield crises in which there are many wafers with low yields, indicating a major equipment or process problem, (2) reacting to more than 5 wafers per production lot with substandard yields, and (3) reacting to a yield deviation by a few wafers per lot or by an individual lot.

In case (1), when the device engineer who monitors yields observes that a crisis has occurred, he or she instructs the operators to put all lots on hold. This will trigger the formation of a cross-functional team that spans work areas and a meeting to discuss the crisis will be called. At the meeting, the device engineer will report his/her findings, and the team will discuss potential root causes. Experiments and/or lab analysis may be performed to prove identification of root cause. A containment plan will be devised and implemented. The team will meet twice per day until the root cause is found.

One example of this procedure involved two steppers that were not fully printing. It turned out in one of the steppers, the lamp intensity had fallen too low, and in the other, there was too much lens drift. Both problems led to insufficient exposure. The device engineer figured it out by analyzing the run cards to see the equipment commonalties. The crisis team changed the exposure energy to solve the problem. It took about 10-11 days to solve this problem.

These examples demonstrate the integral role of engineers and experienced technicians in solving problems on the shop floor. They also highlight the important relationship between equipment performance and the integrity of the semiconductor production process. In the next section we broaden the analysis to analyze how primary components of the employment system relate to fab-wide performance measures.

III. Methodology and Data

The nature of semiconductor manufacturing with its reliance on engineering skills and increasing automation provides a context in which to examine the influence of the employment system in a technology-intensive industry. We analyze three primary facets of the employment system (training and skill development, participation in problem-solving, and employee collaboration) to develop the relationship between employment system and manufacturing performance. For all occupations, training is a necessary but not sufficient condition for effective shopfloor problem solving and innovation. The employment system distributes work activities (*e.g.*, equipment maintenance and statistical process control) across job categories to ensure constant attention to monitoring the production line and troubleshooting problems. The highly integrated production process requires communication both across and within production modules, so fabs typically encourage a variety of team configurations. This study considers the influence of three types of teams—Quality-Improvement Teams/Quality Circles, Self-Directed Work Teams, and Cross-Functional Teams—on manufacturing performance (see Table 1). Because teams can function in a variety of ways, the existence of teams is not sufficient to ensure that they facilitate innovation. The composition of the teams and how they operate affect the sharing of information and the interaction within job categories, across job categories, and across functional areas of the fab.

Our data consist of fieldwork and survey data collected at semiconductor fabrication facilities (fabs) between June 1993 through December 1994 and between December 1996 and December 1997 as part of the Competitive Semiconductor Manufacturing program at U.C. Berkeley.[8] We collected data from sixteen fabs producing 6" wafers during the first period and from seven fabs producing 8" wafers during the second period (see Table 2).[9] We assign location of fabs based on their geographic location and not their corporate headquarters. Teams of roughly eight researchers, including both economists and engineers, visited each fab for two days and conducted extensive interviews with managers, engineers, technicians, and operators as well as observed the manufacturing process. The site visits followed the receipt of a detailed written survey of over two hundred pages completed by the fab management. The bulk of the data collected on the employment system variables and manufacturing performance variables came from the written survey. The site visits permitted verification of the data collected through the written survey.

Below we examine training across occupations and the relationship between training and job tasks. We then consider the integration of problem-solving activities into the job tasks of operators, technicians, and engineers. In particular, we analyze the degree of involvement of the three occupations in equipment maintenance and statistical process control (SPC). Finally we consider the nature of collaboration on the shopfloor through teamwork.

Training and Skill Development. In this section, we consider how semiconductor companies develop the skills required by both front line workers and engineers. The semiconductor industry provides high level of training across all occupations (see Table 3). To remain competitive in the industry, semiconductor companies routinely introduce new generations of their production processes, modify their production equipment, and upgrade their automation and information systems. Manufacturing facilities rely on training to assist workers with problem solving in this changing environment. Workers receive three to four weeks of initial training on average. In our sample fabs during the first three years of work, operators receive nearly eleven weeks of training per year on average, engineers receive roughly eleven weeks, and technicians receive nearly 13 weeks of training per year.

Across the twenty-three fabs in our sample, we find that less training is done in the 8" fabs than in the 6" fabs. The number of days spent in initial training declined substantially for technicians and slightly for operators, and rose slightly for engineers. Training during the first three years declined across all three occupations in 8" fabs compared to 6" fabs. The fall in technician training may be attributable to greater educational attainment by applicants to the technician positions or greater reliance on vendor support by fabs.

Compared to operators in traditional manufacturing jobs, the operators in the 6" wafer fabrication plants oversee a highly technical process and often undertake relatively complex technical tasks. Operators are involved in fairly high skilled procedures, including various types of SPC and equipment maintenance activities. Many of the skilled job tasks of operators in the 6" fabs have been computerized in the 8" fabs. In both types of fabs, most operators are involved in data collection and monitoring, but operator involvement declines as the difficulty of the task increases. Fabs generally limit operator involvement in problem solving to identifying the nature of the problem and notifying technicians or engineers. In a few fabs, operators are involved in performing some routine maintenance. Overall, operators perform tasks that require training and skill development. However, operators are limited in their skill development and career growth, as well as wage growth, unless they become technicians, and this has become even more pronounced in the 8" fabs.[10]

In both 6" and 8" fabs, technicians have attended a technical high school or a two-year technical college, while the majority of engineers hold an undergraduate BS degree in engineering or science. Operators are usually women with high school degrees and without any college. Vendor training on new equipment is a critical part of technician training, and vendor engineers and technicians usually provide on-site support when a new machine is installed and may service the equipment periodically. Technicians working in the newer 8” fabs execute similar job tasks as in 6” fabs but face even more stringent equipment calibration requirements to ensure processing uniformity across the larger wafers. Automation systems in 8” fabs both in terms of material handling and in-line data collection add complexity to the technician’s job when repairing equipment or optimizing the interfaces between production tools. The work of engineers increases in complexity in 8" fabs compared to 6" fabs, as the engineers integrate the data collection, production, and automation systems.

Overall the introduction of new production technologies increases skill demands on engineers, reduces skill demands on operators, and demands similar skills from technicians although may require greater assistance from vendor personnel.

Participation in work activities: Equipment Maintenance. Equipment maintenance activities include a variety of tasks, from daily cleaning, inspecting and recording activity to modifying, repairing and annual maintenance. Equipment that is chronically down, dirty, or out-of-alignment can prevent world class manufacturing performance, and we anticipate that equipment maintenance activities are a necessary (but not sufficient) condition for high performance. To capture the variation across fabs in terms of their use of equipment maintenance activities, we grouped the activities in our survey according to their degree of difficulty (from 1 for low level to 3 for high level) and derived fab scores for each occupation. To control for the generation of manufacturing technology, we report the use of the thirty equipment maintenance activities across the three occupations for the 6” fabs only (see Figure 1).[11] Moving from examining the data by activity across all fabs to tallying the data on a fab-by-fab basis, we report the fabs’ scores (with the 6” fabs separated from the 8” fabs) in Figure 2. An individual fab’s score is the sum of the scores for the operators, technicians, and equipment engineers.[12] These figures demonstrate, as expected, that *technicians* and *equipment engineers* shoulder the greatest level of responsibility for equipment maintenance and troubleshooting. Although operators do not play an extensive role in either long-term maintenance or modifications, they are in intimate contact with the equipment—recognizing and documenting abnormalities, cleaning and/or lubricating the equipment, and performing daily or weekly inspections. The fabs are listed in order of yield performance in Figure 2, and this chart illustrates there is no simple relationship between equipment maintenance tasks and fab performance.[13] Furthermore, a closer inspection reveals that a trade-off between using technicians and equipment engineers for equipment maintenance does not exist, as might be expected in a high-volume manufacturing setting: In only a few fabs in our sample does technician involvement in equipment maintenance exceed the involvement of equipment engineers.

Overall the use of equipment maintenance fell slightly and it became much less variable across 8" fabs compared to 6" fabs. The equipment maintenance activities declined substantially for operators and slightly for technicians but rose for equipment engineers in 8" fabs compared to 6" fabs (see Table 4). For the "typical" worker (*i.e.*, the equipment maintenance score weighted by the proportion of workers across occupations), the equipment maintenance score fell slightly (from 81 to 80) in 8" fabs compared to 6" fabs.

Participation in work activities: Statistical Process Control. The charts depicting employee involvement in SPC show a similar pattern as those for equipment maintenance (Figures 3 and 4).[14] As depicted in Figure 3, the tasks performed by the operators and technicians overlap to some degree with the engineers’ tasks (*e.g.*, creating X-bar, R charts or brainstorming), but in many areas, they are complementary (*e.g.*, operators and technicians enter quality data about the process flow into the computer and the engineers use the data for problem identification). Of the three occupations, process engineers are clearly the most involved in advanced problem solving. As found for equipment maintenance activities, fabs vary in their use of line workers in SPC activities and in their total use of SPC activities, and no simple relationship between use of SPC and fab performance exists (see Figure 4). In addition a close inspection of the bar chart indicates there is no apparent trade-off between the use of operators and process engineers in SPC activities, because the fabs with the highest scores for operators' SPC fall in both the highest and lowest groups for process engineers' SPC scores.

The use of SPC activities declined fairly dramatically across all three occupations in 8" fabs as the sophisticated IT automated many of the SPC tasks. However the decline was smaller for technicians compared to operators, and smaller still for the process engineers. For the typical worker, the SPC score fell by one-third in 8" fabs compared to 6" fabs (see Table 5).

Collaboration. Effective execution of work activities in problem solving may require extensive cross-occupational cooperation. Cooperation entails knowledge sharing across job categories and team problem solving. By examining the workings of teams in the fabs in the CSM-HR sample, we documented the structure of group problem solving. Teamwork is commonplace in the majority of fabs in our sample, and teams at different fabs share many characteristics. Although most fabs have instituted group problem-solving activities, our interviews with teams during site visits taught us that their level of effectiveness actually varies greatly.

The use of teams varies across fabs. In addition to collecting information on the types of teams (Quality Improvement Teams or Circles, Self-Directed Work Teams, and Cross-Functional Teams as defined in Table 1 above), we inquired about their autonomy and pervasiveness. We found that the autonomy of the teams was a distinguishing characteristic of teams rather than the presence of particular types of teams. and the proportion of engineers were the important characteristics of teams rather than the team type. In general, the twenty-three fabs in our sample had all three types of teams, with Asian fabs placing slightly more emphasis on Quality Circles while European fabs emphasized Cross-Functional teams.

Through team activities, the fabs in our sample emphasize both collaboration across multiple work areas *and* quality improvement activities in a single work area. The importance placed on cross-functional problem solving reflects an interesting feature of the semiconductor industry: The complicated interplay of processing steps requires that workers in different equipment areas communicate regularly. In terms of techniques employed during problem-solving activities, only two fabs reported that their teams do not use formal problem-solving techniques.

To calibrate the pervasiveness of teams within a fab, we calculated the average number of teams per worker (Team Participation). On average, workers reported participating on 0.5 teams (or 50% of workers participated on one team), and the level of team participation ranged from a low of 0.02 teams to a high of 1.5 teams (see Table 6). We also asked about team autonomy in terms of who (team, joint team and manager, manager) decides on the team's projects, on expenditures, and on assignments and deadlines. We created a team decision-making variable (Team Autonomy) that ranges from 1 to 3, with a low score indicating that a manager makes most decisions and a high score indicating that the team makes most decisions (see Appendix Tables 3 and 4 for additional information). The teams in our sample function with a high degree of autonomy and averaged 2.3 for Team Autonomy. Eight fabs received Team Autonomy scores of 3 (high autonomy), and only two fabs received scores of 1 (low autonomy).

Through our site visits, it became clear that engineers play a critical leadership role on teams. We calculated the prevalence of engineers on teams (*i.e.*, engineers' share of team membership). On average engineers made up one-third of team members, although their share ranged from 0% at two fabs, which only had teams for operators, to 100% at one fab, which only had teams for engineers. The average share of engineers on teams exceeded their average share of fab employment—11% at the 6" fabs and 18% at the 8" fabs. In general, teams play an important problem-solving and communication role at the fabs, operate fairly autonomously, and rely upon the engineers for leadership.

IV. Empirical Findings

In this section, we determine how the primary components of the employment system are associated with manufacturing performance. Because the fabs in our sample span two generations of manufacturing technology, we also examine the influence of technological change on performance. We use simple least squares regressions to estimate these relationships.[15]

The performance metrics used as the dependent variables in the regressions are divided into two general categories—quality (defect density and line yield) and efficiency (direct labor productivity, stepper throughput, and cycle time). Overall productivity of a fab reflects both the quality and efficiency variables, because the latter determines the total output and the former determines the percent of usable output.

The performance metrics are defined as follows[16]:

- *Defect density* is the percent of fatal defects per square centimeter of wafer surface area.[17]
- *Line yield* is the average fraction of wafers started that emerge from the production line as completed wafers. Incomplete wafers include wafers damaged from scratches or breaks, or wafers aborted because of misprocessing.
- *Direct labor productivity* is the average number of wafer layers completed per production worker per day.
- *Stepper throughput* provides a measure of factory throughput. More specifically, it measures the average number of wafer operations per day across the photolithography machines, steppers, that project the patterns of the circuitry onto the wafer.[18]
- *Cycle time* per layer is the average time duration of wafer lots from the beginning of the process until they leave the fab, controlling for the number of layers of circuitry.[19]

Definitions of the employment system variables with descriptive statistics can be found in Tables 3 and 4 of the Data Appendix. Tables 7 and 8 present correlation matrices that include the performance data and a subset of the employment system variables that will be used in the regression analysis below. The correlations in Table 7 include only the data from the sixteen 6" fabs, whereas Table 8 also includes the data from the seven 8" fabs. As shown in the tables, a number of the performance metrics are positively correlated.[20] Regarding the importance of training at our sample fabs, initial training for technicians is positively correlated with a measure of quality (line yield) and a measure of efficiency (direct labor productivity). In correlations not reported, initial training of engineers is also positively correlated with these two performance variables (both at the 6" fabs and for the whole sample), while initial training of operators is positively correlated with line yield (6" fabs) and with direct labor productivity (whole sample).

The data include not only the amount of training but also the content, permitting us to determine the relevance of training for the problem-solving activities undertaken by each occupation. However, the interaction variables that link training related to equipment maintenance and SPC tasks to the level the three occupations engage in these tasks are not positively correlated with the performance metrics, and in some instances exhibit *negative* correlations. For example, the interaction between training in areas associated with equipment maintenance (classroom or on-the-job training in machine operation, machine maintenance, or cleanroom procedures) and the execution of equipment maintenance tasks is negatively correlated with defect density, line yield, and direct labor productivity across the whole sample (correlations not reported). This may suggest that offering both classroom and on-the-job training may be excessive and interfere with the execution of job tasks.

Also counter to our expectations, we found that training over the first three years of employment and the level of engagement in SPC activities positively correlated with performance metrics *only* for the engineering job category for the 6” fabs. Although the importance of equipment maintenance was apparent during our fieldwork, the engagement in equipment maintenance by the job categories did not correlate with superior manufacturing performance.

Although we found that the categories of teams did not distinguish the companies in our sample (almost all of the fabs had the three team types), the *autonomy* of teams is positively correlated with quality measures of manufacturing performance—defect and line yield improvements—across the whole sample. Again across all twenty-three fabs, the extensive use of teams correlates positively with one measure of efficiency—direct labor productivity—but negatively with another—cycle time.

We first ran regressions that included the HR variables for problem-solving participation, skills and knowledge, and team activities. We also performed regressions using two measures of the actual training in the job tasks by occupation (the breadth of training in job tasks for SPC and equipment maintenance and the interaction between training for SPC or equipment maintenance and the tasks done). We reran the regressions with only the variables that had a standard error less than the coefficient.

The employment system variables used in the regressions include[21]:

- *Problem-Solving Activities*: SPC activities by engineers.
- *Training and Skill Development*: initial training of technicians and training during the first three years for operators and engineers.
- *Collaboration*: team autonomy in decision making, participation in teams.

In addition, we included a dummy variable to indicate which fabs were 8" (so the 6” fabs act as the reference group).

The results are presented in Table 9. Given the small sample size, the performance metrics were significantly related to only a few of the HR variables, which explained approximately 30% of the variance in performance across the fabs.

We ran the stepper throughput regressions only with the 6" inch observations, because we felt the increased level of automation in the stepper equipment modules of 8" fabs would make throughput comparisons with 6" fabs misleading. Because the stepper module often creates the bottleneck in the fab, and because the photolithography equipment is some of the most expensive equipment in the fab, this module became more automated than the other modules. The employment system is dramatically changed by the introduction of new automation technology in the stepper modules in 8" fabs, which have automated material handling as well as automated recipe download and automated selection of circuit patterns, called "reticles." We did not think that the inclusion of the INCH dummy variable would be adequate for differentiating the 8" from the 6" fabs in terms of stepper throughput. As we did not have sufficient degrees of freedom to interact the INCH variable with the other variables, we decided to exclude the 8" fabs from the stepper regression.

The regression findings are consistent with the pair-wise correlation between the team variables and the performance metrics. Fabs in which workers participate on many in teams face reduced efficiency through slower cycle times. This may indicate that having many teams in operation may hinder moving the scheduled lots through the fab. Whereas team autonomy appears to heighten quality through defect density reductions.

As reported above, among the job tasks variables, only the SPC activities of engineers were positively associated with high performance in the 6" fabs in terms of improved line yield and direct labor productivity (Table 7), but the coefficients on this variable in the regressions was not significant.

The regressions demonstrate that training is associated with high performance. Which occupations receive training and when the training is given appear to be important. The continuous training of engineers, measured by the training received in the first three years, is associated with reduced defect density and higher stepper throughput. Initial training of technicians is associated with improving line yield and direct labor productivity. Overall the training of engineers and technicians improved both quantity and quality variables. The regressions also underscore how technological change has influenced manufacturing performance. The more automated 8" fabs perform better than the 6" fabs in terms of higher line yield and labor productivity and shorter cycle times, as captured by the INCH dummy variable.

Because our sample includes only 16 to 23 observations, we must be careful in extending our results. The statistical analysis indicates that job task, training, and characteristics of collaboration can explain some of the difference in performance across fabs. However we will need a larger sample to say with confidence if and how the employment system variables are linked together to affect fab performance.

VI. Conclusion

Even though labor costs rarely exceed 10% of semiconductor manufacturing costs, semiconductor factories require human creativity and involvement in problem solving to keep the equipment and production process running problem free. Based upon fieldwork and data analysis, this study finds that companies can improve manufacturing performance through the involvement of trained workers in problem solving under the leadership of engineers. A high performing employment system in this technology-intensive setting can be created where engineers are tapped for the depth of their knowledge while involving line workers in the timely identification of problems. The majority of fabs in our sample coordinate troubleshooting through team work on the shop floor, where engineers constitute, on average, one-third of the team membership. Through this constellation, a fab can draw on its engineering expertise, ensure the timely identification of problems, and formulate creative solutions in a coordinated fashion.

Our findings for the semiconductor industry are limited in their ability to contribute to the broader theoretical and empirical literature concerning the use of well-integrated employment systems with consistent components to create high performing organizations. In our small sample, interactions between the HR components exhibited limited statistical significance. The statistical analysis contained in this study does not support our expectations about the importance of linking training to work activities. Instead we found that the amount of training rather than its relevance to work activities was associated with fab performance. Furthermore we do not find statistical evidence that the involvement of operators or technicians in SPC or equipment maintenance is associated with fab performance. The only work activity associated with improved fab performance is the SPC activities of engineers.

Overall the use of continuously-trained engineers with initially-trained technicians within well-functioning teams appeared to be the hallmark of the employment system in high-performing fabs. In particular, defect density is lower in fabs with autonomous teams and continuously-trained engineers. The other quality metric, line yield, is higher in fabs where technicians receive more initial training. Similarly, a measure of efficiency—direct labor productivity—is also positively associated with technicians receiving initial training. Another measure of efficiency, stepper throughput, is higher in 6" fabs with continuously-trained engineers. The final quantity metric, cycle time, appears adversely affected by the presence of many teams. Technological change represented by next-generation production systems at the 8” fabs was consistent with enhanced performance across our sample along both quality and quantity dimensions.

Although our statistical results offer only weak links between manufacturing performance and the employment system, our fieldwork observations, coupled with comparisons of the employment system variables in 8" fabs compared to 6" fabs, highlight the importance of problem solving led by engineers in this high-tech industry. Furthermore, the differences exhibited between the 6" and 8" fabs indicate that the importance of engineers relative to direct labor in fab performance will grow with the increased use of automation and information technology. Even though technician and operator knowledge and skills can be useful in continuous improvement and problem-solving activities, engineers drive the fab’s operations and guide the vast majority of improvement projects.

Our results are consistent with many of the lessons learned from Strauss about industrial relations—particularly concerning the circumstances under which workers’ participation in management leads to successful outcomes (e.g., Strauss and Rosenstein 1970; Strauss 1992). His own research led Strauss to conclude that participation can improve product quality and productivity when a strong union is present. In contrast to traditional manufacturing operations, unions play a diminished role in semiconductor fabs especially in the United States where only a couple of fabs are unionized. This limits direct labor’s representation in the decisions to restructure jobs and responsibilities as new technology is introduced. With greater union representation, operators’ and technicians’ involvement in problem solving might not have declined as rapidly with technological change as this research has shown. With representation, the rise in the importance of engineers and the fall in the importance of operators and technicians may not occur to the extent experienced in the semiconductor industry. The outlook for direct labor with the spread of material handling systems and information technology to industries with greater union presence will not be as bleak as suggested by the outcomes in the semiconductor industry.

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Table 1. Team Definitions[22]

Name of Team	Definition
Quality Improvement Teams/ Quality Circles: (QITs/QCs)	Structured employee participation groups in which employees from a particular work area meet regularly to identify and suggest improvements to work-related problems.
Self-Directed Work Teams:	Also termed autonomous work groups, semi-autonomous work groups, self-managing work teams, or simply work teams. The work group (in some cases acting without a supervisor) is responsible for work in its area of the fab, and it makes decisions about task assignments and work methods.
Cross-Functional Teams:	Structured employee participation groups in which employees from multiple work areas meet regularly to identify and suggest improvements to problems.

Table 2. Sample Fabs

Location	Number of 6" Fabs	Number of 8" Fabs	Number of Distinct Companies
Asia	6	5	7
Europe	3	0	3
United States	7	2	9

Table 3. Average Levels of Training across Occupations

	Initial Training+ (mean days)		Training first 3 years+ (mean days)	
	6"	8"	6"	8"
Operators	20	15	172	136
Technicians	18	8	204	151
Engineers	18	18	172	158

+ For each job category, Wilcoxon rank-sum tests did not find statistically significant differences across the 6” and 8” fabs.

Table 4. Work Activities by Occupation and across Generations of Technology

	Equipment Maintenance[+]			
	Operator	Technician	Equipment Engineer	Typical Worker
6" fab (mean)	44	134	153	81
8" fab (mean)	27	125	165	80

[+] For each job category, Wilcoxon rank-sum tests did not find statistically significant differences across the 6” and 8” fabs.

Table 5. Work Activities by Occupation and across Generations of Technology

	SPC Activities[+]			
	Operator***	Technician*	Process Engineer*	Typical Worker*
6" fab (mean)	43	53	79	51
8" fab (mean)	20	36	62	35

[+] Wilcoxon rank-sum tests found that the populations across the 6" and 8" fabs are statistically different at the following significance levels: ***1%, *10%.

Table 6. Characteristics of Collaboration

	Mean	S.D.	Range
Team Participation (teams per worker)	0.49	0.42	0.02-1.5
Team Autonomy (1 is low; 3 is high)	2.27	0.70	1-3
Share of Engineers (%per team)	34.31	31.36	0-100

Table 7. Correlations between Regression Variables for 6” Fabs Only
(correlation coefficients, significance levels, and number of observations reported)

	1 Defect Density+	2 Line Yield	3 Direct Labor	4 Stepper Thruput	5 Cycle Time+	6 SPC Eng	7 Training First 3 yrs-Eng	8 Training First 3 yrs-Op	9 Initial Training Tech	10 Team Participation	11 Team Autonomy
1	1										
	14										
2	-0.6655*	1									
	0.0094										
	14	16									
3	-0.5564*	0.5909*	1								
	0.0388	0.0159									
	14	16	16								
4	-0.3389	0.1524	0.6861*	1							
	0.2358	0.5732	0.0033								
	14	16	16	16							
5	0.0651	-0.0167	-0.1761	-0.2494	1						
	0.825	0.9511	0.5141	0.3516							
	14	16	16	16	16						
6	-0.2524	0.4465*	0.5702*	0.1782	-0.0454	1					
	0.3841	0.083	0.0211	0.509	0.8673						
	14	16	16	16	16	16					
7	-0.3541	0.1188	0.322	0.4680*	-0.0503	0.3176	1				
	0.2142	0.6612	0.2239	0.0675	0.8532	0.2307					
	14	16	16	16	16	16	16				
8	-0.1438	0.1492	0.0518	0.2166	-0.2583	0.0025	0.5474*	1			
	0.6238	0.5812	0.8489	0.4203	0.3341	0.9926	0.0282				
	14	16	16	16	16	16	16	16			
9	-0.3837	0.6289*	0.5400*	0.0136	-0.1296	0.5063*	0.0646	0.0068	1		
	0.1756	0.0091	0.0308	0.9602	0.6323	0.0454	0.8121	0.98			
	14	16	16	16	16	16	16	16	16		
10	0.0267	0.1943	0.3039	0.2297	0.3717	0.355	0.1296	0.1624	0.3067	1	
	0.9277	0.4709	0.2524	0.3921	0.1564	0.1772	0.6323	0.5479	0.248		
	14	16	16	16	16	16	16	16	16	16	
11	-0.4527	0.3099	0.4169	0.0305	0.0599	-0.0158	-0.1432	-0.2192	0.3937	0.031	1
	0.1041	0.2428	0.1082	0.9107	0.8255	0.9538	0.5967	0.4148	0.1314	0.9092	
	14	16	16	16	16	16	16	16	16	16	16

+ the lower the defect density and cycle time, the better the performance, so variables negatively correlated with these variables are associated with improved performance.

* denotes correlation coefficients with significance levels at the 10% level or better.

Table 8. Correlations between Regression Variables for All Sample Fabs
(correlation coefficients, significance levels, and number of observations reported)

	1 Defect Density[+]	2 Line Yield	3 Direct Labor	4 Stepper Thruput	5 Cycle Time[+]	6 SPC Eng	7 Training First 3 yrs-Eng	8 Training First 3 yrs-Op	9 Initial Training Tech	10 Team Participation	11 Team Autonomy
1	1										
	21										
2	-0.7134*	1									
	0.0003										
	21	23									
3	-0.5250*	0.5405*	1								
	0.0145	0.0078									
	21	23	23								
4	-0.3755*	0.2697	0.2944	1							
	0.0934	0.2134	0.1726								
	21	23	23	23							
5	0.2043	-0.192	-0.214	-0.2283	1						
	0.3743	0.38	0.3268	0.2948							
	21	23	23	23	23						
6	0.054	0.1101	0.1881	-0.3451	-0.0567	1					
	0.8161	0.6171	0.39	0.1068	0.7973						
	21	23	23	23	23	23					
7	-0.236	0.0305	0.3325	0.0889	-0.0142	0.1495	1				
	0.3031	0.8902	0.1211	0.6867	0.9486	0.496					
	21	23	23	23	23	23	23				
8	0.0222	-0.0298	0.0592	-0.134	-0.1156	0.1491	0.6565*	1			
	0.9239	0.8926	0.7885	0.5423	0.5994	0.4972	0.0007				
	21	23	23	23	23	23	23	23			
9	-0.2056	0.3902*	0.4632*	-0.1478	0.0452	0.3301	0.1888	0.1767	1		
	0.3712	0.0656	0.026	0.5011	0.8379	0.124	0.3882	0.4198			
	21	23	23	23	23	23	23	23	23		
10	0.0532	0.0846	0.3999*	0.0079	0.3749*	0.0479	0.249	0.2584	0.3961*	1	
	0.8187	0.701	0.0587	0.9715	0.078	0.8281	0.2519	0.2339	0.0613		
	21	23	23	23	23	23	23	23	23	23	
11	-0.4546*	0.3668*	0.2609	0.0664	-0.0385	-0.0376	-0.2343	-0.2441	0.1945	-0.0625	1
	0.0384	0.0851	0.2291	0.7633	0.8617	0.8649	0.2818	0.2616	0.3738	0.777	
	21	23	23	23	23	23	23	23	23	23	23

[+] the lower the defect density and cycle time, the better the performance, so variables negatively correlated with these variables are associated with improved performance.

* denotes correlation coefficients with significance levels at the 10% level or better.

Table 9. Regression Results: The influence of the employment system on manufacturing performance

Performance Metric	Defect Density	Line Yield	Direct Labor	Stepper Thruput[a]	Cycle Time
Observations	n=21	n=23	n=23	n=16	n=23
Constant	3.03** (0.80)	78.4*** (5.4)	12.6 (7.7)	186*** (50)	3.82*** (0.64)
Problem-Solving Activities					
SPC Tasks-Engineers		0.078 (0.069)			-0.008 (0.007)
Skill Development					
Engineer Training-first 3 yrs	-0.004* (0.002)		0.043 (0.035)	0.51* (0.26)	
Operator Training-first 3 yrs					-0.003 (0.002)
Technician's Initial Training		0.21** (0.07)	0.44** (0.21)		
Collaborative Activities					
Team Participation			8.89 (8.69)		0.71** (0.31)
Team Autonomy	-0.64** (0.30)				
8" fab	-0.51 (0.43)	10.5*** (2.8)	13.5* (7.2)		-0.79** (0.30)
Adjusted R^2	0.27	0.43	0.30	0.16	0.29
F-Value	3.45**	6.53***	3.33**	3.93*	3.21**

***Significance level: 1%.
**Significance level: 5%.
*Significance level: 10%.
[a] Stepper throughput regression only includes the 6" fabs.
Standard errors in parentheses.

Figure 1. Participation in Equipment Maintenance by Occupation: Weigthed (n=15 fabs for operators; n=16 fabs for techs and engineers)

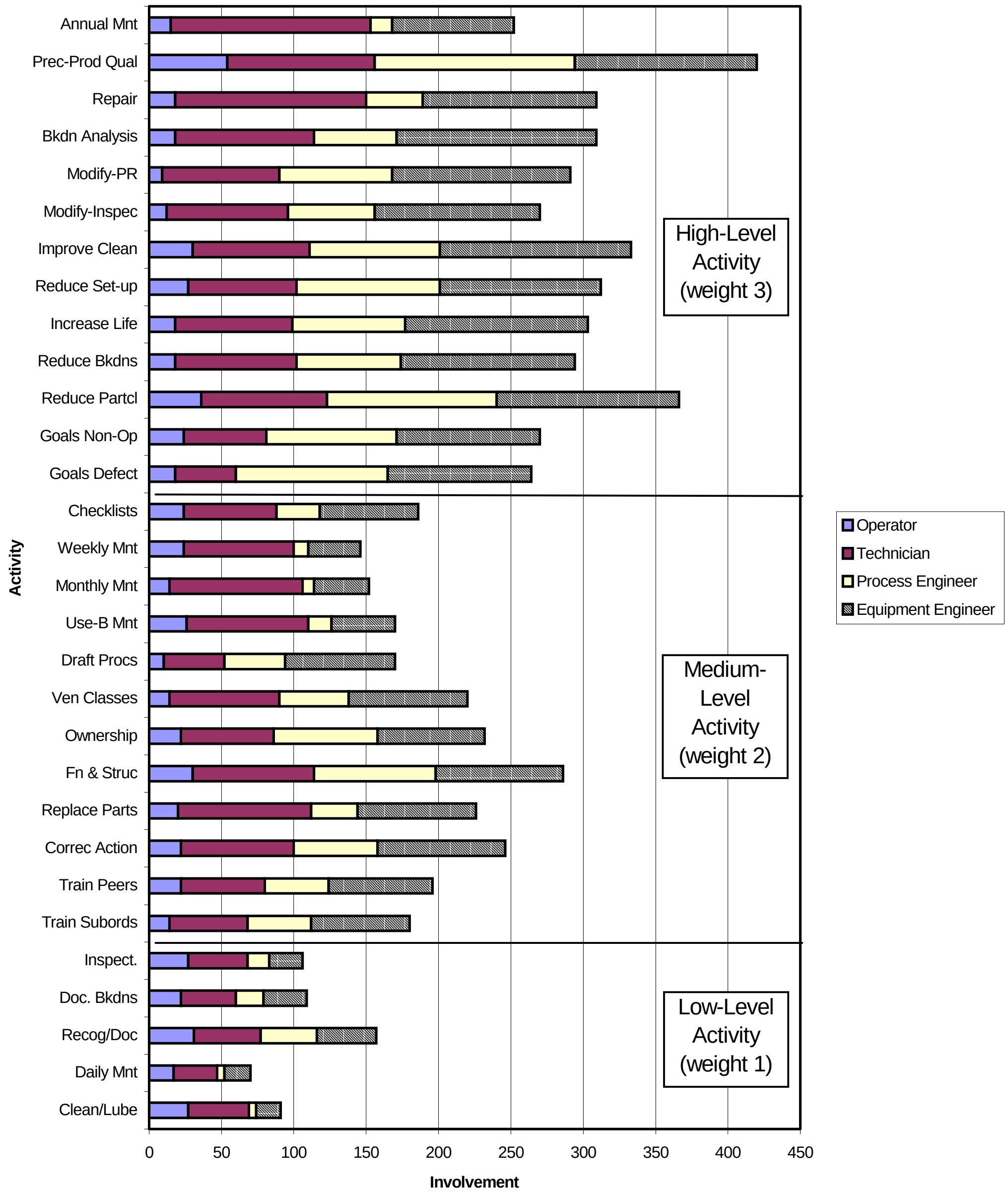


Figure 2. Use of Equipment Maintenance
(Fabs sorted by line yield for each wafer size)

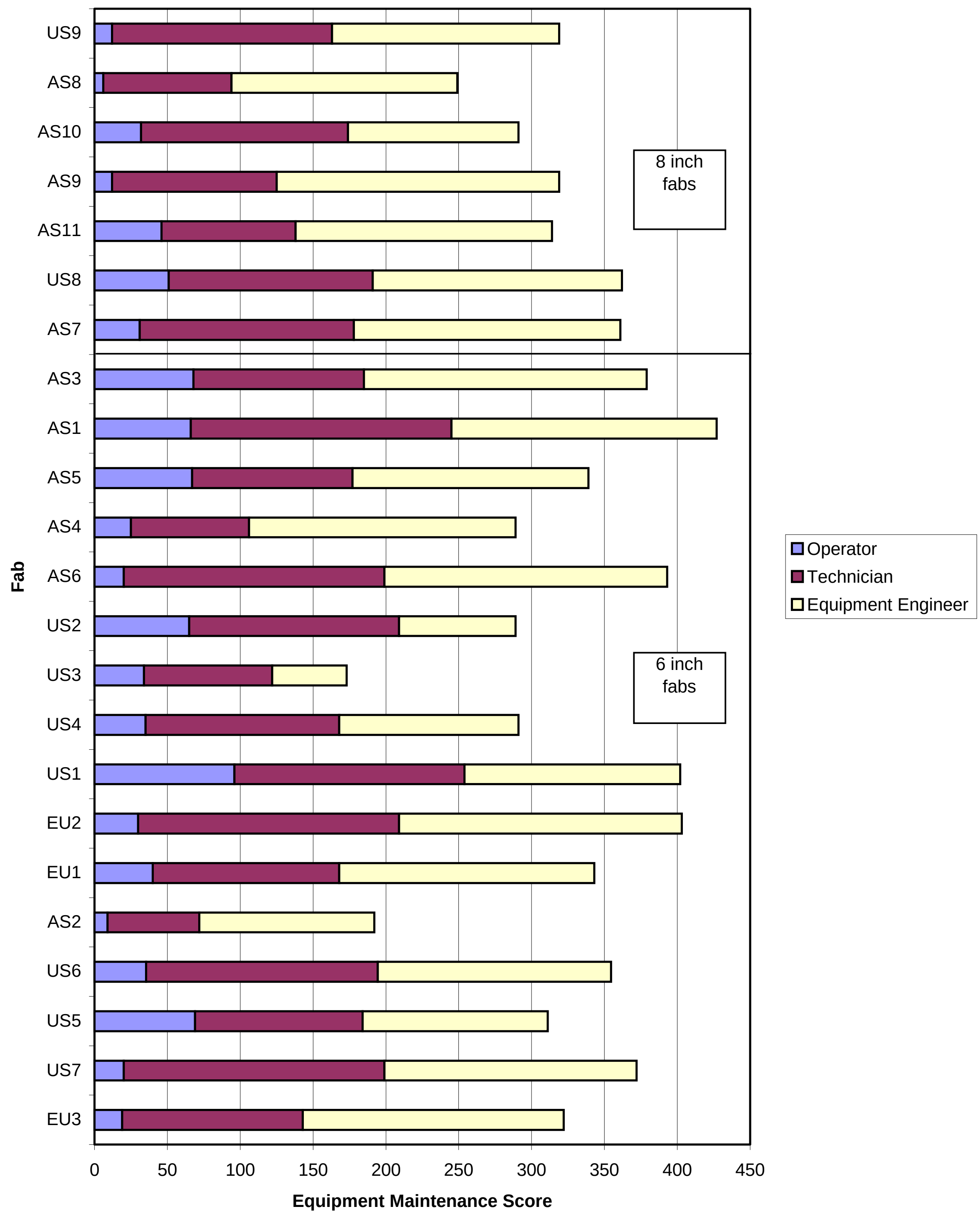


Figure 3. Participation in SPC by Occupation: Weighted
(n=15 for operations and eqmt engineers; n=16 for techs and process engineers)

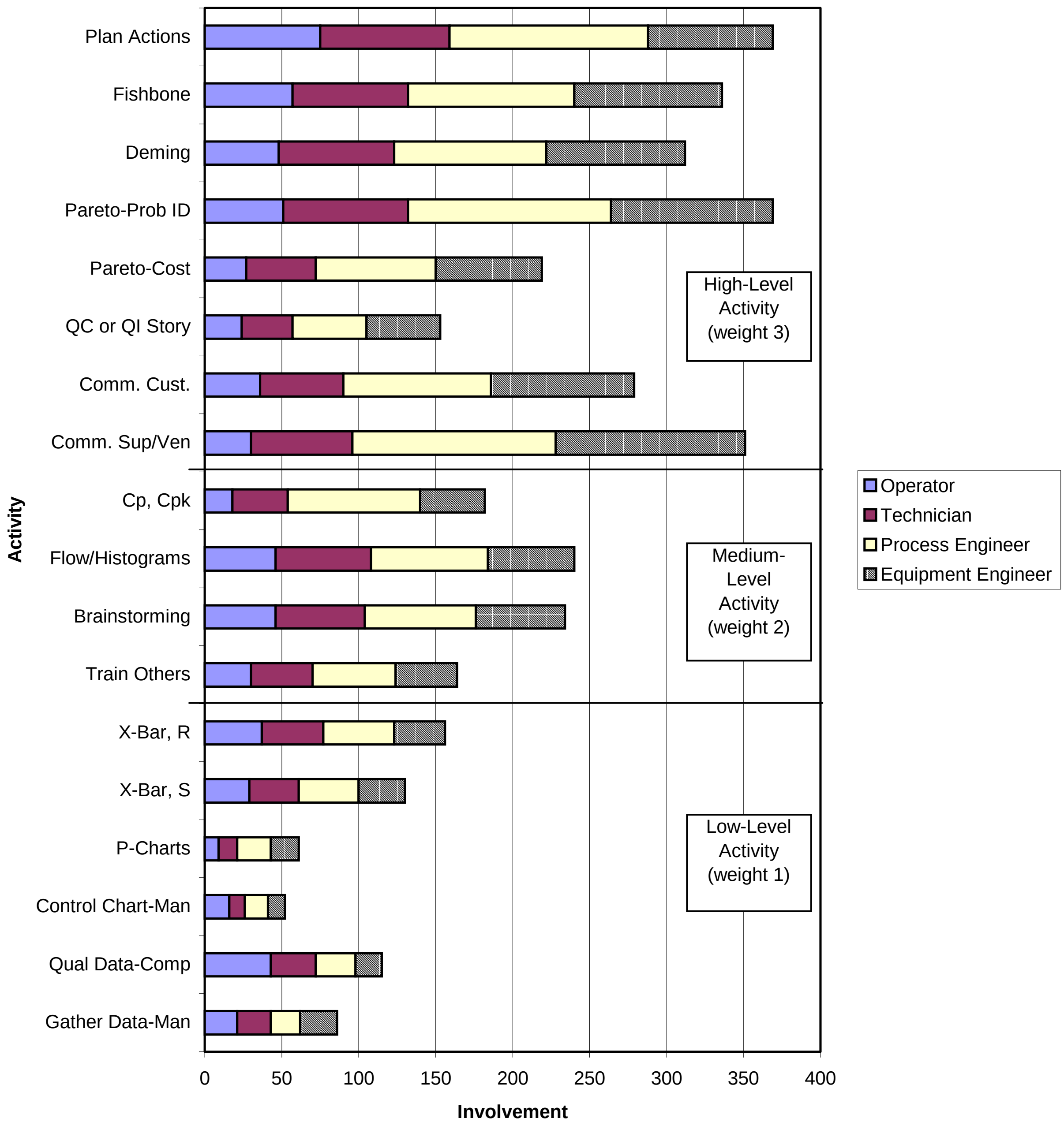
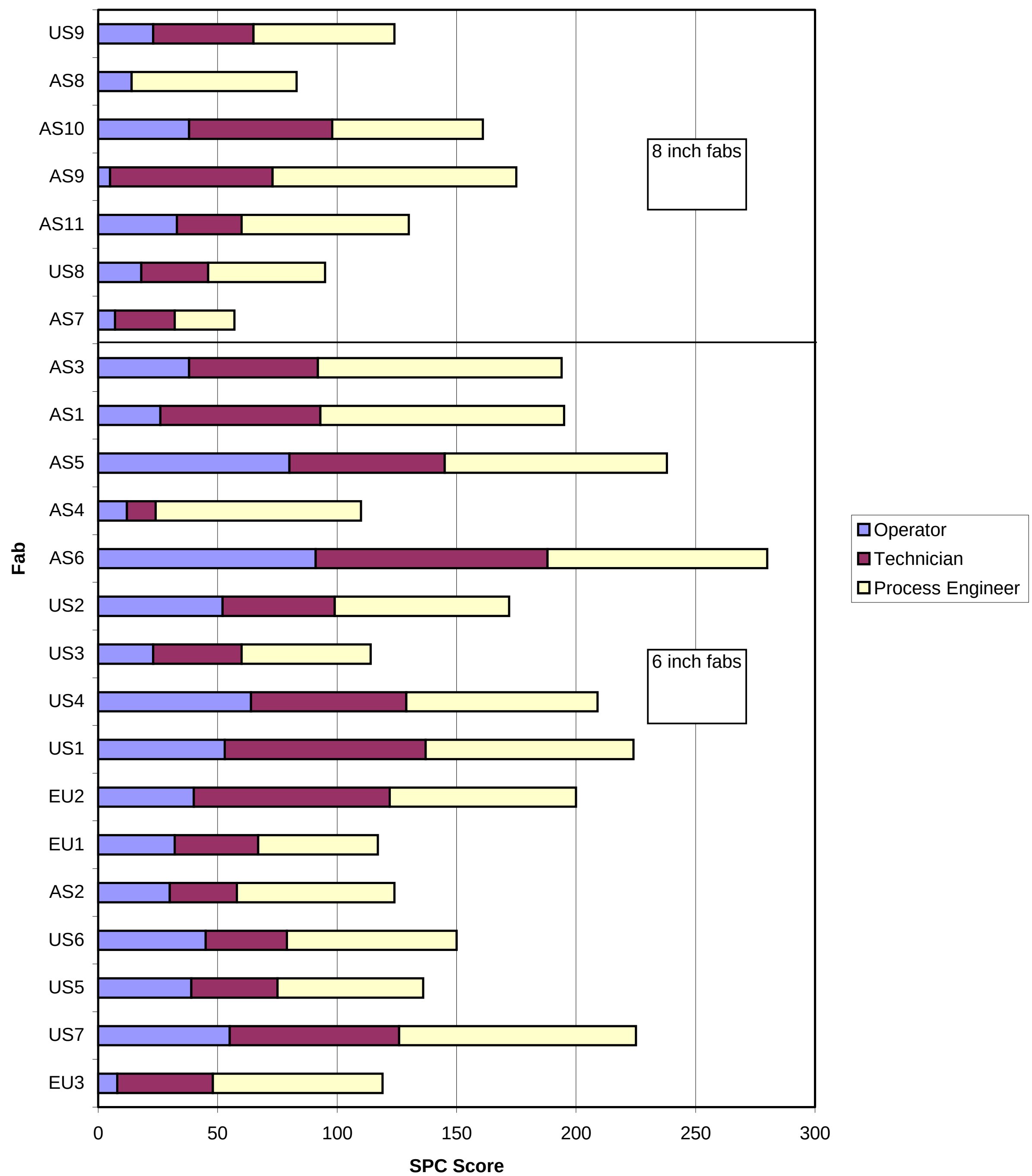


Figure 4. Use of Statistical Process Control
(Fabs sorted by line yield for each wafer size)



Data Appendix

I. Equipment Maintenance and SPC Scores

Figure 1 depicts the weighted scores for each equipment maintenance activity for all job categories across the 16 6" fabs (except where noted). Appendix Table 1 lists the activities and their weights. The scores are calculated for each job category for each activity by:

- summing together the level of involvement of the particular job category (High Involvement=3, Some=1, None=0) in the particular equipment maintenance activity (where High Involvement=75% or more of the employees in that job category perform the activity; Some= less than 75% but greater than 0; None=0 of the employees in that job category perform the activity);[23]

- then multiplying by the weight for each equipment activity according to Appendix Table 1 (High-Level=3, Medium-Level=2, Low-Level=1). These weights were derived from discussions with engineers on the CSM project team.

Therefore, if all 16 fabs had scores for all 4 job categories (operator, technician, process engineer and equipment engineer), the maximum possible score for a High-Level activity would be 576 (16 fabs* 4 job categories* 3 (High Involvement)* 3 (High-Level activity).

Figure 2 presents the equipment maintenance score for each fab. For the three occupations—operator, technician, and equipment engineer—we derived the scores by:

- weighting each equipment activity according to Appendix Table 1 (High-Level=3, Medium-Level=2, Low-Level=1). These weights were derived from discussions with engineers on the CSM project team;

- then multiplying the scores by weights based on the fab's response (High Involvement=3, Some=1, None=0) for each activity (where High Involvement=75% or more of the employees in that job category perform the activity; Some= less than 75% but greater than 0; None=0 of the employees in that job category perform the activity);

- and finally summing together the double-weighted scores from for the thirty equipment maintenance activities for each occupation for each fab.

Therefore, the maximum score a fab could achieve for one job category is 204: 15 (High Involvement in the 5 Low-Level activities) + 72 (High Involvement in the 12 Medium-Level activities) + 117 (High Involvement in the 13 High-Level activities). Given there are 3 job categories represented by each bar, the maximum possible score per bar is 612.

Appendix Table 1. Equipment Maintenance Activities

High-Level (weight 3)	Medium-Level (weight 2)	Low-Level (weight 1)
a. Perform Annual Equipment Maintenance (Annual Mnt)	a. Produce Checklists for Inspecting Equipment (Checklists)	a. Daily or Weekly Inspection (Inspect.)
b. Know Relation between Equipment Precision and Product Quality (Prec-Prod Qual)	b. Perform Weekly Equipment Maintenance (Weekly Mnt)	b. Document Equipment Breakdowns (Doc. Bkdns)
c. Ability to Repair Equipment (Repair)	c. Perform Monthly Equipment Maintenance (Monthly Mnt)	c. Able to Recognize and Document Equip. Abnormalities (Recog/Doc)
d. Perform Analyses of Equipment Breakdowns (Bkdn Analysis)	d. Perform Use-Based Equipment Maintenance (Use-B Mnt)	d. Perform Daily Equipment Maintenance (Daily Mnt)
e. Modify Equipment to Improve Process Yield (Modify-PR)	e. Draft Equipment Clean/Maint. Procedures for Routine Activities (Draft Procs)	e. Clean and/or Lubricate Equipment (Clean/Lube)
f. Modify Equipment for Easier Inspection and Maintenance (Modify-Inspec)	f. Attend Equipment Inspec./Maint. Classes Offered by Vendor (Ven Classes)	
g. Analyze and Improve Equipment Clean/Maint. Activities (Improve Clean)	g. Ownership of Individual Equipment or Equipment Type (Ownership)	
h. Find Ways to Reduce Equipment Set-Up/Adjustment Time (Reduce Set-up)	h. Knowledge of Function and Structure of Equipment (Fn & Struc)	
i. Find Ways to Increase the Life Span of Equipment (Increase Life)	i. Ability to Replace Simple Equipment Parts (Replace Parts)	
j. Find Ways to Reduce Unexpected Equipment Breakdowns (Reduce Bkdns)	j. Authorized to Take Corrective Action on Equipment (Correc Action)	
k. Find Ways to Reduce Equipment Particle Generation (Reduce Partcl)	k. Train Peers in Equipment Inspection, Maint. or Cleaning Procedures (Train Peers)	
l. Set Specific Goals for Reducing Equipment Non-Operating Time (Goals Non-Op)	l. Train Subordinates in Equipment Inspection, Maint. or Cleaning Procedures (Train Subords)	
m. Set Specific Goals for Defect Reduction (Goals Defect)		

The data in Figures 3 and 4 for SPC participation are calculated in the same fashion as described above for equipment maintenance. Appendix Table 2 contains the weights for each SPC activity. Again, these weights were derived from discussions with engineers on the CSM project team.

For Figure 3, again if all 16 6" fabs had all 4 job categories, the maximum score for the High-Level activities would be 576.

For Figure 4, the maximum score a fab could achieve for one job category is 114: 18 (High score on the 6 Low-Level activities) + 24 (High score on the 4 Medium-Level activities) + 72 (High score on the 8 High-Level activities).] Therefore, for 3 job categories, the maximum score would be 342.

Appendix Table 2. SPC Activities

High-Level (weight 3)	Medium-Level (weight 2)	Low-Level (weight 1)
a. Plan Action based on Control Charts (Plan Actions)	a. Cp and Cpk (Cp, Cpk)	a. X-Bar, R (X-Bar, R)
b. Cause-and-Effect or "Fishbone" Diagrams (Fishbone)	b. Flow Charts and/or Histograms (Flow/Histograms)	b. X-Bar, S (X-Bar, S)
c. Deming Cycle (plan-do-check-act) (Deming)	c. Brainstorming (Brainstorming)	c. p-charts (P-Charts)
d. Pareto-Problem ID (Pareto-Prob ID)	d. Train Others in SPC Methods (Train Others)	d. Manual Control Charts (Control Chart-Man)
e. Pareto-Cost (Pareto-Cost)		e. Quality Data-Computer (Quality Data-Comp)
f. QC or QI story (QC or QI Story)		f. Manual Gather Data (Gather Data-Man)
g. Communicate with Customers (Comm. Cust.)		
h. Communicate with Suppliers/Vendors (Comm. Sup/Ven)		

Appendix Table 3. Employment Systems Variables

Statistical Process Control: Operators: as calculated above.
Statistical Process Control: Technicians: as calculated above.
Statistical Process Control: Engineers: as calculated above.
Equipment Maintenance: Operators: as calculated above.
Equipment Maintenance: Technicians: as calculated above.
Equipment Maintenance: Engineers: as calculated above.
SPC-Typical Worker: (the SPC score x number of workers for each occupation)/(total workers)
Equip Maint-Typical Worker: (the equip maint score x number of workers for each occupation)/(total workers)
Number of Engineers Per Team: average % engineers on all teams
Teams per Worker: (total team membership)/(total workers)
Autonomous Team Decision Making: (1 is manager decides projects and authorizes expenditures; 3 is team makes these decisions)
Initial Training Days: Operators
Initial Training Days: Technicians
Initial Training Days: Engineers
Training Days in First 3 Years: Operators
Training Days in First 3 Years: Technicians
Training Days in First 3 Years: Engineers
Breadth of Training in SPC: Operators (Number of types of SPC courses given)
Breadth of Training in SPC: Technicians
Breadth of Training in SPC: Engineers
Breadth of Training in Equip. Maint.: Operators (Number of types of Equip Maint courses given)
Breadth of Training in Equip. Maint.: Technicians
Breadth of Training in Equip. Maint.: Engineers
Interaction between Training & Job Tasks: Operator, SPC: (SPC score for operators)x(No. of SPC courses given to operators)/(max. possible courses for operators in SPC)
Interaction between Training & Job Tasks Technician, SPC: (SPC score for techs)x(No. of SPC courses given to techs)/(max. possible courses for techs in SPC)
Interaction between Training & Job Tasks: Engineer, SPC: (SPC score for engs)x(No. of SPC courses given to engs)/(max. possible courses for engs in SPC)
Interaction between Training & Job Tasks: Operator, Equip. Maint: (Equip maint score for operators)x(No. of courses given to operators)/(max. possible courses for operators in Equip Maint)
Interaction between Training & Job Tasks: Tech., Equip. Maint: (Equip maint score for techs)x(No. of Equip maint courses given to techs)/(max. possible courses for techs in Equip maint)
Interaction between Training & Job Tasks: Engineer, Equip. Maint: (Equip maint score for engs)x(No. of Equip maint courses given to engs)/(max. possible courses for engs in Equip maint)

Appendix Table 4. Sample Statistics of the Semiconductor Survey Data

		Obs	Mean	Std. Dev.	Min	Max
Performance Metrics						
Defect Density		21	0.82	1.02	0.11	4.09
Line Yield		23	90.56	7.51	69.75	98.56
Direct Labor Productivity		23	35.01	18.35	14.85	71.66
Stepper Throughput		16	274.95	100.19	130.37	439.88
Cycle Time Per Layer		23	2.79	0.70	1.34	4.43
Human Resource Variables						
Statistical Process Control: Operators		23	35.91	22.60	5	91
Statistical Process Control: Technicians		23	48.00	24.31	0	97
Statistical Process Control: Engineers		23	74.00	19.85	25	102
Equipment Maintenance: Operators		23	38.63	23.72	6	96
Equipment Maintenance: Technicians		23	130.83	33.96	63	179
Equipment Maintenance: Engineers		23	156.39	37.76	51	194
SPC-Typical Worker		23	46.44	18.78	13.26	92.62
Equip Maint-Typical Worker		23	80.98	17.69	49.48	114.12
Number of Engineers Per Team		23	34.31	31.36	0	100
Teams per Worker		23	0.49	0.42	0.02	1.51
Autonomous Team Decision Making		23	2.27	0.70	1	3
Initial Training Days: Operators		23	18.55	25.30	1.00	92.86
Initial Training Days: Technicians		23	15.38	18.03	1.00	64.29
Initial Training Days: Engineers		23	17.94	19.84	1.00	64.29
Training Days in First 3 Years: Operators		23	161.31	69.35	39.60	279.35
Training Days in First 3 Years: Technicians		23	188.19	81.54	41.00	317.87
Training Days in First 3 Years: Engineers		23	167.83	96.20	28.47	338.08
Breadth of Training in SPC: Operators		23	4.09	0.79	3	6
Breadth of Training in SPC: Technicians		23	5.00	1.81	1	8
Breadth of Training in SPC: Engineers		23	7.28	1.89	5	10
Breadth of Training in Equip. Maint.: Operators		23	3.66	0.94	2	6
Breadth of Training in Equip. Maint.: Technicians		23	4.69	1.14	3	6
Breadth of Training in Equip. Maint.: Engineers		23	4.28	1.10	2	6
Interaction between Training & SPC: Operator		23	18.64	13.60	2.50	56.88
Interaction between Training & SPC: Technician		23	30.34	19.21	0	65
Interaction between Training & SPC: Engineer		23	53.58	17.14	17.50	83.70
Interaction between Training & Equip Maint: Operator		23	21.88	13.73	5	48
Interaction between Training & Equip Maint: Tech		23	100.21	32.02	42	151
Interaction between Training & Equip Maint: Engineer		23	109.05	34.00	42.50	175

Endnotes

[1] Sattler and Sohoni use interview data that were then quantified from fifteen fabs. We use data that were collected subsequently using a quantitative survey data from twenty-three fabs. Six fabs from the two samples are the same.
[2] Bailey's sample covers eight fabs, three of which overlap with our sample.
[3] For more extensive examinations of new process development in the semiconductor industry, see Appleyard, *et al.* (2000), Appleyard and Brown (1999), Iansiti and West (1999), and Appleyard (1996).
[4] In the current transition to silicon wafers 12" in diameter, automation is even more pervasive because, for example, the weight of the box containing the production lot of silicon wafers has become too heavy for operators to routinely carry between production steps. Although the industry has discussed adopting lot sizes of 13 or fewer wafers versus the common 24 wafer lots for 8" wafers, the industry is clearly headed towards fully automating material handling and production control.
[5] For a 3-D animation of the photolithography production module, see: http://www.darden.virginia.edu/it/explore/.
[6] The developer solution sprayed onto the wafers works like the chemicals used in darkrooms for traditional photographic processes. In this case, the image left behind on the silicon wafer will become the template for the circuitry for the semiconductor device.
[7] As an example, etching steps commonly follow the application of the developer in the photolithography module.
[8] See Brown (1996) and Leachman (1996) for detailed discussions of the data collection procedures.
[9] The ratio of 8" to 6" fabs for each region should not be interpreted as representative of such ratios for the industry as a whole. For example, a number of 8" fabs exist in Europe even though none appear in our sample.
[10] Using the same sample of semiconductor fabs as employed in this paper, Brown and Campbell (forthcoming) find that although technological change widens the skill gap between occupations and is biased toward employment of high-skill workers, technological change does not lead to increased wage inequality in semiconductor fabs.
[11] The Data Appendix provides details of the weighting scheme.
[12] The score for the *process* engineer was eliminated from the equipment maintenance fab scores. Similarly, the score for the *equipment* engineer was eliminated for the statistical process control fab score discussed below.
[13] In Figure 2 and Figure 4 below, the fabs are sorted within each wafer size by their line yield performance, with the highest fabs in the chart achieving the highest line yields. Line yield was selected as the sort criterion, because it is significantly correlated with the other quality performance metric (defect density) and one of the quantity performance metrics (direct labor productivity). See Section IV for a presentation of the correlations and more details pertaining to the performance metrics.
[14] The same weighting scheme was used for SPC activities as for equipment maintenance activities to derive the fab SPC scores (see Data Appendix).
[15] We also used factor analysis to group all the HR variables for training and job tasks, and then regressed the performance metrics on the HR factors. We report only the regressions using the actual HR variables, because these regressions had higher F-statistics and explained more of the variance in the regressions on defect density, line yield, and cycle time. They performed as well as the factor analysis for direct labor productivity and stepper throughput.
[16] See Leachman and Hodges (1996) for more information on the creation of these performance metrics by U.C. Berkeley's Competitive Semiconductor Manufacturing team.
[17] This metric employs a widely used routine (the Murphy model) to convert actual die yield for each major process flow into a defect density score.
[18] The formula is computed for 5X steppers only, and is defined as $(WS/D)(NS)(LY')$, where WS is the average number of wafer starts per week and is divided by the number of calendar days per week (D). NS is the number of layers in the process flow, and LY' is an adjusted line yield.
[19] This metric measures the average amount of time it takes to complete all operations associated with a single layer of circuitry, accounting for processing time, lot waiting time, and lot movement time.
[20] The correlations discussed in the ensuing paragraphs exhibit a level of significance of 10% or better.
[21] See Brown (1997) for a discussion of the employment system variables and preliminary analysis of the HR systems.
[22] When constructing the definitions of teams, we incorporated input from Edward E. Lawler, Marshall School of Business, University of Southern California.
[23] These three categories (at least 75% of the people in the occupation, between 0 and 75%, and none) were the categories that appeared on the written survey. The assignment of the 3, 1, 0 weights to these categories was arbitrary. The weight of 3 for the "at least 75%" category slightly inflates the scores at the high end, but we decided to round up to 3 instead of assigning a weight of 2.33 that would have resulted from a ratio of the midpoints of the two ranges (87.5/37.5 = 2.33).