Technological Change, Training, and Job Tasks in a High-Tech Industry

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Abstract

Using data from 23 semiconductor plants, we study how automation of information handling and material handling affects development, use, and compensation of skills. Information handling automation is skill-biased technical change using relatively more technicians and engineers. It widens the skill gap across occupations, and it goes with higher initial wages for all employees and shorter career ladders for engineers. Material handling automation also widens the skill gap, but goes with employment of relatively more operators and with lower pay across all occupations. Overall, technological change goes with higher demand for skilled workers, decreased training, and deskilling of low-skill jobs and up-skilling of high-skill jobs coupled with little change in compensation structures except for a flattening of career ladders for engineers. Our findings that technological change has negative impacts on labor market outcomes for all skill groups should concern us about the outlook for employment and wages in high-technology industries.

This paper analyzes how technological change in the semiconductor industry in Asia and the United States has affected the training, job tasks, and compensation of workers. By analyzing detailed plant-level data in the semiconductor industry, we ask how two types of technological change--automation of material handling and automation of information handling--have affected initial and continuous training of operators, technicians, and engineers; have affected their job tasks in the two key areas of statistical process control and equipment maintenance; and have affected compensation. Answering these questions should help us to understand the impact that these types of technological change are having on the development, use and remuneration of skills across occupations.

Our sample, collected by the Sloan Competitive Semiconductor Manufacturing (CSM) Project, consists of twenty-three fabrication plants primarily in the four major producers (United States, Japan, South Korea, and Taiwan). We compare the workforce composition, training, and job tasks of a subsample of fourteen matched fabs in the four countries to study the impact of the technological change that occurred with transition from 150mm wafers to 200mm wafers, where a wafer is the silicon disk in which the integrated circuits are embedded in the fabrication process. We also analyze the impact of automation of material handling and information technology on employment composition, job tasks, training, and career ladders of the entire fab sample.

In section I, we present an overview of technological change in the semiconductor industry. In section II, we briefly present the findings of other researchers on how technological change has affected skill demands and training. In section III, we analyze our fab-level data. In section IV, we discuss the implications of our findings for training and skill demands as industries continue to introduce automation of materials handling and information technologies.

I. TECHNOLOGICAL CHANGE IN THE SEMICONDUCTOR INDUSTRY

The semiconductor industry is characterized by rapid technological change, high capital costs, continual price declines, and strict quality standards. These industry characteristics result in high risks and returns to product innovation and lead to competitive pressures to bring improved products quickly to market. The semiconductor industry is deeply competitive both in the short run (i.e., less than two years) through lowering prices and in the long run through introducing new and better products.

In our study of semiconductor fabrication, we have identified at least four distinct ways that microelectronics have been used to automate work:

1. automation of *materials handling* (e.g., automated guided vehicles for intrabay movement, conveyor system for interbay movement, reticle stockers);
2. automation of *operations* (e.g., lot recognition, automatic recipe download);
3. automation of *scheduling and process control* (e.g., work in progress (WIP) tracking, production planning and scheduling, on-line scheduling, WIP prioritization; production feedforward or feedback control, especially from in-line testing equipment); and
4. automation of *data collection and analysis* (e.g., automated data entry, real time SPC).

In this study, we classify one as automated materials handling (MHA) and two through four as automated information handling (IHA).

In the transition from 6" to 8" wafer fabrication, companies automated many of the work activities (see Table I). The MHA and IHA scores indicate to what extent materials handling and operations and information, respectively, have been automated[2]. The actual scores for MHA range from 0, where all materials handling is performed by humans, to 24, where 24 of the steps involving materials handling have been automated, such as implementation of a conveyor system to transport wafers in progress between equipment bays, and use of automated guided vehicles in the photlithography area to deliver wafers from the conveyor system to the selected stepper. IHA scores range from 0 to 350 where 0 indicates a fab that has no automatic recipe download, no automatic metrology, no automatic lot tracking, and no automatic scheduling and 350 represents a fab in which every tool has automatic recipe download, automatic lot tracking, and automatic scheduling, and 50% of the tools have automated metrology. The materials handling automation score more than doubled and the information handling automation score increased almost four-fold in 8" fabs compared to the matched 6" fabs. In particular 8" fabs usually have auto-guided vehicles (especially in the lithography bay), automated recipe download, automated lot tracking and scheduling, automated data collection and monitoring, automated in-line testing, and integrated information technology systems so that all systems and the engineers had immediate access to various types of data. The new technology made the computerized systems smarter and eliminated many sources of human (especially operator) error. The new automated technologies are correlated with better fab performance in terms of quality (higher line yield) and efficiency (higher stepper throughput and higher direct labor productivity) and meeting schedule goals (lower cycle time) (see Table II).

These types of automation would be expected to change the required skills of workers according to their occupation (operators, technicians, and engineers). In our fieldwork, we initially observed the skills of operators increase as they moved materials less and operated computer systems more. Over time the computer systems became more autonomous in terms of collecting and analyzing data and then acting upon the information. For example, problems with early automated scheduling systems were mitigated by empowering operators to make scheduling decisions; as the systems improved, operators had to be trained not to override the superior system, which was acting upon more information than available to the operators. Over the past ten years, the skills of operators rose and now are declining as a result of technological change has made computerized systems smarter and more effective. In the transition from 6" to 8" fabs, fewer operators are needed to move materials and capture data, and the role of the remaining operators is to oversee the automated systems to make sure that they are functioning properly.

The skill level of technicians necessary to maintain the equipment seems to be about the same over the past ten years, but the required skills and knowledge are continually changing and require continuous training on the new equipment by the equipment vendors. Skill levels are increasing to the extent that technicians are used in problem solving with engineers, and this varies by fab.

The need for engineering input into the fabrication process has risen with the increased use of automation. Engineers must develop, implement, and monitor the automated manufacturing and IT systems, and this requires software engineers as well as process and equipment engineers. The fab has some leeway in deciding the timing of incorporating automation and information systems for a given process technology, but this primarily affects how quickly the fab wants to have new processes at full volume with high quality and quantity performance and low cycle time.

II. TECHNOLOGICAL CHANGE AND SKILL DEVELOPMENT

The recent increase in the returns to skills or education have led researchers to look at how computerization has increased the demand for and the development of skills as firms introduce new computerized technologies. In particular, researchers have tried to document to what extent the new technologies are skill-biased (i.e., increase the relative demand for more educated workers and/or increase (decrease) the skills used by more (less) educated workers) and to what extent they increase worker productivity and wages. So far the results are mixed, since they seem to vary with the data set used, and national results are at variance with case study results.[2] Case studies analyzing how technological change affects skills, job tasks, and pay have raised serious questions about how to interpret the relationship between skill and technology variables and wages in studies using national data sets (Moss 1997).

The actual mechanism by which new technology affects skills, job tasks, productivity, and employment composition remains a mystery in studies of national data sets. At the national level, Krueger (1993) found a positive correlation between wages and use of computers. However DiNardo and Pischke (1997) demonstrated that there is a positive correlation between wages and other job tasks, such as pencil-use. They argued that the interpretation of the correlation between wages and computerization is problematic since there may be underlying factors driving the correlation. Here we mention three national studies that have included the role of training in their investigations of how technological change affects the workplace in order to see to what extent recent technological changes appear to require improved worker skills.

In a study of training and technological change using the National Longitudinal Survey of Youth (1987-1992) for men, Bartel and Sicherman (1998) find that the training gap by education narrows and the proportion of workers receiving training increases at higher rates of technological change. Workers (especially production workers) in industries with higher rates of technological change are more likely to receive formal company training than workers in industries with less technological change (controlling for worker, job, and industry characteristics). More educated workers are more likely to receive company training, but the training gap by education narrows as the rate of technological change increases.

Bresnahan, et al. (1998), using original firm-level data, find information technology use (IT measured by value of computer equipment and processing power) is correlated with both skills (measured by educational requirements, percent receiving training, and skill level of jobs) and decentralized work organization (measured by use of employee-involvement teams and degree of autonomy and decision-making). Empirically the combination of IT and work organization is a better predictor of the demand for skills than is IT alone, and workplace organization and skills are good predictors of IT use. Increased IT investment is associated with higher output increases in firms with decentralized work organization or high levels of skills, or both. They work also finds that find that productivity is not significantly associated with worker skill or with the interactive term of IT and percent professional workers and is associated with decentralized work organization (including employee voice) and its interaction with IT capital.

Similar results are found in a national study of the relationship between investments in new technology and productivity and human resource (HR) practices. Using a special survey of manufacturing establishments, Black and Lynch (1997) find that investments in new technology are associated with significantly higher establishment productivity but that training is not significantly related to productivity. Productivity is higher when the proportion of non-managerial workers who use computers is higher, while the proportion of managers using computers is not significantly related to productivity. High productivity is associated with how work practices are implemented within the establishment rather than if the employer adopts a particular practice, such as TQM.

At the establishment level, most researchers agreed that the impact of new technology depends upon the nature of the technology, and so they identify and study a specific technology. Being able to study a specific technological change is one of the strengths of case studies as opposed to national studies, where technology is often only vaguely defined (e.g. computers). Here we refer to three studies that focus on the importance of shifts in technology that have changed the nature of work, increased skill requirements, and opened new output possibilities for companies.

Zuboff (1988) shows how digital technology has dramatically changed work by automating routine tasks and allowing some workers to perform new kinds of work in both manufacturing and service companies. She argues that although technology automates routine tasks, its true potential lies in its ability to “informate” work and organizations by making key information more widely and easily accessible, by generating new information, and by revealing previously hidden relationships. The use of this information transforms the experience of work, requires developing workers’ potential for learning, and opens new possibilities for the organization.

Levy and Murnane (1996) and Murnane, Levy, and Autor (1999) reach a similar conclusion about the way new computer technology has changed work in a large urban bank. They argue that job tasks include routine or rule-based problem-solving operations, which can easily be done by a computer, and exceptions or model-based problem solving, which cannot be done economically by a computer. The use of computers results in the exceptions shaping the demand for labor both in terms of quantity and skills. In their case study of the bank's accountants (Levy and Murnane 1996), when computerization increased the demand for skilled labor in the redesigned job, the bank chose to provide in-house training rather than increase the wages and skill requirements for new hires. Murnane, Levy and Autor (1999) studied the how the lower-skilled jobs in check processing were redesigned with the introduction of image processing technology. The outcomes for these jobs were complicated in that instances of both increases and decreases in skill and pay occurred. The transformation required a structured training program and worker buy-in to be successful. Together these studies indicate that the computerization of work in this bank was skill-biased and was accompanied by training programs.

In our study of the impact of technological change on training and skill development, we want to see to what extent our case study of automation in the semiconductor industry includes skill-upgrading, training, work reorganization, and improved compensation. We see this type of case study as a critical ingredient in understanding how technological change is affecting labor market outcomes both on the shop floor and at the national level.

III. THE FAB EMPLOYMENT SYSTEM

Characteristics of the Data

Data collection covers 23 fabs, which includes eighteen 6" fabs and seven 8" fabs during the 1990s. We have extensive institutional knowledge of the sample fabs, which submitted a written questionnaire and opened their doors to an in-depth, two-day site visit by the CSM team, usually composed of eight engineers and economists. Many companies have been visited more than once. A comparison of 8" fabs, which have the latest technology, with the older 6" fabs allows us to have a snapshot of the impact of technological change over time in comparable fabs. For this comparison, we use a subsample that matches each 8" fab with a similar 6" fab, which is often in the same company. Fabs were matched based upon geographical location, product market, and employment institutions. In our analysis of automation technologies on the fab employment system, we use the entire fab sample and examine the correlation of the MHA and IHA technology variables with employee composition, compensation, and job tasks.

Employment

The employment differences in the 6" and 8" fabs were consistent with skill-biased technical change. The automation in the 8" fabs has not led to a decline in overall employment but it has led to a shift in the occupational distribution[4]. The relative use of operators declined by 14% in 8" fabs compared to the matched 6" fabs, while the relative use of technicians and engineers increased 18% and 59% respectively (see Table III). Operators comprise 73% of the workforce in 6" fabs and only 62% in 8" fabs, while engineers increase from 15% to 25% of the workforce.

Information handling automation is correlated negatively with the percentage of operators and positively with the percentage of technicians and engineers in the workforce (see Table IV). Material handling automation is positively correlated with the percentage of operators in the workforce and negatively related to the percentage of technicians and engineers. However none of the correlations is significant at the 10% level. Overall IHA appears to be up-skilling and MHA appears to be down-skilling in their impact on employment composition. MHA does not appear to be implemented as a mechanism to reduce labor costs because fabs in Korea, which have the lowest labor costs of the major semiconductor-producing countries, are more heavily automated than fabs in the U.S. and Japan, which face higher labor costs.

Training

Training declined in the 8" fabs compared to the 6" fabs. The number of days spent in initial training declined substantially for all occupations, and time spent in classroom training during the first three years also declined (data not shown). Initial training (days) decreased by two-thirds for technicians, one-half for operators, and one-third for engineers in 8" fabs compared to 6" fabs. After initial training, workers are more likely to receive as much (or even more) training in the 8" compared to 6" fabs. At the end of three years of employment, workers in 8" fabs have received 70% (operators and technicians) to 82% (engineers) of the training received by workers in 6" fabs. If we look at the breadth of training in SPC and equipment maintenance, we find that all production employees have broader SPC training and equipment maintenance training in 8" fabs compared to 6" fabs.

Companies seem to be replacing initial training, which often is focused on knowledge about the company and basic operation of tools, with classroom training about the job activities during the first year (see Table VI). On-the-job training increases for operators, decreases for technicians, and remains the same for engineers during the first year. After the first year, the classroom training declines dramatically in 8" fabs and falls below the classroom training given in 6" fabs. On-the-job training remains high after the first year, and even increases above first year levels, in 8" fabs. The 8" fabs relied much more heavily on OJT for experienced workers than did the 6" fabs. After the first year, the percent time spent in training increases substantially for all three occupations, so that workers in 8" fabs are considered to be learning during 40% or more of their work time.

Initial training days and training during the first three years for both operators and technicians are negatively correlated with IHA (see Table VI). In contrast, IHA and MHA are correlated positively with initial training and training during the first three years for engineers. Only the positive correlations of MHA and initial training of engineers is significant. Overall automation of materials handling and information appears to reduce the training needs for technicians and to increase the training needs for engineers.

Work Activities and Skills

The introduction of automation systems in the 8" fabs had different impacts in the SPC and equipment maintenance activities across occupations (see Table VII)[5]. Overall, SPC and equipment maintenance scores declined sharply for operators in 8" fabs compared to 6" fabs. SPC scores fell modestly for technicians and engineers; equipment maintenance scores rose slightly for technicians and moderately for engineers in 8" fabs compared to 6" fabs. Overall technological change in 8" compare to 6" fabs decreased skills used by operators in SPC and equipment maintenance activities, and engineers increased their importance compared to technicians in equipment maintenance. SPC activities declined and the equipment maintenance activities remained the same for the typical worker (i.e., the activities weighted across all occupations) in 8" fabs compared to 6" fabs.

IHA is correlated with lower SPC scores for all workers (especially operators) and with lower equipment maintenance scores for operators and technicians (see Table VIII). These correlations are significant at the 10% level. MHA is correlated with a decline in SPC scores for operators and an increase in equipment maintenance scores for engineers. Overall the technological changes with IHA, and MHA to a lesser extent, were skill-biased in terms of skills used in work tasks. If we look at the combined impact on the typical worker, only IHA had a significant impact on the reduction of average skills used in SPC activities.

SPC and equipment maintenance activities are among the most difficult tasks for operators and technicians, whose job tasks are typically manual and require few analytic skills. The primary task of engineers is high-level problem solving, and SPC and most equipment maintenance are among the least difficult of their tasks. Elimination of SPC and equipment maintenance activities lowers the average skill level necessary for operator and technician jobs and increases the average skill level necessary for engineering jobs, and these changes widen the skill gap between occupations in the fab.

MHA directly alters the job tasks for operators. Because operators no longer need to spend their time doing manual labor, they might have been more efficiently utilized by performing high-skilled tasks, for example SPC and equipment maintenance. In practice this did not happen, and MHA facilitated the down-skilling of operators. MHA leads to more complex mechanical systems throughout the manufacturing process, which results in more equipment, more equipment interfaces, and the utilization of better information technology. The more complex equipment requires engineers to perform high-skilled tasks such as process control and maintenance of the connectivity of the equipment. The increase in information technology necessary to control the sophisticated materials handling systems has removed responsibilities from the operators and technicians and increased the fab's reliance on engineers.

Career Ladders and Occupational Differences

Compensation systems were ranked according to the extent to which performance determines pay. A low score indicates that the compensation system values seniority and other non-productivity measures, a high score indicates that the compensation values performance and productivity. In the matched sample the range goes from 1, compensation system places a low value on performance and a high value on seniority, to 3, compensation system places a high value on performance and a low value on seniority. Compensation systems in 8" fabs tend to be slightly more seniority-oriented than in 6" fabs (see Table IX). This surprised us, since the companies emphasize their goal of more performance-oriented compensation systems, and many labor economists have predicted that the new technology will undermine internal labor markets in large companies.

Career ladders were summarized by the minimum entry level pay and the maximum base pay for operators, technicians, and engineers[6]. Clear differences in the career ladders stand out between the 6" and 8" fabs as the career ladders of operators and engineers deteriorate. Operators in 6" fabs could triple their wage rate, while operators in 8" fabs only have wage growth potential of 250%. The flattening of engineers' career paths is even more dramatic: in 6" fabs engineers could potentially triple their initial salary, while in 8" fabs engineers can only double the average initial pay.

These results do not seem consistent with the observed changes in work activities, skills and training. If wages reflect productivity, then the work activity scores in 8" compared to 6" fabs would lead us to expect that the relative wages of operators would decline and the relative wages of engineers would increase. Overall automation dramatically improved fab productivity and allowed greater production flexibility, but career ladders indicate that the workers do not share in the improved fab performance.

Fabs with high levels of IHA tend to have performance-based compensation and to pay higher wages to their employees (see Table X). However, IHA is positively related to engineers' initial pay and negatively related to engineers' maximum pay, which indicates that IHA leads to a shortening of career ladders for engineers. Employees must learn a more complicated interface when using tools equipped with IHA, and the cost of errors or downtime is very high. However fabs that are equipped with IHA have less room for occupational advancement because many high-level tasks are now done automatically. For example, an industrial engineer in a fab without IHA has the potential for a long career path because as she becomes more skilled she can advance to perform high-level production scheduling. In a fab outfitted with high IHA, all production scheduling is automated so the engineer’s career trajectory is effectively shortened because fewer engineers are needed to perform the highest level of tasks.

Fabs with high levels of MHA also tend to have performance-based compensation but they tend to pay lower wages to their employees. MHA levels are negatively correlated with initial and maximum pay for all occupations. For operators these expected negative correlations reflect the down-skilling that is associated with MHA. Higher MHA scores mean the fab has more robots, interbay railroads, and automated stockers, which are very complex and difficult to maintain. Their maintenance is critical because a shutdown on the MHA system will halt all production in the fab. However these factors have not translated into an increase in the implicit bargaining power of technicians and engineers.

CONCLUSIONS

Two of the technological frontiers along which the semiconductor industry is advancing are information handling automation and material handling automation. The decision to automate is typically driven by the expected improvement in performance with little thought to the impact on employment systems and labor costs. The implementation of automation is generally correlated with improved performance, but it also affects workforce composition, compensation, and job requirements.

The implementation of information handling automation is an excellent example of skill-biased technical change. It goes with a reduction in the percentage of operators in the workforce and an increase in the percentage of technicians and engineers, and it widens the skill gap across the occupations in the fab. IHA goes with higher initial wages for all employees and shorter career ladders for engineers.

Material handling automation goes with an increase in the employment of operators and a decrease in the employment of engineers which is consistent with a skill-equilibrating technical change. However MHA also goes with deskilling of operators jobs and up-skilling of engineers jobs which appears to be skill-biased. Despite the conflicting impacts on jobs and employment, MHA is correlated with lower pay across all occupations.

Comparing 8" fabs to matched 6" fabs, we find higher demand for skilled workers, decreased overall training, and a deskilling of low-skill jobs and an up-skilling of high-skill jobs coupled with little change in compensation structures except for a flattening of career ladders for high-skill workers. We see that the information handling automation, which is an excellent example of skill-biased technical change, has the expected correlation with training but not with wages, which do not become more dispersed. We see an example of skill-biased technical change without a change in relative wages across occupations. Materials handling automation has a positive impact on the relative demand for low-skill workers but goes with relatively more training for engineers. Overall the decline in demand for low-skilled occupations is compounded by the deskilling of low-skill jobs, while the decline in demand for high-skilled occupations is off-set by the increase in fab complexity, which increases the value of engineers who can minimize machine downtime.

Our findings supports Moss (1997), who demonstrates that case studies pay have raised serious questions about how to interpret the relationship between skill, technology, and wages found in studies using national data sets. Our results also support DiNardo and Pischke's (1997) response to Kreuger (1993) about how to interpret the observed positive correlation between wages and computer use. We find no systematic relationship between wage level and technology, which indicates that factors other than technology-use are driving wage determination. Contrary to Bartel and Sicherman (1998), automation technologies increase the training gap between engineers and less-skilled workers. The introduction of the automated technologies go with better fab performance. However automation of information handling appears to be relatively less-skill biased and automation of materials handling to be more-skill biased in terms of labor demand. However both automation technologies appear to deskill operator and technician jobs as the technologies go with lower SPC and equipment maintenance scores; IHA also goes with less training for technicians.

We cannot interpret our findings about the impact of automation technologies at the semiconductor plant level as positive news. Our findings that employment opportunities for the least-skilled workers have declined, that workers have not shared in the fruits of the technological changes through improved wages, and that the career ladders for the highly-skilled engineers have deteriorated should concern us about the outlook for employment and wages in the increasingly important high-technology industries.

ENDNOTES

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[2] The Materials Handling Automation Score was constructed by first breaking the fabrication process into each component process step. An indicator variable was assigned to each process step on the basis of whether materials handling was implemented in the area. The variables were then summed across the fab to create the MHA score. The Information Handling Score was created by calculating the percent of the fabrication process that implements each of four specific information technologies. The percentages were then summed across the technologies within the fab and multiplied by 100.

[3] For a review of the literature see Brown and Campbell (1999a).

[4] Wafer starts per month for the matched 6" fabs averaged 8121 and the fabs were operating at close to capacity. The data collection phase for the 8" fabs occurred during a global recession for the semiconductor industry. The actual mean wafer starts per month of 6282 for the matched 8" fabs does not reflect the average fab capacity of approximately 20,000 wafer starts per month.

[5] For further information on the construction of the Work Task variables see Appleyard and Brown (1999).

[6] For further detail on the relationship of technology and wages in the semiconductor industry see Brown and Campbell (1999).

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TABLES

Table I. Mean Automation Scores (Matched Fabs)

	6"	8"
Materials Handling Automation Score	8.71	19.71
Information Handling Automation Score	92.86	335.71

Table II. Means and Correlations of Selected Metrics (Matched Fabs)
Significance levels are in parentheses.

	Means		Correlations	
	6"	8"	IHA	MHA
Cycle Time	2.84	2.38	-0.415*	-0.362*
			(0.049)	(0.090)
Stepper Throughput	292.12	441.70	0.468*	0.393*
			(0.024)	(0.064)
Direct Labor Productivity	46.25	40.42	0.355*	0.552*
			(0.097)	(0.006)
Line Yield	93.26	95.50	0.507*	0.518*
			(0.014)	(0.011)

* indicates significance at the 90% level

Table III. Mean Headcount and Workforce Composition (Matched Fabs)

	6"	8"
Operators	547.2	470.20
Technicians	90.5	107.00
Engineers	114.2	181.40
Total	751.9	758.60
% Operators	0.728	0.624
% Technicians	0.120	0.130
% Engineers	0.152	0.246

Table IV. Correlations of Automation and Workforce Composition (Matched Fabs)
Significance levels are in parentheses.

	IHA	MHA
% Operators	-0.162	0.322
	(0.615)	(0.307)
% Technicians	.058	-.208
	(0.858)	(0.517)
% Engineers	.097	-.106
	(0.765)	(0.744)

Table V. Mean Training Variables (Matched Fabs)

	Initial Training		Training in 1st 3 years		Breadth of Training in SPC		Breadth of Training in Equipment Maintenance	
	6"	8"	6"	8"	6"	8"	6"	8"
Operators	31.50	15.02	197.85	136.38	3.71	4.17	3.14	4.17
Techs	26.15	8.36	215.87	151.41	4.52	5.33	4.29	4.83
Engineers	25.54	17.81	191.81	157.69	7	7.33	4	4.5

Table VI. Correlations of Automation and Training (All Fabs)
Significance levels are in parentheses.

	IHA	MHA
Initial Training Days: Operators	-0.075	0.157
	(0.734)	(0.474)
Initial Training Days: Technicians	-0.195	0.164
	(0.373)	(0.454)
Initial Training Days: Engineers	0.084	0.518*
	(0.705)	(0.011)
Training Days in First 3 Years:	-0.099	0.007
Operators	(0.652)	(0.975)
Training Days in First 3 Years:	-0.196	-0.095
Technicians	(0.371)	(0.665)
Training Days in First 3 Years:	0.007	0.276
Engineers	(0.976)	(0.203)

* indicates significance at the 90% level

Table VII. Mean Work Activity Scores (Matched Fabs)

	6"	8"
Operator SPC score	37.29	19.71
Technician SPC score	44.29	35.71
Engineer SPC score	82.29	62.43
Operator Equipment Score	47.71	27.14
Tech. Equipment Score	111.71	124.71
Engineer Equipment Score	137.29	164.57
SPC score for Typical Worker	47.41	35.36
Equipment Score for Typical Worker	76.01	80.08

Table VIII. Correlations of Automation and Work Activities (All Fabs)
Significance levels are in parentheses.

	IHA	MHA
Operator SPC score	-0.530*	-0.386*
	(0.009)	(0.069)
Technician SPC score	-0.379*	-0.117
	(0.074)	(0.595)
Engineer SPC score	-0.341	0.002
	(0.111)	(0.993)
Operator Equipment Score	-0.290	-0.175
	(0.180)	(0.424)
Tech. Equipment Score	-0.260	-0.089
	(0.230)	(0.686)
Engineer Equipment Score	0.065	0.270
	(0.768)	(0.214)
SPC score for Typical Worker	-0.430*	-0.220
	(0.041)	(0.314)
Equipment Score for Typical Worker	-0.103	0.096
	(0.641)	(0.664)

* indicates significance at the 90% level

Table IX. Compensation Systems (Matched Fabs)

	6"	8"
Compensation Score: Operators	1.57	1.43
Compensation Score: Technicians	1.57	1.43
Compensation Score: Engineers	1.86	1.43
Initial Pay: Operators (hourly)	5.88	7.12
Initial Pay: Technicians (hourly)	6.68	9.12
Initial Pay: Engineers (monthly)	1784.6	2381.34
Maximum Pay: Operators	15.47	18.44
Maximum Pay: Technicians	11.50	15.83
Maximum Pay: Engineers	5019	4688.92

Table X. Correlation of Automation Variables and Compensation System (All Fabs)
Significance levels are in parentheses.

	IHA	MHA
Compensation Score: Operators	0.328	0.573
	(0.127)	(0.004)
Compensation Score: Technicians	0.284	0.501
	(0.190)	(0.015)
Compensation Score: Engineers	0.247	0.341
	(0.256)	(0.111)
Initial Pay: Operators	0.288	-0.320
	(0.417)	(0.367)
Initial Pay: Technicians	0.329	-0.422
	(0.354)	(0.224)
Initial Pay: Engineers	0.276	-0.478
	(0.473)	(0.193)
Maximum Pay: Operators	0.087	-0.204
	(0.812)	(0.571)
Maximum Pay: Technicians	0.145	-0.479
	(0.690)	(0.161)
Maximum Pay: Engineers	-0.229	-0.539
	(0.554)	(0.135)