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"Managing" Learning by Doing: An Empirical Study in Semiconductor Manufacturing

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This article examines the contributions of human resource and organizational practices to the development and supply chain management interface. It addresses this issue in the context of the semiconductor industry by highlighting the importance of these practices for learning-based improvement in manufacturing. One of the most important factors for competitiveness in the semiconductor industry is the ability to manufacture new process technologies with high yields and low cycle times. The more effective management of new process technologies within the manufacturing facility aids firms in managing production costs, volumes, and inventories. Efficient management of new process development and introduction translates into enhanced internal supply chain management performance by improving the design of internal workflows, manufacturing performance, and the acquisition and installation of new manufacturing processes. Because much of the knowledge that underpins semiconductor manufacturing is idiosyncratic, however, firm-level differences in human resource and organizational practices are likely to have consequences for performance. The article derives learning curve models of the rate of improvement in manufacturing yield (i.e., the rate of learning) and cycle time (i.e., the speed of production) following the introduction of a new process technology in a manufacturing facility. It then tests the influence of the use by semiconductor manufacturers of teams for problem solving and intrafirm knowledge transfer, the level of internal adoption of information technology (IT), and more extensive and effective workflow and production scheduling systems on manufacturing performance. It finds that the manners in which semiconductor manufacturers allocate engineering resources to problem-solving activities, utilize information technology in the manufacturing facility, schedule production, and control the "shop floor" influence the levels and rates of improvement in both manufacturing performance measures. The article makes several contributions to the literature on product and process development and, accordingly, to research on the product development/supply chain interface. In particular, the model of organizational-based learning provides a better understanding of the determinants of learning-based performance improvement. In particular, better manufacturing performance results not strictly from greater cumulative volume but also from the

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actions of managers that affect the organization of establishment-level problem-solving activities and information exchange. The article also demonstrates that human resource and organizational practices in both the development and the adoption of new process technologies improve manufacturing performance by accelerating new product introduction, improving workflow, and enhancing the efficiency of manufacturing processes.

Introduction

This article examines the contributions of human resource and organizational practices to the development of firms' capabilities in the coordination of new manufacturing process development and manufacturing management. Because new semiconductor products normally require more advanced processes for their manufacture, fast and efficient process development has a direct impact on the commercial success of new product introductions. In addition, successful management of the adoption of new process technologies within the manufacturing facility aids firms in managing production costs, volumes, and inventories. Efficient management of new process development and introduction, therefore, translates into enhanced supply chain management performance by improving firms' design of internal workflows and manufacturing performance—especially in the early phases of production "ramps"—and especially in firms' acquisition (often, from internal sources) and installation (which may involve the transfer of a new process among different facilities) of new manufacturing processes. Firms' performance in new process development and implementation within the manufacturing facility—including the coordination of new product and new process technology development—thus directly affects the quality of their management of the product development/supply chain interface.

We analyze the contributions of human resource and organizational practices within the firm to manufacturing performance in the introduction of new manufacturing processes using two performance measures. The first measure is the rate of improvement in manufacturing yield (i.e., the rate of learning) following the introduction of a manufacturing process to a full-volume manufacturing facility. The second measure is the rate of improvement in cycle time (i.e., improvements in the speed of production or throughput). The analysis tests the influence on performance of (1) the use by semiconductor manufacturers of teams for problem solving and intrafirm knowledge transfer, (2) the level of internal adoption of information technology (IT), and (3) more extensive and effective workflow and production scheduling systems.

This article makes several contributions to the literature on product and process development and, accordingly, to research on the product development/supply chain interface. We develop detailed measures of human resource and organizational practices and examine their influence on elements of manufacturing performance that are critical to competitive advantage in the semiconductor industry. Second, our model of organizational-based learning provides a deeper understanding of the determinants of learning-based performance improvement. Although many studies argue that "learning by doing" plays a central role in firm performance, the majority of these analyses rely solely on cumulative volume as an explanation for improved performance (Argote, 1999). Third, the article focuses on the management of process technology, a topic that has received limited scholarly treatment in the management literature (particularly by comparison with new product development), despite its importance in many process-dependent (Pisano, 1997; Pisano and Wheelwright, 1995) industries. Finally, the article demonstrates that human resource and organiza-

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tional practices in both the development and the adoption of new process technologies improve manufacturing performance by accelerating new product introduction, improving workflow, and enhancing the efficiency of manufacturing processes.

The next section of this article provides a short overview of research in learning-based improvement in manufacturing performance. Section three develops several testable empirical implications concerning the influence of firms' management practices on learning and manufacturing performance. Section four develops a model of learning and performance in semiconductor manufacturing; describes the sources and characteristics of the data, estimation methodology, and construction of the variables used in the analysis; and presents and discusses the empirical results. Section five makes concluding comments.

Theory

The literature on "learning by doing" and manufacturing performance is extensive (Argote, 1999). The most common approach examines the relationship between cumulative output and the direct labor costs of manufacturing. In one of the first examinations, Wright (1936) found that with every doubling of cumulative output, the direct labor costs of airframe manufacture fell by 20%. Many other studies have corroborated this finding in a variety of other industries.[1] Research in learning by doing argues that experience lowers costs or speeds production. Because experience is difficult to measure, this literature employs a variety of different proxies for experience. Although cumulative volume is the most common measure, some research includes cumulative investment or cumulative time as alternative measures (Arrow, 1962; Hatch and Mowery, 1998; Lieberman, 1984; Rapping, 1965; Sheshinski, 1967). Other empirical studies have looked beyond the learning-manufacturing performance relationship in considering the role of learning by doing in market structure and pricing (Arrow, 1962; Fudenberg and Tirole, 1983; Lieberman, 1984), predatory pricing (Cabral and Riordan, 1994), trade policy (Gruber, 1996), or collusion (Mookherjee and Ray, 1991).

It is unlikely, however, that cumulative volume alone adequately proxies for the experience that contributes to learning-related performance improvement. Manufacturing performance improvements do not result solely from cumulative production, but rather are the product of deliberate actions aimed at resolving productivity bottlenecks or quality problems. In particular, learning by doing is the result of analysis by engineers that seeks to discover sources of manufacturing problems and implement corrective solutions. This article examines the contributions of specific human resource and organizational practices to these problem-solving efforts. We emphasize the role of these management practices in providing additional information on problem causes and solutions and/or contributing to the codification and intrafirm dissemination of previously "tacit" information. By capturing and transmitting information in a very complex operating environment, these actions accelerate learning and manufacturing performance improvement (von Hippel and Tyre, 1995).

Although these factors are widely acknowledged by scholars and practitioners, their influence on performance has rarely been the focus of empirical research, largely because of the proprietary nature of the necessary data. But the use in many empirical studies of cumulative production volume or cumulative time permits only the demonstration of their influence on "learning" and performance improvement, rather than an identification of the mechanisms underpinning such learning-based improvement (Hatch, 2001; von Hippel and Tyre, 1995). As a result, our understanding of the ways in which particular human resource or organizational practices affect learning and performance improvement is limited. One exception is Adler and Clark (1991), who use detailed case study data from several divisions of a high-technology firm to identify the role of indirect labor in learning. We adopt a similar approach, developing measures for the use by firms of specific human resource and organizational practices and test whether these practices improve learning and performance improvement by facilitating problem-solving efforts in the manufacturing facility. We argue in particular that the deployment of specific human resource and information technology practices in both process development and process adoption

[1] Learning by doing has been documented in airframes (Alchian, 1963; Wright, 1936), automobile assembly (Baloff, 1971), chemical processing (Lieberman, 1984), housing construction (DeJong, 1957), machine tools (Hirsch, 1952), metal products (Dudley, 1972), nuclear plan construction (Zimmerman, 1982), petroleum refining (Hirschman, 1964), printing and typesetting (Levy, 1965), radar (Preston and Keachie, 1964), rayon (Jarmin, 1994), and semiconductors (Bohn, 1995; Dick, 1991; Gruber 1992, 1996; Hatch and Mowery, 1998; Irwin and Klenow, 1994), among other industries.

within the manufacturing environment improves learning and performance. We are able to examine process innovation and manufacturing performance in only one industry, semiconductor process development and manufacturing, which may reduce the generalizability of our results, but supports a more accurate measurement of the influence of firm-specific technology practices on learning and performance improvement.

Model Development

Performance and Learning in Semiconductor Manufacturing

For several reasons, superior performance in the development and introduction of new manufacturing processes is critical to competitive performance in the semiconductor industry. First, as is true in other "process-intensive" industries, including biopharmaceuticals, specialty chemicals, and advanced materials (Pisano, 1997), semiconductor product innovations generally require process innovations. The introduction of a new semiconductor product typically necessitates significant changes and innovations in the underlying manufacturing process. Second, the ability to increase output of a new semiconductor chip rapidly—before imitators enter—is crucial to profitability. Third, the high fixed costs associated with semiconductor manufacturing—new fabrication facilities cost more than $2 billion and are considered "state-of-the-art" for no more than three years (ICE, 2001)—mean that low manufacturing yields (a small fraction of output can be sold commercially) and long cycle times (an inability to meet customer demand in a timely fashion) reduce profitability and threaten firm survival. All three of these factors also mean that successful process innovation and adoption are essential to effective management by producers of their internal supply chains.

We examine the rate of improvement in manufacturing performance following the introduction of a new production process, which is conceptualized in terms of movement down a learning curve or improvement in some other index that measures manufacturing performance improvement. Movement down a learning curve is important to sustained performance because of the unforgiving competitive environment that characterizes the semiconductor industry. Short product life cycles and rapid price declines necessitate rapid and effective introduction of new semiconductor products and manufacturing processes. These industry conditions mean that semiconductor firms that improve manufacturing performance more quickly than their competitors in similar market segments are likely to realize superior returns. The ability to react more quickly to changing market and customer needs by developing new and innovative solutions or by adjusting production to meet fluctuations in demand swings also improves the responsiveness and efficiency of manufacturers' internal supply chains. We focus on supply chain management processes internal to the firm, as opposed to supply chain processes outside the firm that connect it to its suppliers or customers. Similar to supply chain processes with customers and suppliers, internal supply chain processes are important components of competitive performance as they help to tie and reconcile the supply side with the demand side. These internal supply chain processes include semi-finished goods inventory, production, logistics, and scheduling, among others. The management and optimization of internal supply chain processes helps to determine firms' abilities to react and adapt to changing industry conditions.

A semiconductor is any microelectronic device fabricated on "semiconducting" material (usually silicon) but is normally an integrated circuit or set of electronic components that is connected in a certain way to perform a particular function. Manufacturing a semiconductor consists of constructing layers of conducting and insulating materials on "wafers" of silicon in intricate patterns that give the integrated circuit (*IC* or *die*) its function. Wafer fabrication is characterized by complex process flows, unpredictable yields, and rapid technology changes.

Yield is an integral part of semiconductor manufacturing and is generally expressed in terms of line yield, the proportion of wafers that are not scrapped, and die yield, the proportion of die on a successfully processed wafer that pass functionality tests. Yield is in many ways a measure of the "quality" of the process. Common line yield losses derive from broken and damaged wafers or skipped production process steps that render all of the ICs on the wafer nonfunctional. Die yield losses are due either to random particles or to parametric processing problems. Airborne particles can land on critical parts of a die and destroy its functionality by causing "short" or "open" circuits. Extensive air filtration systems and protective enclosures for equipment and/or wafers to reduce contaminants are employed to create ultra-clean environments. A more pervasive source of die yield losses is due to parametric problems that result from either insufficient control of the production process or incomplete understanding of the parameters of the process technology. Each "ingredient" in the "recipe" of a process step must be applied within a certain range to have the desired effect.[2]

A second performance metric in the semiconductor industry is cycle time, or the time required to manufacture a semiconductor device. Semiconductor manufacturing uses many different types of equipment to perform hundreds of interrelated steps. Most semiconductor processes consist of several distinct "process modules" that are repeated once for each layer of circuitry. Shorter cycle times mean that production facilities can produce more output or adjust more quickly to changes in customer and market demand, an increasingly important competency in this industry.

Because many process steps are neither well understood nor easily replicated on different equipment sets or in different production facilities, manufacturing performance depends on knowledge accumulated through experimentation and experience. Knowledge gained from these activities yields tighter specification limits and refined target and equipment operation parameters. The widespread application of such knowledge, however, especially in different manufacturing facilities, often requires its codification. Certain human resource and organizational practices aid the learning process by bringing more knowledge to bear on the problem-solving activities of firms and by codifying previously tacit information. These practices not only improve the identification of sources of yield loss or cycle time excursions, but also support faster implementation of corrective solutions. We therefore examined the effects of particular practices on the level and rate of improvement in die yield (i.e., the *rate of learning*) and cycle time (i.e., the *speed of production*).

[2] A "recipe" is exactly that—a codified description of ingredients, steps, and machine and equipment operation involved in a particular semiconductor operation. Many process steps are too complex to identify the optimal ranges for all the ingredients through physics and engineering, and parametric processing problems occur when the ingredients fall outside of a particular range or a process step does not perform as specified. Unexpected interactions between and among inputs also can destroy the functionality of the die.

Human Resource Practices

Management of its human resources is a critical influence on the development of the "repository of knowledge stocks" that some scholars take as the definition of the firm (Foss, 1996). And this is no less true of the management of new process development and implementation. For example, a common problem associated with new process development is the hand-off of a new process technology from development to the production facility. Manufacturability issues often appear only after a new process has been transferred to the manufacturing facility from a development site because of differences between the development and production facilities in equipment, production volumes, worker skills, and numerous other factors.

In an effort to improve integration and knowledge transfer between development and manufacturing, some semiconductor firms undertake new process development activities with cross-functional teams that span functional areas from research, product development, process development, and manufacturing.[3] Cross-functional process development teams can improve communication among different functional groups within the firm that are involved in the development and implementation of a new process technology in the manufacturing facility. Greater team diversity (i.e., the inclusion of more functions within team membership) provides closer integration between process development and manufacturing personnel, supporting the earlier identification of manufacturing problems and the faster implementation of corrective solutions.

Several studies have looked at human resource practices and manufacturing performance in semiconductors. Appleyard and Brown (2001) find that the participation of workers in problem-solving teams under the leadership of engineers is associated with superior manufacturing performance. Sattler and Sohoni (1999), on the other hand, conclude that

[3] Cross-functional teams can improve coordination and dissemination of organizational learning (Nonaka, 1991) by spanning organizational boundaries (Ancona, 1990; Tushman, 1977), and thereby reduce development cycle time (Denison et al., 1996). Cross-functional teams in product development can increase the likelihood of project success by minimizing miscommunication (Brown and Eisenhardt, 1995) by facilitating internal communication (Dougherty, 1990) and by drawing on a greater number of information sources (Imai et al., 1985). Cross-functional product development teams also speed development because they better link upstream and downstream activities so that manufacturing considerations are factored into design activities and because they push decision making down to those who possess the relevant expertise (Eisenhardt and Tabrizi, 1995).

worker participation enhances manufacturing quality but does not improve production throughput. The authors suggest that their results reflect a tendency for manufacturing yield or quality problems to be more easily linked to specific causes, while production throughput is affected by scheduling and product demand, factors that are largely beyond the purview of problem-solving teams within the production facility. A larger number of team types operating within the production facility may improve the focus of problem-solving activities on particular areas of manufacturing or increase the number of problems that can be examined (Bailey, 1998). But diversity in team types also strengthens problem-solving capabilities by increasing the diversity of different areas in the manufacturing environment that can be examined (Appleyard and Brown, 2001).

Another human resource practice that affects performance in the development and implementation of new process technologies is the colocation of development and manufacturing personnel, enabling manufacturing personnel to participate in process technology development. In some firms, engineers from development move with the process technology to the manufacturing site to facilitate the flow of tacit information from development to production. Even where development occurs in the production facility, colocating development and manufacturing may simplify intrafirm knowledge transfer (Hayes et al., 1996; Iansiti, 1995). The parallel organization of various process development and implementation activities that is implicit in colocation of development and manufacturing personnel also can save time and support more accurate and timely identification of problems (Cordero, 1991; Smith and Reinertsen, 1991; Zirger and Hartely, 1996). Colocation of a larger fraction of the critical process development and manufacturing personnel should improve the rate of learning for both yield and cycle time.

Information Technology Practices

The increasing complexity of semiconductor manufacturing processes and the greater flow of information on manufacturing performance that information technology (IT) and computer integrated manufacturing (CIM) applications make available to managers have made investment in IT-based process controls more important to new product and process introductions. An especially common use of advanced IT applications is in greater automation of material and information handling. The closely related automation of process equipment reduces operator error, replaces unreliable material handling, and increases overall equipment efficiency, making manufacturing "mistake proof" and more repeatable.

Higher levels of automation of information handling and retrieval in the manufacturing facility improve the speed of data collection and enhance the reliability and accessibility of data on manufacturing and equipment performance, all of which enable faster identification and diagnosis of manufacturing problems. Automated collection of process information also reduces demands on operators to manually enter or record data, reducing variance in operator performance and data collection and enabling faster identification of processing problems. Automated download of process "recipes" into semiconductor processing equipment frees operators from having to load the right recipe for a given wafer lot and computerized "sanity checks" of the machine and wafer lot. Higher levels of automation in information handling and retrieval accelerate learning because information can be more readily captured, codified, and used in the manufacturing facility.

Many semiconductor manufacturers also keep computerized records of each wafer lot as it progresses through the production facility, recording equipment start and stop times, machine and operator identification, and process control parameters and equipment efficiency parameters at each process stage. Statistical analysis of these integrated databases enables engineers to more accurately set process parameter windows, identify high-priority areas in which to focus efforts to improve yield and cycle time, and compare the productivity of different equipment sets. Use of such integrated relational databases is likely to have the greatest positive effects on yield improvement rather than cycle time.

Scheduling Practices

The scheduling of production and the design of work and inventory flow in the manufacturing environment are critical to the management of process technology development and implementation in the production facility. Production scheduling in particular affects firms' cycle time performance and therefore is crucial to on-time delivery performance. Despite its importance for fab performance, few if any formal systems for strategic enterprise-wide production planning are employed in the semiconductor industry (Leach et al., 1997; Leachman, 1994). Limited use of such systems reflects a lack of off-the-shelf scheduling software. The absence of such "standard" applications software underscores the fact that scheduling wafer production is a monumental task, because of the volume of data required, the diverse requirements of individual wafer lots and customers, volatile processing priorities, and unpredictable equipment availability.

Nevertheless, some semiconductor manufacturing facilities have developed effective systems to regulate wafer starts and monitor and control the flow of inventory and equipment, and have implemented production-planning systems that regulate starts to meet demand and keep "bottleneck resources" (e.g., a critical piece or suite of production equipment) fully utilized. These fabs also have systems in place to monitor inventory flow and build-up in real time. Improved practices such as these around scheduling and planning improve the management of the internal supply chain and should therefore have a positive impact on manufacturing performance.

Summary

Table 1 summarizes this discussion of the basis for the empirical implications tested below concerning the relationships among human resource practices, information technology practices, internal supply chain management practices, and new process development and deployment on performance. The increased use and deployment of these practices is expected to improve learning-by-doing performance. However, we examine below whether there are any differences in the influence of these practices on our two key performance measures, cycle time and yield improvement.

Empirical Specification

Semiconductor Manufacturing Learning Model

The traditional model for learning by doing is embodied in the following equation:

$$C_N = C_1 N^{-\lambda} \tag{1}$$

where C_N is the cost of the N^{th} unit produced, N is the cumulative amount produced, and C_1 is the cost of the first unit produced. This formulation models learning as a function of cumulative volume, but as we noted earlier, a variety of other measures of "experience" have been used in other studies. But the influence on learning of deliberate actions aimed at overcoming sources of productivity bottlenecks has received surprisingly little attention.

Our model of learning draws on Hatch and Mowery (1998) and Hatch and Macher (2002), which show that improvements in manufacturing productivity are driven in part by factors and practices that improve engineers' analysis of production volume and production problems. We extend and differentiate our learning model in two ways. First, this model utilizes two measures of manufacturing performance, rather than manufacturing yield alone. Second, we develop and test the influence on learning of measures of firms' human resource and organizational practices that have not been previously employed in analyses of process technology innovation and learning.

We measure the accumulation of manufacturing experience by the cumulative number of wafers fabricated devoted to manufacturing productivity

Table 1. Empirical Implications

Practice	Description	Expected Impact on Performance
Human Resource	Extent of cross-functionality in individual teams and diversity of team types for problem-solving activities within the fabrication facility	+
	Extent of colocation of development and manufacturing engineers during new process development within the fabrication facility	+
Organizational	Extent of information technology practices within the fabrication facility	+
	Extent of production and capacity planning, scheduling, and shop floor control practices	+

improvement. Firms acquire process-specific knowledge through engineering analysis of production volume to identify and eliminate sources of yield loss or cycle time excursions. Denoting cumulative volume at time t as CV_t, the "learning index" for a manufacturing process is defined as:

$$L_t = \beta_1 \cdot CV_t + L_0 \quad (2)$$

where L_0 is the level of knowledge or experience in the first period.[4] In order to link learning by doing to specific measures of manufacturing performance, we assume that the learning curves for both defect density and cycle time are additively separable into a static component and a dynamic (learning by doing) component:

$$P_t = h_1(L_t) + h_2(\cdot) \quad (3)$$

where P_t represents either the defect density or cycle time parameter and L_t is the unobservable "learning index" defined in Equation 2. The second term in Equation 3 includes the influence of variables that do not directly affect the rate of learning but that index the underlying technological "difficulty" of the manufacturing process and the associated learning-based improvements in it. Among these static variables are the linewidth of the manufacturing process (LW), the wafer size (WS), the cleanliness of the clean room (CR), and the number of mask layers (ML). *P*rocess linewidth (LW) is a measure of technological sophistication (smaller feature devices are more difficult to produce). The smallest linewidth that defines the technological frontier is shrinking during the period of time covered by our data, and we therefore measure LW for a given manufacturing process by its "distance" from the technological frontier, which we measure from industry sources that document the evolution of the "leading edge" LW over time. Accordingly, LW ranges from near zero (very mature process technologies) to one (leading-edge process technologies). Because linewidths that are closer to the technological frontier introduce greater complexity to the manufacturing process, LW should have a negative influence on both defect density and cycle time. A larger diameter wafer size (WS) also should influence both performance parameters negatively because of the greater complexity of producing large wafers. The number of mask layers (ML) is a proxy for the total number of steps in the process. A larger number of mask layers will extend cycle time and will increase the probability of a fatal defect on the die, *ceteris paribus*. Finally, clean room grade (CR) is a measure of the number of particles per cubic foot in the fabrication facility. The cleaner the manufacturing facility, the less likely particles will rain down on the wafer and produce yield problems.

Neither economics nor engineering provides many insights into the appropriate functional forms for the dynamic and static components of learning (Yelle, 1979). We therefore specify functional forms for the $h_2(\cdot)$ and $h_1(L_t)$ components of learning as follows (Hatch and Macher, 2002; Hatch and Mowery, 1998):

$$h_1(L_t) = \gamma + \psi e^{-\delta \cdot L_t} \quad (4)$$

$$h_2(\cdot) = \beta_2 LW + \beta_3 WS + \beta_4 CR + \beta_5 ML \quad (5)$$

$h_1(L_t)$ allows for both shifts in rate of learning through γ and scalability in the rate of learning through δ, while $h_2(\cdot)$ assumes that the static factors that do not directly affect the learning rate are additively separable. Inserting Equations 4 and 5 into Equation 3 gives:

$$P_t = \gamma + \psi e^{-\delta \cdot L_t} + \beta_2 LW + \beta_3 WS + \beta_4 CR + \beta_5 ML \quad (6)$$

Because the learning index (L_t) cannot be observed directly, it is necessary to solve for L_0 in terms of P_0 (which is observable) and substitute the result. In the initial period (i.e., when $t=0$), the manufacturing performance parameter is:

$$P_0 = \gamma + \psi e^{-\delta \cdot L_0} + \beta_2 LW + \beta_3 WS + \beta_4 CR + \beta_5 ML \quad (7)$$

Solving for L_0 in terms of P_0 gives:

$$L_0 = \frac{\frac{-\ln[P_0 - \gamma - (\beta_2 LW + \beta_3 WS + \beta_4 CR + \beta_5 ML)]}{\psi}}{\delta} \quad (8)$$

Substituting Equation 8 into Equation 2 and then into Equation 6 provides a learning curve with an observable initial period parameter:

$$P_t = \gamma + e^{-[\beta_1 \cdot CV_t]} \cdot [P_0 - \gamma - (\beta_2 LW + \beta_3 WS + \beta_4 CR + \beta_5 ML)] + \beta_2 LW + \beta_3 WS + \beta_4 CR + \beta_5 ML \quad (9)$$

[4] Time t represents the time from the first observation and L_0 represents the learning that has been accumulated prior to the first observation of the process. Hatch (2001) notes it is difficult to imagine a situation where some manufacturing knowledge or experience does not exist before the first observation.

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where γ and β are redefined accordingly ($\gamma = \delta \cdot \gamma$, $\beta_i = \delta \cdot \beta_i \forall_i$). Equation 9 represents a generic learning-by-doing model for both defect density and cycle time. In order to capture the influence of human resource and organizational practices on learning performance, the learning index is redefined as $L'_t = L_t + HRP + OP$, where HRP and OP represent, respectively, the knowledge gained by implementing particular human resource and organizational practices in the fab. These practices influence learning not only directly, but also indirectly, by enhancing the productivity of the underlying sources of learning delineated in Equation 2. The "indirect effects" of these management practices on learning are captured through an interaction term between the particular human resource and organizational practice variables and the cumulative volume (CV_t) variable. Including HRP and OP in Equation 2 and solving the model as described above gives:

$$\begin{aligned} P_t = \gamma + e - [\beta_1 \cdot CV_t + HRP \cdot (\alpha_1 + \alpha_2 \cdot CV_t) \\ + OP \cdot (\alpha_3 + \alpha_4 \cdot CV_t)] \cdot [P_0 - \gamma - (\beta_2 LW \\ + \beta_3 WS + \beta_4 CR + \beta_5 ML)] + \beta_2 LW + \beta_3 WS \\ + \beta_4 CR + \beta_5 ML \end{aligned} \tag{10}$$

Equation 10 provides the basis for our tests of the influence on learning-based manufacturing performance improvement of the human resource and organizational practices discussed above.

Data

Data for this article were collected as part of a global empirical investigation of semiconductor manufacturing.[5] The wafer fabrication facilities of U.S., European, Japanese, Korean, and Taiwanese semiconductor firms operating domestically and offshore are included in the study. Semiconductor firms were selected from a list of "best in class" manufacturers and contacted to assess their willingness to participate. After firms agreed to participate, questionnaires were sent to elicit fab-specific information on products, processes, and manufacturing equipment, the response to which were verified and elaborated by field visits to the production sites. The surveys and field visits collected data on manufacturing performance, including such measures as yield, cycle time, throughput, equipment efficiency, etc., but also gathered data on the human resource, organizational, and management practices of the fabrication facilities in the study. Data were collected for each fab's "major process groups," production lines accounting for at least 75% of the output of the fab. Most production facilities also provided historical data that enabled the construction of time series on the performance of the fab during the development, introduction, ramp-up, qualification, and full-scale operation of new processes.

Dependent Variables

We compare two dimensions of learning-based manufacturing performance. The first dimension is die yield (DY), but because die yield is affected by particulate contamination on the surface of the silicon wafer, reported die yield is sensitive to the average size of die on a wafer. In order to control for differences in average die size, yields are translated into an equivalent "defect density," or number of fatal defects per square centimeter on a wafer, using the Murphy model.[6] The relationship between die yield and the average number of fatal defects per cm^2 is given by:

$$DY = \left[\frac{1 - e^{-A \cdot DD}}{A \cdot DD}\right]^2 \tag{11}$$

where A is the die area and DD is the defect density parameter.

Figure 1 presents initial defect density and early-stage rates of improvement in defect density for a subset of new processes in our sample. Superior performance in yield management is revealed in low initial defect densities and steep improvement rates in defect density. Semiconductor manufacturers with superior human resource and organizational practices should have better (lower) initial defect

[5] This multi-year research effort is called the Competitive Semiconductor Manufacturing (CSM) Program and is a joint project of the College of Engineering, the Walter A. Haas School of Business, and the Department of Economics at U.C. Berkeley. The project was sponsored by a grant from the Alfred P. Sloan Foundation, with the cooperation of semiconductor producers from Asia, Europe, and the United States. Program directors are David Hodges and Robert Leachman of U.C. Berkeley's College of Engineering. This research effort has collected data on the manufacturing performance of 36 wafer fabrication facilities around the world.

[6] The list of commonly used models includes the Poisson model, the Murphy model, and the negative binomial model. The Murphy model extends the Poisson model to account for the observed clustering of defects on wafers. In particular, this model assumes a triangular approximation of the Gaussian distribution. See Stapper (1989) for an overview of the defect density literature.

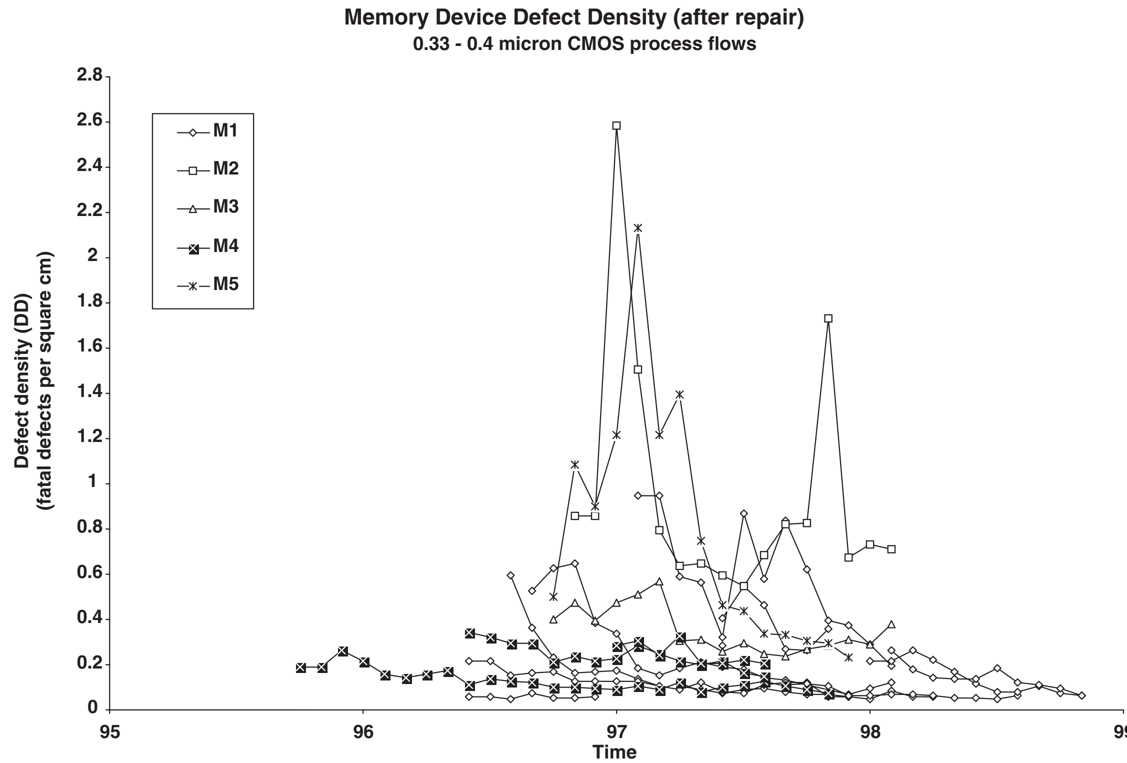

Figure 1: Memory Device Defect Density (after repair) 0.33–0.4 Micron CMOS Process Flows

densities. Significant variance among the firms in the sample is displayed in Figure 1, with initial defect densities of the worst performing fabs roughly five times that of the best performing fabs. Figure 1 also displays the rate of improvement in defect density for each fab displayed. Although all semiconductor manufacturers improve in this manufacturing performance measure, the slopes of these production ''learning curves'' vary greatly among the individual production facilities.

The second dimension is cycle time, or the length of time required to manufacture a semiconductor product. Because semiconductor firms manufacture products that require different numbers of circuitry layers, we normalize cycle time by the number of ''mask'' layers (*CTPL*) necessary for each semiconductor product in the sample. The second dependent variable therefore takes the form:

$$CTPL = \frac{CT}{ML} \tag{12}$$

where CT represents cycle time and ML is the number of mask layers the product requires.

Figure 2 presents initial cycle time and early-stage rates of improvement in cycle time for a subset of new processes in the sample. Similar to defect density, superior performance is revealed in low initial cycle times and steep ''learning curve'' slopes, and like yield improvement, Figure 2 reveals considerable variance in both the starting point and rate of improvement in this key performance measure.

Independent Variables

We use two variables to test the influence of firms' use of cross-functional teams to resolve manufacturing and process development problems. *Team Diversity* measures the diversity within a particular team, that is, the degree to which both direct (i.e., operators and technicians) and indirect (i.e., engineers and supervisors) personnel are involved in problem-solving activities within the manufacturing facility. Testing the influence of this variable on manufacturing performance improvement tests our hypothesis that greater diversity in team composition improves problem-solving skills. *Team Number* measures

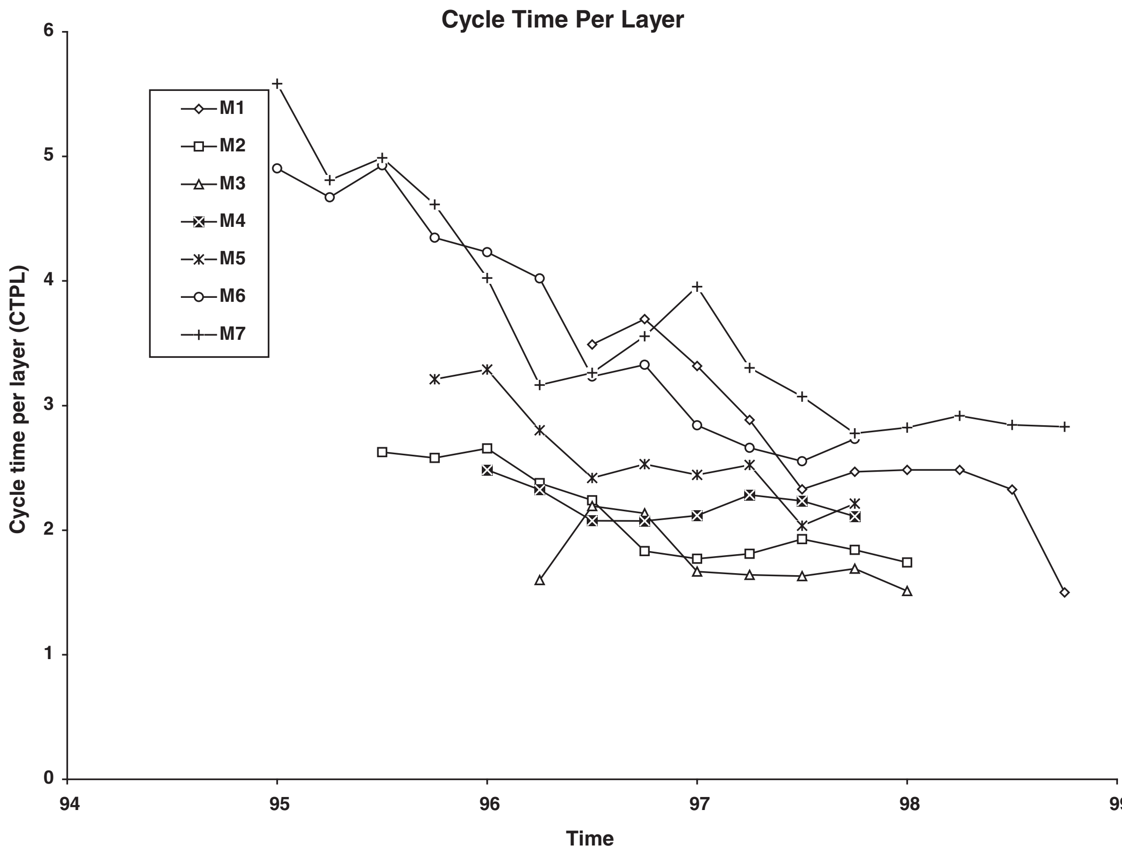

Figure 2: Cycle Time Per Layer

the diversity of problem-solving team types operating in the facility, and serves to test the validity of our hypothesis that greater diversity in the types of teams engaged in problem solving results in faster implementation of corrective solutions, thereby accelerating the rate of performance improvement in new manufacturing processes.[7] *Colocation* assess the influence of colocating engineering resources, which measures whether manufacturing engineers are transferred to development and/or development engineers are transferred to manu-facturing (see Table 2 for a summary description of the construction of these and other independent variables).

We test the effects of higher levels of IT and CIM investment in materials handling and information capture and analysis through four variables: the extent of use of automated *Material Handling* in critical functions; the extent and use of automated *Information Handling*; the extent of use of integrated *Database Analysis* of production performance and problem solving; and the extent of use of production *Scheduling* systems. Each variable is measured by categorizing each fab included in our study according to its level of adoption of these practices. Unequal weights are assigned to *Materials Handling*, reflecting the fact that interbay materials handling automation is more complex and potentially more valuable to performance improvement. Conveyor systems receive a higher weight because industry experts considered them to be more important than systems that load and unload production lots.[8] The automation of *Information Handling* is constructed from measures of the extent of adoption of three types of automated

[7] The number of teams may have a similar effect as the number of team types in terms of increasing the number of manufacturing issues that can be addressed, but would not necessarily increase the breadth of issues that would be addressed. Team types would include Quality Improvement Teams, Quality Function Deployment Teams, Quality Circles, Continuous Improvement Teams, Total Preventive Maintenance Teams, and Self-Directed Work Teams, among others.

[8] Interbay systems connect two or more bays, while intrabay systems are limited to a single bay. In semiconductor manufacturing, it is more difficult to develop a material handling system within a bay than between bays because this entails connecting automatic guided vehicles to conveyors, stockers, and robots and then directly to manufacturing equipment. All weighting schemes for all variables were derived from discussions with fab managers and engineers based on their sense of importance. Other weighting schemes were implemented in the empirical analysis with no significant influence on the results.

Table 2. Variable Definition

Variable	Unit	Weight	Description
Defect Density	Defects/cm^2		Number of fatal defects per centimeter squared
Cycle Time	Days/ml		Time (in days) to manufacture single mask layer
Cumulative Volume	1K wafer starts		Thousands of wafers starts
Team Diversity	Dif/In Between/Same (2/1/0)		Diversity of team composition in problem-solving activities
Team Number	Many/Several/Few (2/1/0)		Number of problem-solving teams operating in the fab
Colocation	Both/One/None (2/1/0)		Indicator of development and manufacturing groups colocated
Material Handling	[0…2]		Weighted variable of extent of material handling automation
	0–1.0	0.60	Percentage of manufacturing interbays that use automatic guided vehicles to transport wafers
	0–1.0	0.60	Percentage of manufacturing inter- and intrabays that use conveyor systems to transport wafers
	0–1.0	0.40	Percentage of intrabays that use robots to load/unload wafers from AGVs/conveyors and/or processing equipment
	0–1.0	0.40	Percentage of intrabays that use stockers to load/unload wafers from AGVs/conveyors and/or processing equipment
Information Handling	[0…2]		Weighted variable of extent of information-handling automation
	H/M/L (2/1/0)	0.50	Automatic process recipe downloaded by CAM system
	H/M/L (2/1/0)	0.25	Automatic process metrology and equipment data capture by CAM system
	H/M/L (2/1/0)	0.25	Automatic track-in and track-out (time) of wafer lots by CAM system
Data Analysis	[0…2]		Weighted variable of extent of integrated data analysis in fab
	H/M/L (2/1/0)	0.75	Process and equipment information readily available in an integrated relational database
	H/M/L (21/0)	0.25	Statistical tools directly connected to database
Scheduling	[0…2]		Weighted variable of extent of production and scheduling systems
	H/M/L (2/1/0)	0.3	Sophistication of production planning system
	H/M/L (2/1/0)	0.3	Sophistication of capacity planning system
	H/M/L (2/1/0)	0.1	Capability of fab simulation in the fab
	H/M/L (2/1/0)	0.3	Sophistication of automatic scheduling system of wafer lots and/or machines
Linewidth	[0…1]		Normalized linewidth of individual process to technological frontier
Mask Layers	#		Number of mask layers for device
Clean Room Grade	#		Maximum clean room grade (particles/ft^3)
Wafer Size	#		Normalized size of wafer manufactured (100 mm as base)

information handling: (1) automated download of process "recipes" into semiconductor processing equipment; (2) automated capture of process (metrology) and equipment performance data; and (3) automated wafer lot tracking.

As mentioned above, some semiconductor manufacturers collect data such as equipment start and stop times, machine and operator identification tracking, and process (metrology) and equipment efficiency parameters as each wafer lot progresses through the fabrication facility. Some semiconductor firms also have developed detailed databases that track each production lot as it progresses through the facility and advanced statistical tools to analyze the information gathered. The greater use of an integrated database provides engineers the ability to more accurately set process parameter windows and track equipment productivity, thereby improving both yield and cycle time performance. We measure the extent of adoption of integrated database systems based on the degree to which the manufacturing facility employs a relational database that collects these integrated data, and whether statistical tools are directly connected to this database as opposed to requiring the engineering staff to download data from (separate) databases to some other environment where these statistical tools are available.

Investments in integrated databases are essential to improved manufacturing performance, as these databases enable more sophisticated approaches to production scheduling, inventory management, and equipment utilization, all of which can improve performance in yield and cycle time improvement. The extent of adoption of advanced production *Scheduling* systems is captured by ratings of individual fabs according to the capabilities of their production and capacity planning systems, the ability of scheduling systems to simulate fab operations, and the extent of the scheduling system's capabilities in wafer lot and equipment scheduling.

Consistent with our description of the model in the previous section, we include several other variables in the estimation. *Linewidth* measures the distance from the "technological frontier" of the smallest features in the process geometry used in the new process developed for each of the manufacturing processes in our analysis. The coefficient for this variable, which captures the technical difficulty of new processes, should be negative in our analyses of performance improvement. The number of mask layers on the wafer, as we noted earlier, is another measure of the technological sophistication of a manufacturing process. *Mask Layers* is set equal to the number of mask layers used in the process and its coefficient in analyses of the rate of improvement in die yield should be positive.[9] *Cleanroom Grade* represents the maximum clean room grade that exists in the fab, and is a measure of the maximum number of particles per cubic foot present in the manufacturing facility. This variable captures both the technological complexity of a given manufacturing process and the magnitude of investments in steps to accommodate this complexity. We therefore make no predictions of the sign of the coefficient for this variable. Finally, *Wafer Size* represents the dimension of wafers manufactured normalized to the industry standard.

Defect Density is either given directly by the semiconductor manufacturers or constructed from the data in the sample using the Murphy model. *Cycle Time per Layer* is normalized according to the number of mask layers required by the device to not penalize product types with larger areas. *Cumulative Volume* is constructed as the sum of wafer starts from the initial observation to the current period, and is scaled to represent units of 1000 wafer starts. Table 3 provides descriptive and correlation statistics for our dependent and independent variables.

Empirical Results

Table 4 displays the results for cycle time improvement using four separate models of the specification in Equation 10; the same models in Table 5 use yield as their dependent variable. All models are estimated using a nonlinear maximum likelihood estimator using a first-order (AR1) correction for serial correlation.[10] Fixed effects for each manufacturing facility are included in the estimation, but are not reported because of space constraints. Log likelihood ratio tests reported at the bottom of each table indicate that each successive model in its respective table is a statistically significant improvement in comparison to the initial model.

Model 1 in Table 4 is a "baseline" cycle time model that employs only *Cumulative Volume* and the static

[9] Note that this control variable is appropriate only when die yield or defect density is the manufacturing performance variable being tested.

[10] The initial parameters were varied over a wide range to ensure that the estimates represent the global maximum of the likelihood function.

Table 3. Summary Statistics and Correlations

	Defect Density	*Cycle Time per Layer*	*Cumulative Volume*	*Team Diversity*	*Team Number*	*Colocation*	*Material Handling*	*Information Handling*	*Data Analysis*	*Scheduling*	*Linewidth*	*Wafer Size*	*Clean Room Grade*	*Mask Layers*
Summary Statistics														
Mean	1.00	2.80	50.29	2.26	1.20	1.64	0.37	0.88	1.24	1.22	0.80	1.67	1361.38	15.99
SD	1.52	0.98	66.26	1.26	0.59	0.62	0.41	0.62	0.85	0.45	0.38	0.26	2799.14	4.62
Min	0.05	0.58	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.60	0.25	1.25	10.00	5.00
Max	27.58	9.00	385.26	4.00	2.00	2.00	1.52	2.00	2.00	2.00	1.00	2.00	10000.00	28.00
Correlations														
Defect Density	1.00													
Cycle Time per Layer	−0.10	1.00												
Cumulative Volume	**−0.23**	**−0.06**	1.00											
Team Diversity	**−0.07**	**0.10**	**−0.11**	1.00										
Team Number	**−0.33**	**−0.41**	**0.15**	**0.16**	1.00									
Colocation	**0.18**	**0.24**	−0.03	**−0.11**	**−0.38**	1.00								
Material Handling	**−0.27**	**−0.20**	**−0.08**	**0.10**	**0.36**	**−0.42**	1.00							
Information Handling	**−0.31**	**−0.34**	0.04	**0.40**	**0.30**	**−0.19**	**0.62**	1.00						
Data Analysis	**−0.07**	**−0.39**	**−0.16**	**−0.14**	0.04	−0.04	**0.10**	−0.03	1.00					
Scheduling	**−0.34**	**−0.50**	**0.12**	**0.14**	**0.81**	**−0.28**	**0.46**	**0.43**	**0.51**	1.00				
Linewidth	**0.08**	**0.15**	**0.19**	**0.05**	**−0.29**	0.05	**−0.61**	**−0.42**	**−0.45**	**−0.52**	1.00			
Wafer Size	**−0.23**	**−0.23**	**−0.18**	**0.11**	**0.46**	**−0.12**	**0.71**	**0.60**	**0.38**	**0.62**	**−0.88**	1.00		
Clean Room Grade	−0.05	**−0.08**	**0.08**	**−0.37**	**−0.13**	**0.21**	**−0.29**	**−0.17**	**0.35**	**0.10**	**0.14**	**−0.18**	1.00	
Mask Layers	0.02	−0.04	**−0.16**	−0.05	**0.30**	**0.14**	**0.26**	**0.44**	**0.29**	**0.42**	**−0.74**	**0.67**	**−0.12**	1.00

variables measuring characteristics of the manufacturing process and fab. As production increases, cycle time performance improves, consistent with earlier work.[11] Cumulative volume is an important determinant of learning because it provides first-order information about cycle time losses, which are eliminated through engineering analysis (Adler and Clark, 1991). But performance improvement in manufacturing does not arise solely from repetition, but rather can be enhanced by the problem solving and other activities of manufacturing personnel (Bohn, 1995; Hatch and Macher, 2002; Hatch and Mowery, 1998). Models 2–4 test for the influence of these ''learning-enhancing'' activities within our sample of fabs.

Model 2 incorporates measures of the use of teams and colocation of development and production personnel. The sign and value of the coefficient provide the direct effect on the level of cycle time, that is, a shift up or down in the learning curve. The sign and value of the interaction of the coefficient with *Cumulative Volume* give the indirect effect of these practices, that is, the steepening or flattening of the slope of the learning curve that is associated with their use. The results demonstrate that greater diversity in team types and greater colocation within the manufacturing facility have statistically significant direct and indirect effects on learning. Interestingly, both variables initially shift the cycle time learning curve up, implying some cycle time penalty associated with their use, but they accelerate learning in the face of new manufacturing processes, indicated in the positive coefficients for the interaction terms using cumulative production. A greater number of team types and more colocation impede problem solving and learning at low product volumes, but improve the rate of learning as production volume expands. Greater diversity within a particular team worsens cycle time at low production volumes and has no effect on the rate of learning, consistent with the argument that engineers rather than operators are critical to performance improvement in semiconductor production (Appleyard and Brown, 2001).

Model 3 replaces the human resource variables with the organizational practices related to IT and CIM. *Information Handling*, *Data Analysis*, and *Scheduling* have significant effects on both the level and slope of the cycle time learning curve, although once again, the direct and indirect effects differ. The learning curve initially shifts up from the greater implementation of these practices, worsening cycle

[11] Because of the functional form used in the empirical estimation, a positive (negative) coefficient on variables included in the learning index (i.e., $h_1(L_t)$) improves (worsens) manufacturing performance, while a positive (negative) coefficient on static variables (i.e., $h_2(\cdot)$) worsens (improves) manufacturing performance.

Table 4. Empirical Estimation Results (Cycle Time)

Model	(1)			(2)			(3)			(4)		
	Est.	***SE***	***p-val***	***Est.***	***SE***	***p-val***	***Est.***	***SE***	***p-val***	***Est.***	***SE***	***p-val***
Constant	**9.907**	4.0156	[.014]	**−37.503**	15.201	[.014]	**−1029.120**	323.962	[.001]	**−231.50800**	52.06540	[.000]
Cumulative Volume	**0.00097**	0.00023	[.000]	**0.00066**	0.00024	[.006]	**0.00002**	0.00001	[.011]	**0.00035**	0.00008	[.000]
Team Diversity				**−0.00923**	0.00443	[.037]				**0.00227**	0.00110	[.038]
Team Number				**−0.00878**	0.00333	[.008]				**−0.01359**	0.00453	[.003]
Colocation				**−0.04610**	0.01628	[.005]				**−0.01463**	0.00320	[.000]
Team Diversity X Cumulative Volume				0.00000	0.00001	[.689]				0.000002	0.000005	[.761]
Team Number X Cumulative Volume				**0.00006**	0.00003	[.015]				0.000005	0.000016	[.760]
Colocation X Cumulative Volume				**0.00032**	0.00012	[.006]				**0.000128**	0.000030	[.000]
Material Handling							**0.03599**	0.01076	[.001]	**0.04170**	0.01087	[.000]
Information Handling							**−0.06118**	0.01904	[.001]	**−0.03616**	0.00798	[.000]
Data Analysis							**−0.03241**	0.01007	[.001]	**−0.05214**	0.01212	[.000]
Scheduling							**−0.00160**	0.00052	[.002]	**−0.00563**	0.00145	[.000]
Material Handling X Cumulative Volume							**−0.000014**	0.000007	[.049]	**−0.000091**	0.000033	[.005]
Information Handling X Cumulative Volume							**0.000018**	0.000007	[.012]	**0.000102**	0.000031	[.001]
Data Analysis X Cumulative Volume							0.000002	0.000001	[.098]	−0.000013	0.000012	[.304]
Scheduling X Cumulative Volume							**0.000002**	0.000001	[.020]	0.000008	0.000006	[.199]
Linewidth	**2.518**	1.227	[.040]	**3.668**	1.732	[.034]	3.003	1.930	[.120]	0.08724	1.19990	[.942]
Wafer Size	**8.057**	2.416	[.001]	5.573	3.248	[.086]	**399.540**	122.839	[.001]	**59.94710**	12.48610	[.000]
Clean Room Grade	−0.00027	0.00017	[.113]	−0.00217	0.00138	[.115]	**−0.06770**	0.02167	[.002]	0.00308	0.00197	[.118]
ρ	0.01271	0.03138	[.000]	**0.12975**	0.01951	[.000]	**0.02821**	0.00270	[.000]	**0.12466**	0.00637	[.000]
N		1307			1305			1307			1305	
Log-Likelihood		6435.5			10931.3			26836.5			32394.5	
LR Test (R-U)					8991.6	0.000		40802.0	0.000		51918.0	0.000

Nonlinear maximum likelihood estimator (MLE) corrected for autocorrelation using an AR(1) model with fixed effects.

time performance. But as more wafers are manufactured, the rate of improvement in cycle time curve increases—that is, the cycle time learning curve steepens. However, more extensive *Material Handling* initially improves cycle time but produces slower rates of cycle time improvement as production volumes grow.

Model 4 in Table 4 analyzes the combined effects of the human resource and technological practices on cycle time performance. The signs and magnitudes of the results obtained are broadly consistent with those obtained in Models 2 and 3, although some of the practices lose statistical significance. *Colocation* of development and manufacturing personnel and *Information Handling* remain statistically significant. Consistent with the results of Model 2, both of these variables appear to shift the cycle time learning curve up but steepen its slope. *Materials Handling*, however, shifts the cycle time curve down and flattens its slope, consistent with the results in Model 3.

Model 1 in Table 5 presents results of our baseline model with yield (defect density) replacing cycle time as the dependent variable. The results are broadly consistent with Model 1 in Table 4, as yield performance improves as cumulative volume increases. Model 2 incorporates the human resource practices related to the use of teams and colocation. The results are broadly consistent with those obtained for cycle time, as more extensive use of teams of different types and the colocation of development and manufacturing personnel improve yield performance. Also similar to the results in Table 4 is the presence of offsetting effects for both of these practices—the yield improvement curve shifts up, but its slope steepens. Greater *Team Diversity* has no statistically significant effect on yield performance. Model 3 examines the influence of the IT and CIM organizational practices on defect density performance. *Information Handling* initially shifts the yield curve up but steepens its slope, as was the case for Model 3 in Table 4. More extensive use of *Data Analysis* and production *Scheduling* have no statistically significant effects on defect density improvement. The lack of influence of an integrated data analysis capability on yield improvement is surprising in view of the importance of data analysis in yield management, and may reflect the fact that the levels of investment in this type of IT are less important than the details of its organization and deployment within the fab, aspects of IT investment that our measures capture very imperfectly. The lack of influence of automated scheduling systems of yield improvement is less surprising, as production scheduling affects production volumes and queues, which are more important for cycle time than for yield improvement.

Model 4 in Table 5 presents our results for the combined influence of all of these technology management practices on yield improvement. The signs and magnitudes of the coefficients in Model 4 are broadly consistent with those for Models 2 and 3. The number of problem-solving teams and colocation once again shift the defect density improvement curve up but steepen its slope, although the results fail to achieve statistical significance. Information handling automation remains statistically significant and integrated data analysis is marginally significant, and both of these factors exert a negative "direct" and a positive "indirect" influence, raising the learning curve but steepening its slope. Finally, materials handling automation flattens the defect density learning curve and shifts the yield curve up, while production scheduling has no statistically significant effect.

Discussion

The results obtained show generally similar effects from the implementation of human resource and organizational practices on yield and cycle time performance. The introductions of several of the practices examined initially have a negative influence on manufacturing performance at low production volumes, but tend to increase the rate of improvement as production volumes expand. Semiconductor manufacturers that implement a larger number of types of problem-solving teams and policies that move or colocate production and development engineers and other key personnel also appear to learn more quickly. These human resource practices may derive their effectiveness by improving the ability of semiconductor firms to make better use of tacit knowledge, which is typically "locked up" within individual engineers or operators within the organization. The use for problem solving of teams of different types and the colocation of engineering personnel allow this type of technical or manufacturing information to be more widely disseminated.

Our results also suggest that semiconductor firms with superior information handling automation and data analysis capabilities also can more

Table 5. Empirical Estimation Results (Defect Density)

Model	(1)			(2)			(3)			(4)		
	Est.	SE	*p-val*	*Est.*	*SE*	*p-val*		*SE*	*p-val*	*Est.*	*SE*	*p-val*
Constant	3.86230	5.94006	[.516]	**−269.46100**	86.49160	[.002]	−177.17500	92.15510	[.055]	**−310.41500**	141.63600	[.028]
Cumulative Volume	**0.00085**	0.00019	[.000]	**0.00061**	0.00019	[.001]	**0.00029**	0.00013	[.030]	**0.00034**	0.00015	[.023]
Team Diversity				−0.00028	0.00025	[.267]				0.00040	0.00027	[.134]
Team Number				**−0.05247**	0.01555	[.001]				−0.00392	0.00237	[.099]
Colocation				**−0.00148**	0.00062	[.017]				**−0.00064**	0.00032	[.046]
Team Diversity X Cumulative Volume				−0.000001	0.000001	[.564]				0.000002	0.000002	[.325]
Team Number X Cumulative Volume				**0.000414**	0.000125	[.001]				0.000022	0.000024	[.361]
Colocation X Cumulative Volume				0.000011	0.000007	[.085]				0.000002	0.000005	[.645]
Material Handling							**−0.02057**	0.00881	[.020]	**−0.04717**	0.02002	[.018]
Information Handling							**−0.04247**	0.01936	[.028]	**−0.02902**	0.01248	[.020]
Data Analysis							**−0.00114**	0.00063	[.070]	**−0.00698**	0.00322	[.030]
Scheduling							**−0.00137**	0.00076	[.071]	0.00043	0.00049	[.379]
Material Handling X Cumulative Volume							−0.000095	0.000049	[.055]	−0.000122	0.000054	[.024]
Information Handling X Cumulative Volume							**0.000313**	0.000144	[.030]	0.000310	0.000132	[.018]
Data Analysis X Cumulative Volume							0.000003	0.000004	[.460]	0.000022	0.000014	[.107]
Scheduling X Cumulative Volume							0.000002	0.000002	[.254]	0.000005	0.000007	[.515]
Linewidth	3.58281	2.54748	[.160]	**12.85440**	5.34050	[.016]	**54.51810**	24.97840	[.029]	**43.72760**	19.01340	[.021]
Wafer Size	**−9.31801**	2.16981	[.000]	**85.69370**	27.90760	[.002]	75.33200	39.46900	[.056]	**149.35000**	67.93610	[.028]
Clean Room Grade	**0.00045**	0.00018	[.016]	−0.00044	0.00078	[.569]	**−0.00850**	0.00395	[.031]	**−0.01040**	0.00475	[.029]
Mask Layers	**−0.54429**	0.13269	[.000]	−0.16969	0.14539	[.243]	**−2.47766**	1.19725	[.039]	**−3.16288**	1.45164	[.029]
ρ	**−0.98907**	0.02515	[.000]	**−0.39831**	0.01088	[.000]	**−0.64168**	0.00982	[.000]	**−0.62937**	0.00997	[.000]
N		1239			1235			1239			1235	
Log-Likelihood		7022.5			17274.8			18436.9			19650.5	
LR Test (R-U)					10589.4	0.000		22828.9	0.000		25256.0	0.000

Nonlinear maximum likelihood estimator (MLE) corrected for autocorrelation using an AR(1) model with fixed effects.

quickly improve die yield and cycle time. These IT-based organizational practices support higher levels of codification of otherwise tacit knowledge within the firm, facilitating its internal dissemination and accelerating firm-wide learning. Human resource policies therefore may improve manufacturing performance by making better use of tacit information, while IT and CIM practices codify this information into forms more suitable for analysis. These benefits aid innovation and internal supply chain management, while enhancing management of the interface between product development (which in semiconductor manufacturing cannot be divorced from process innovation) and the firm's internal supply chain.

Nevertheless, our empirical findings provide little or no evidence of significant benefits from other practices, nor do these activities affect all dimensions of performance equally. Higher levels of materials handling automation do not improve either yield or cycle time performance, a finding that is surprising in view of the significant investments made by many semiconductor firms in these technologies. Regardless of the performance benefits of materials-handling automation, the impending shift within the semiconductor industry to 300 mm (or 12 inch) wafers will require greater investment in such automation in order to handle these larger, more valuable, and much heavier wafers (Ham et al., 1998). Colocation of engineers appears to improve cycle time performance but has little effect on yield improvement, perhaps because of the fact that yield improvement following new process introduction relies more heavily on tacit information within the manufacturing environment and may benefit less from the experience of development engineers. More rapid "qualification" of a new process in the manufacturing environment, on the other hand, relies heavily on such tacit information and is likely to accelerate cycle time improvement.

Conclusion

New product innovation in the semiconductor industry raises uniquely challenging issues in the management of the product development-supply chain management interface. The characteristics of semiconductor technology mean that product innovation requires complementary innovation in process technologies. Moreover, new process technologies must be implemented within an extraordinarily complex manufacturing environment rapidly and efficiently, in order to increase yields and reduce costs if a new product is to be profitable. New equipment and "recipes" must be introduced—a process that is often imperfectly understood, due to their development in a nonmanufacturing environment and implementation in a different production setting by personnel that may be unfamiliar with the details of their development—and new characteristics and problems associated with these new process technologies must be understood and resolved quickly. Failure to manage these activities successfully can have catastrophic consequences for the utilization of extremely costly production capacity and for firms' abilities to meet customer requirements for delivery of new products. Few if any other technology-intensive products place comparable demands on the product development-supply chain interface.

Our analysis provides new insights into the mechanisms underpinning the widely acknowledged improvements in production performance that accompany increased cumulative volume in semiconductors and other industries. Improved semiconductor manufacturing performance results from detailed engineering analyses of yield problems and cycle time excursions and implementing corrections and improvements, rather than being a "free good" accompanying cumulative production volume. Human resource practices that support better exploitation of the often tacit "knowledge stocks" that are embedded in firms' engineers and operators rely on improved internal communication and expansion in the number of information sources available to manufacturing personnel. Investments in information technology also can bring information to bear on problem solving more efficiently and rapidly, helping the organization improve quality, reduce inventory levels, and improve capacity utilization. These and other practices represent firm-specific capital that aids in management of the development and internal supply chain interface. Furthermore, because this knowledge is idiosyncratic and has a tacit component, the time required by other firms to develop comparable organizational practices poses a barrier to imitation (Teece et al., 1997).

The results of this analysis agree with other research that examines industries outside of semiconductors and concludes that "learning by doing" can be influenced by the actions of managers. In particular, our empirical results suggest that human resource practices that affect the organization of establishment-level problem-solving activities and information exchange increase the learning obtained from higher levels of output. In other words, "learning by doing" can be accelerated by certain activities other than repetitions of specific fabrication operations (Pisano, 1996). But our results clearly indicate that both higher levels of cumulative production and these human resource practices are necessary to accelerate learning, possibly because of the need for firms to "learn to learn by doing," improving their implementation of the human resource practices that interact with production expansion to improve performance. Similarly, firms' investments in specific types of information capture and information-handling automation appear to yield greater benefits when cumulative production volumes are higher. Production experience thus provides a large reservoir of potentially valuable knowledge. These investments by firms appear to accelerate the intrafirm communication, understanding, and exploitation of such knowledge, thereby accelerating performance improvement. Indeed, the ability of some firms to capitalize on their ability to learn more rapidly than others may contribute to the strong performance of specialized semiconductor manufacturers, the so-called "foundries." Our results therefore suggest to practitioners who operate in organizations where management of learning curves are important to competitive performance that investments in both the organization of human resources and the organization of information for problem-solving purposes are important factors. Our results also suggest that these practices aid organizations not only in creating more mistake-proof manufacturing environments, but also in developing rapid problem identification, characterization, and solution capabilities when errors are made. Importantly, however, well thought out strategies and analytical techniques that support manufacturing improvement and are solidly integrated with firms' broad objectives are critical, as opposed to inconsistent team formation and objective policies or to blind automation, for instance.

This empirical analysis also extends our understanding of two aspects of the performance of high-technology manufacturing firms that have been neglected by theorists and empiricists alike. The majority of empirical work on manufacturing performance has focused on firm-level differences in the speed or quality of product development. Little work has been done on intrafirm practices and interfirm performance differences in process innovation, and we hope that this work will inspire others to pursue further work on this important topic. The particular organization of process innovation in many semiconductor manufacturing firms, which involves the development of a new manufacturing process in one site and the subsequent transfer and "debugging" of this very complex process in a different and often distant manufacturing facility, means that process innovation in many cases provides vivid (and, occasionally, unsettling) illustrations of the difficulties of transferring technologies, especially those involving a great deal of tacit knowledge, within a firm. Even the replication of a complex technology within a single organization is a demanding task. Nonetheless, the sheer difficulty of replicating and transferring technologies in semiconductor manufacturing, one of the most knowledge-intensive manufacturing industries in this economy, underscores the complexities of the relationships among scientific and technological knowledge and organizational practice that characterize the product development-supply chain interface in this and other high-technology industries, including pharmaceuticals, specialty chemicals, and advanced materials, among others. The manufacture of the products of many of these industries remains as much an art as a science, something that has important implications for competitive dynamics and industry structure.

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