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HUMAN CAPITAL AND LEARNING AS A SOURCE OF SUSTAINABLE COMPETITIVE ADVANTAGE

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This paper seeks to identify the sources of wide and persistent variations in learning performance in the semiconductor manufacturing industry. In the resource-based view of the firm, human capital is frequently assumed to contribute to competitive advantage due to its inimitability based on its intangible, firm-specific, and socially complex nature. Consistent with this view, we find that investments in firm-specific human capital have a significant impact on learning and firm performance. More specifically, human capital selection (education requirements and screening), development through training, and deployment significantly improve learning by doing, which in turn improves performance. However, we find that acquiring human capital with prior industry experience from external sources significantly reduces learning performance. We also find that firms with high turnover significantly underperform their rivals, revealing the time-compression diseconomies that protect firm-specific human capital from imitation. These results provide new empirical evidence of the inimitability of human capital.

INTRODUCTION

The resource-based view of the firm seeks to explain sustained differences in firm performance by identifying differences in firm resources. A firm with resources that are valuable and rare may *generate* a competitive advantage over its rivals, thereby resulting in superior financial performance (Barney, 1991; Conner, 1991; Mahoney and Pandian, 1992; Peteraf, 1993; Wernerfelt, 1984). For a firm to *sustain* its competitive advantage, the resources must also be inimitable and non-substitutable to prevent rivals from replicating the value of the resources and competing away their benefits. The duration of a firm's competitive advantage is directly related to the strength of 'isolating mechanisms' (Rumelt, 1984), such as firm specificity, causal ambiguity, social complexity, path dependence, and time compression diseconomies, that protect resources from imitation (Dierickx and Cool, 1989; Lippman and Rumelt, 1982; Reed and DeFillippi, 1990).

Given the ease with which human resources can move between firms, it would seem on the surface that it should be difficult to protect human capital from expropriation by rivals.[1] However, human capital is most valuable and most inimitable when it is firm-specific and resides in the environment where it was originally (optimally) developed (Hitt *et al*., 2001; Klein, Crawford, and

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[1] In this paper, we define human resources as workers and human capital as their knowledge and skills. In this definition, some human capital (e.g., education) is generic, while some is firm-specific.

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Alchian, 1978; Lepak and Snell, 1999). When a firm acquires human capital from one of its rivals, it surely appropriates some of the rival's knowledge, but it must also undergo a period of dynamic adjustment costs[2] while the best uses of the human capital are discovered and tailored to the needs of the new environment (Cappelli and Singh, 1992; Mahoney and Pandian, 1992; Mahoney, 1995; Penrose, 1959; Prescott and Visscher, 1980; Teece, Pisano, and Shuen, 1997). Thus, human capital can generate sustained rents to the degree that it is specific to the originating firm and adjustment costs in a new environment prevent immediate expropriation by rivals.

The same isolating mechanisms that protect resources from expropriation also hinder our efforts to identify, measure, and estimate the relationship between resources and competitive advantage. One opportunity to observe and measure the role of human resources is in their impact on learning by doing performance. In the process of learning within a firm, human capital becomes more firm-specific and potentially less useful to rivals. That portion of firm-specific human capital that is tacit knowledge is particularly inimitable (Liebeskind, 1996; Mowery, Silverman, and Oxley, 1996; Szulanski, 1996). Moreover, the ability of human resources to learn is enhanced by their human capital investments in experience and problem-solving (Hitt *et al*., 2001). Thus, we see a feedback effect in the relationship between human capital and learning: learning creates specific human capital (tacit knowledge) that in turn enhances the firm's learning performance. The resource-based view predicts that superior human capital, when it is firm-specific, can create competitive advantage as human capital improves learning by doing, thereby reducing the firm's cost.

Drawing upon a rich set of proprietary data from the semiconductor industry, this paper tests propositions of the resource-based view related to the impact of firm-specific investments in human capital on learning by doing performance. We find that firms that are superior at acquiring, developing, and deploying human capital enjoy sustained advantages in learning and ultimately cost. As employees acquire increasingly firm-specific knowledge, they are capable of making increasingly inimitable contributions to the learning performance of the firm, a result that satisfies the necessary condition for human capital to be a source of competitive advantage. The fact that human capital significantly improves performance is particularly interesting because the semiconductor manufacturing industry is characterized by large (fixed-cost) capital investments.

Some prior studies have found performance effects attributable to human capital and assume that competitive advantage is sustainable based on the intangible, socially complex nature of human capital (Arthur, 1994; Huselid, 1995; Koch and McGrath, 1996). In contrast, rather than *assume* sustainability of the competitive advantage, we find *empirical* evidence that rivals cannot quickly or costlessly imitate or substitute for the value of firm-specific human capital. This paper also contributes to our understanding of how management of learning, through management of human capital, contributes to sustainable competitive advantage.

LEARNING, HUMAN CAPITAL, AND COMPETITIVE ADVANTAGE

Learning by doing refers to the observed phenomenon of manufacturing costs falling as manufacturing experience increases.[3] Wright's (1936) pioneering study detailed systematic reductions in labor costs with every doubling of airframe production and spawned a flurry of studies to verify learning curves in other industries.[4] The pattern of cost reductions is defined by the learning curve, which traditionally takes the form

$$C(x) = ax^{-\lambda} \tag{1}$$

[2] Kor and Mahoney (2000) describe a number of mathematical models of dynamic adjustment costs for both human and physical capital, including Ingham (1992), Mortensen (1983), Penrose (1959), Slater (1980), and Treadway (1970).

[3] Formally, learning by doing refers to reductions in direct labor requirements as cumulative volume increases. We refer to learning by doing as a generic term for all of the variations of learning that have been identified, e.g., learning by experience, learning by using, learning before doing.

[4] For example, learning by doing has been documented in airframes (Alchian, 1963; Wright, 1936), automobile assembly (Baloff, 1971), chemical processing (Lieberman, 1984), clerical activities (Kilbridge, 1962), housing construction (DeJong, 1957), machine tools (Hirsch, 1952), metal products (Dudley, 1972), nuclear plant construction (Zimmerman, 1982), petroleum refining (Hirschmann, 1964), pharmaceuticals (Pisano, 1994, 1996), printing and typesetting (Levy, 1965), radar (Preston and Keachie, 1964), rayon (Jarmin, 1994), and semiconductors (Bohn, 1995; Gruber, 1992; Hatch and Mowery, 1998; Irwin and Klenow, 1994; Webbinck, 1972).

where x is experience (typically measured by cumulative production volume), $C(x)$ is unit variable cost after x units of experience, a is the starting cost, and λ is the constant-elasticity learning parameter. The slope of the learning curve is traditionally communicated by the degree of cost reduction associated with a doubling in experience. For example, with an 80 percent learning curve, cost falls to 80 percent of its previous level (i.e., falls by 20%) with every doubling in experience. Armed with their estimates of the learning curve, managers have employed learning by doing in pricing strategy, bid preparation, forecasting labor requirements, financial planning, and capacity management.

In strategy, learning by doing can confer competitive advantage as long as what is learned remains proprietary. If early firms can stay ahead of their rivals in the race down the learning curve, they earn a cost advantage (Amit, 1986). If the learning curve is of the right slope—not too steep and not too flat—learning by doing also promises to deter rivals from entering because they are unwilling to face a competitor with a large, sustainable cost advantage (Lieberman, 1987, 1989; Spence, 1981). Thus, learning by doing has the potential to simultaneously confer cost advantages and prevent new market entry. One path to competitive advantage, espoused by the Boston Consulting Group (1972), is to win the market share battle. The firm with the highest market share eventually has the highest cumulative volume and expects the lowest costs and highest profits.

In practice, however, the expected benefits of learning often did not materialize (Abernathy and Wayne, 1974; Alberts, 1989; Hall and Howell, 1985). The inability of some firms to realize competitive advantage revealed gaps in our understanding of the learning curve and its role in competitive advantage (Dutton and Thomas, 1984; Montgomery and Day, 1985). The Boston Consulting Group's approach to strategizing on the learning curve assumed a uniform rate of learning for all firms in an industry. Thus, firms sought above-average performance through greater experience. However, subsequent research has shown that when knowledge diffuses across firm boundaries, some of the benefits of the knowledge originally obtained through learning by doing 'spills over' to rival firms (Ghemawat and Spence, 1985; Irwin and Klenow, 1994; Jarmin, 1994; Lieberman, 1987). Because of these spillovers, some of the value of experience is expropriated by rivals with less experience. If the rate of knowledge diffusion is high enough, any potential competitive advantage is completely eroded.

Competitive advantage through cumulative volume may also fail to materialize when learning is the product of factors other than cumulative volume. In this case, the capability to manage the drivers of learning generates heterogeneous rates of learning by doing across firms even if cumulative volume in the firms is identical (Adler and Clark, 1991; Hatch and Mowery, 1998). In other words, firms can cede the market share battle and still win the cost war. For example, from 1989 to 1999, Chrysler has been the lowest-cost (most profitable) U.S. automaker with the least market share, while GM has been the highest-cost (least profitable) automaker with the highest market share (Dyer, 2000). Similarly, Toyota has achieved cost advantages on low unit volumes with its U.S. suppliers by actively transferring cost reduction know-how to suppliers (Dyer and Hatch, 2004). The biggest obstacle to statistical analysis of the determinants of the learning curve is the proprietary nature of the required data. A few studies have overcome this obstacle and have enabled us to peer inside the 'black box' of learning and see the importance of engineering activities (Adler and Clark, 1991; Hatch and Mowery, 1998), experimentation (Bohn, 1995; Pisano, 1994), process innovation management (Hatch and Mowery, 1998; Pisano, 1996; Pisano, Bohmer, and Edmondson, 2001; Terwiesch and Bohn, 2001), quality improvement (Ittner, Nagar and Rajan, 2001; Lapré, Mukherjee, and Van Wassenhove, 2000; Zangwill and Kantor, 1998), and workforce training (Adler and Clark, 1991) as determinants of learning performance.

For the determinants of learning to confer competitive advantage, they must be protected by some isolating mechanism. Firm-specific human capital is a resource that is fundamental to knowledge creation through learning by doing and is not readily expropriated by rival firms (Hitt *et al*., 2001). Specific human capital is typically the product of individual learning and, in turn, enhances ongoing learning within the firm. Thus, human capital may be costly to imitate because it is firm-specific. Competitive advantage realized through human capital may be sustained, even if some of the knowledge is imitable, because human capital provides continuing superiority in the rate of knowledge creation and cost reduction over the life of a product and across multiple generations of products. As Stata (1989) observed, 'The rate at which organizations learn may become the only sustainable source of competitive advantage'.

Prior research has shown that some types of knowledge are more likely to confer advantage. While knowledge within firms may reside in many forms and places, it is ultimately people who must learn (Grant, 1996; Hitt *et al*., 2001) and human resources become a primary repository of both codifiable and tacit knowledge (Lado and Wilson, 1994; Prescott and Visscher, 1980; Tomer, 1987). Codified knowledge can be articulated and is at risk of expropriation, while tacit knowledge can not be articulated and is isolated from rivals because it is embedded in the firm's routines, human skills, and relationships (Liebeskind, 1996; Nelson and Winter, 1982; Polanyi, 1967; Winter, 1987; Zander and Kogut, 1995). Codified knowledge typically sustains competitive advantage only to the degree that firms are successful in protecting it. However, even when knowledge is codifiable and people and processes are seemingly easy to imitate, more effective and rigorous implementation and monitoring of codified processes may produce sustainable advantages (Knott, 2003). Tacit knowledge may be so well protected from imitation that it is difficult to diffuse even within the firm where it originates (Hatch and Mowery, 1998; Szulanski, 1996).

The role of human resources in creating competitive advantage through learning is amplified by their intertwined relationship with tacit knowledge. Technical knowledge created through learning by doing in a high-technology environment such as semiconductor manufacturing is partially codified into refinements in process specifications and process control limits. The rest of the knowledge remains tacit in the understanding and skills of the employees. Generally speaking, knowledge acquired through engineering analysis will be codified, while the knowledge residing in equipment operators and technicians, obtained through repetition and experience (observations that amount to informal, natural experiments) is tacit knowledge. This knowledge serves to improve further learning in the form of codification of unknown elements of the process technology. The objective of this paper is to identify the factors that influence the size of this reservoir of firm-specific knowledge and the impact of bringing this potentially untapped strategic resource to bear on the learning activities of the firm.

Where does human capital come from and how do firms manage it to competitive advantage? Human capital begins with human resources in the form of knowledge and skills embodied in people. The stock of human capital in a firm comes from its employee selection, development, and use (Koch and McGrath, 1996; Snell and Dean, 1992). Selection, development, and use are a sequence of human resource management functions that represent increasing human capital, increasing firm specificity, and decreasing imitability. In other words, these human resource management functions may contribute to sustainable competitive advantage. Initially, firms must identify applicants in the external job market that promise to be productive employees. The human capital embodied in these new employees is not firm-specific so firms work to develop the employees, making investments in specialized human capital that improve their productivity and subsequently improve the rate of learning in the firm. However, hiring and developing human resources is not enough to ensure competitive advantage; deployment is critical. Unless the human resources are put to productive use, their potential goes unfulfilled (Huselid, 1995; Penrose, 1959). Finally, for human capital to create sustainable competitive advantage, rivals must be prevented from quickly and costlessly expropriating the value of the human capital (Barney, 1991).

Human resource selection: Hiring external sources of human capital

A new job applicant can be thought of as the clay that, through investments in firm-specific knowledge, is shaped into a productive resource in the firm's particular environment. Better educated human resources are expected to result in more productive human capital (Hitt *et al*., 2001). In this case, the level of education is a proxy for employee cognitive skills (e.g., absorptive capacity) and a motivational need for achievement. While education should increase the ability of workers to acquire and employ specific knowledge, education will not typically result in competitive advantage if similarly qualified human resources are readily available to rivals. Competitive advantage requires some strategic factor market imperfection to prevent rivals from obtaining equally qualified human resources (Barney, 1986; Koch and McGrath, 1996; Lado and Wilson, 1994). In local labor markets, human resources are generally mobile and human resources of similar education can be acquired by all firms. However, labor is typically not fully mobile across global product markets. Factors that prevent labor mobility include: (1) search costs—the cost of finding jobs that require the employee's skill set and offer adequate pay; (2) uncertainty about job success—usefulness of the employee's skill set and compatibility with new co-workers cannot be known with certainty before joining the new firm; (3) social costs—removal from existing social networks, disruption of family members' social circles, costs of relocating, etc. Thus, in global product markets like the semiconductor industry, firms face substantial differences in local job markets that persist due to local customs, infrastructure, education systems, etc. These labor market imperfections, in the form of geographic uniqueness (Barney, 1986), provide an advantage to firms in regions with better educated employees willing to work for relatively low wages and may penalize firms in regions with a scarcity of qualified workers. Better educated employees will learn more quickly and, in turn, contribute more to the firm's learning activities.

Hypothesis 1a: Higher human resource education levels increase learning by doing performance.

Clearly, education level is an imperfect measure of the productive potential of human resources since employees with identical education levels exhibit heterogeneous productivity *ex post*. Firms may generate competitive advantage by selecting, either through foresight or luck, human resources that are undervalued in the market (Barney, 1986). While firms may occasionally select superior human resources through luck, firms that are consistently luckier than others reflect an underlying capability in identifying productive human resources. Screening tests during the hiring process offer the potential for superior foresight in evaluating human resources that are well suited for the firm's specific environment (Hunter and Schmidt, 1982; Ichniowski and Shaw, 1999; Koch and McGrath, 1996). In addition to identifying high-quality candidates, screening tests may be able to distinguish applicants with specific skills that are appropriable in the firm's idiosyncratic environment. In either case, such tests serve to identify needed skills and competencies, such as math, statistics, problem-solving and team skills, that will aid in the adaptation of the new employee to the new firm environment.

Hypothesis 1b: Pre-employment screening tests improve learning by doing performance.

Human resource development: Internal investments in human capital

In addition to trying to generate advantage through the acquisition of superior human resources, firms may attempt to *develop* superior human resources through investments in training. Firms without superior foresight into the productivity of human resources may be able to earn competitive advantage by building the firm-specific human capital of its employees through training. To the degree that internal development results in human capital that is firm-specific, the human capital will be inimitable because rivals will not be able to put the human capital to the same firm-specific use (Klein *et al*., 1978; Mahoney and Pandian, 1992). As training builds firm-specific human capital it speeds the rate at which human resources learn their duties, thereby improving their productivity. With greater tacit knowledge in their role in complex processes, human resources can make meaningful contributions to the improvement of these complex processes and accelerate the firm's descent down the learning curve.

Although firm-specific human capital may be inimitable, firms may be able to substitute training programs of their own to develop rival firm-specific human capital. For competitive advantage to persist, some isolating mechanism must preserve the value of the training program itself. Training is an investment that speeds the flow of both codified and tacit knowledge into the stock of human capital. When rivals initiate similar training programs, their flow of substitute knowledge begins but the stock of human capital can not be imitated without long-term, sustained flows. Thus, time compression diseconomies prevent rivals from immediately replicating the value of training programs (Dierickx and Cool, 1989).

Hypothesis 2: Greater investments in human resource training increase learning by doing performance.

Human resource deployment: Effective use of human capital

Finally, learning advantages can be generated as strategic human resources are effectively deployed within the firm (Amit and Schoemaker, 1993; Lado, Boyd, and Wright, 1992; Mahoney and Pandian, 1992; Penrose, 1959). Human resources are frequently underutilized (Huselid, 1995) and it is no trivial task for managers to identify employee skills and deploy them to their most productive tasks to improve firm performance (Penrose, 1959; Prescott and Visscher, 1980; Tomer, 1987). The capabilities required for this matching of skills to tasks prevent immediate imitation by rivals. In addition to the challenge of matching skills to jobs, effective resource deployment is often difficult to imitate because of the complex social relations and complementary task-specific human capital that evolve as deployment continues (Amit and Schoemaker, 1993). Firms that both (a) deploy more personnel to learning activities, and (b) encourage workers to allocate a greater percentage of time to learning activities, should increase learning by doing performance.

Hypothesis 3: Greater deployment of human capital to learning activities increases learning by doing performance.

Inimitability of human capital

Can firms bypass time-consuming investments in human capital by poaching human resources from rivals? As was emphasized earlier, it is the firm-specificity of certain human capital that holds the greatest promise for contributing to competitive advantage (Aharoni, 1993; Becker, 1975; Mahoney, 1992). In the theory of appropriable rents, firm-specific human capital can earn 'quasi-rents', the difference between the first- and second-best use, when the resource is employed in the environment where it was developed (Klein *et al.*, 1978). Thus, when an individual with firm-specific human capital moves to another firm, only a portion of the individual's accumulated knowledge is applicable in the new environment (Becker, 1975). At best, the rest of the individual's experiences, skills, and knowledge can earn only the 'second-best' value and may actually impede the successful integration and development of new employees in the new manufacturing environment. This problem has been addressed by scholars of individual-level learning in their study of the need for 'unlearning' when existing knowledge reduces performance (Nystrom and Starbuck, 1984; Starbuck, 1996). To illustrate, when Toyota established plants in the United States, it chose *not* to hire employees with prior automotive experience because of the 'unlearning' problem. Thus the processes associated with forgetting (Argote and Epple, 1990; Bailey, 1989; Shafer *et al*., 2001) and relearning (retraining) may be an obstacle to firms in their quest to develop a stock of new firm-specific human capital that contributes to learning performance.

Hypothesis 4a: Greater prior industry experience in newly hired human resources reduces learning by doing performance.

For a rival to fully and quickly imitate the value of human capital, the rival must be able to acquire, develop, and deploy the human capital in a short amount of time. Because employee turnover requires firms to engage in these human resource activities, it is a natural context to test the imitability of human capital. If human capital is not protected from imitation, employee turnover will have virtually no impact on firm performance. If, however, human capital is firm-specific, socially complex, path-dependent, and faces time compression diseconomies, firms with high turnover will suffer a significant competitive disadvantage relative to firms with more stable workforces where human capital can be developed and deployed. As human resources leave they take their tacit knowledge with them and are replaced by new employees without the firm-specific knowledge required to significantly contribute to learning by doing.

Hypothesis 4b: Greater human resource turnover reduces learning by doing performance.

The human capital factors and their hypothesized effects on learning are summarized in Figure 1.

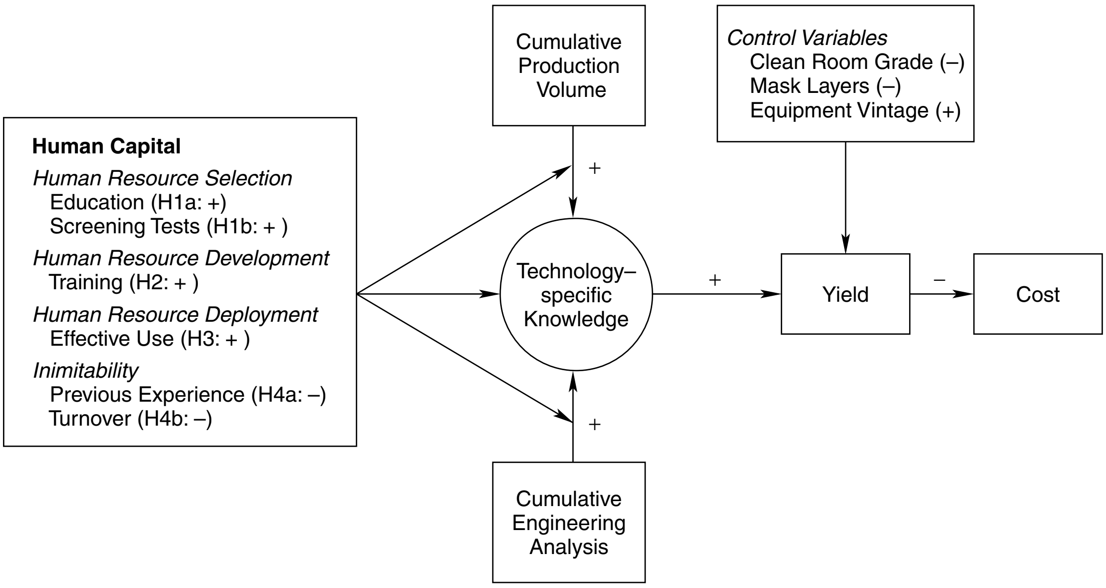

Figure 1. Graphical representation of the model

MODEL OF HUMAN CAPITAL AND LEARNING PERFORMANCE

Background on the empirical setting

Heterogeneity in resources and isolating mechanisms that protect resources from imitation also pose barriers for scholars to observe and measure their impact on firm performance. To partially overcome these barriers, we focus this study within a single industry: semiconductor manufacturing. Drawing upon detailed observations of activities and performance obtained through questionnaires and field interviews, we estimate the long-term performance effects of heterogeneous human capital. Limiting the scope of analysis to a single industry reduces the generalizability of the results but allows for more accurate measurement of human capital and performance (Becker and Gerhart, 1996; Hitt *et al.*, 2001). A brief description of the important details of semiconductor manufacturing follows.

An integrated circuit, commonly known as a chip, is constructed on a wafer of silicon as a complex array of conductive and insulating materials, patterned to provide the intended function. Since the product components are complex and minuscule,[5] manufacturing processes inevitably incur yield losses of two types: line yield losses and die yield losses. Line yield measures the percentage of wafers entering the production process that successfully pass through all processing steps. Line yield losses occur when wafers break or when severe processing errors force the wafer to be scrapped. On all successfully processed wafers, some of the chips do not work. The percentage of functional chips on a wafer is called the die yield.

Once the wafer is processed, each integrated circuit is tested for functionality and performance. Failures represent die yield losses and can generally be attributed to 'random particles' or 'parametric processing' problems. Random particles rain down onto the wafer and cause shorts between conductive lines or holes within them. Particles originate from the ambient air, equipment, and manufacturing personnel and are eliminated through targeted air filtration systems. Since the particles are microscopic, their sources are difficult to find. In new manufacturing processes, parametric processing problems are typically more pervasive than random particles. Many process steps are too complex for science to accurately specify the process parameters *a priori*, resulting in seemingly random yield losses as inputs interact in unexpected ways and fail. The problem is exacerbated by process control limitations that allow unintended input interactions even when the optimal parameters are known.

[5] Minimum feature sizes of semiconductors are as small as 0.15 μm; a human hair has an average diameter of 50–100 μm.

It is not uncommon for yields for new semiconductor processes to start as low as 10 percent, which inflates the manufacturing cost of a good chip by a factor of 10. Eliminating these yield losses generates substantial reductions in manufacturing costs as yields approach 100 percent. Yield losses are primarily eliminated through engineering analysis and experiments that identify and solve particle sources, discover unknown parameters, and improve process control. Since yield improvements are typically permanent solutions to yield losses, the resulting cost reductions are permanent—an identifying characteristic of learning by doing. Learning by doing through yield improvement clearly reduces costs and provides sustainable competitive advantage if there is persistent heterogeneity in rate of yield improvement. Understanding differences in the rate of learning (yield improvement) requires knowledge of the process by which learning occurs.

Traditionally, learning by doing is modeled as though cumulative production volume alone is sufficient to reduce costs. It is doubtful whether production volume is sufficient to characterize the learning curve in semiconductor manufacturing because yield improvements are also caused by engineering analysis. Thus, as Hatch and Mowery (1998) have shown, cumulative production volume and cumulative engineering analysis in combination are the key determinants of learning by doing in semiconductor manufacturing. These variables are not proxies for manufacturing experience, but rather represent the means by which yields and costs improve. This insight has profound implications for seeking competitive advantage through learning by doing because learning is the product of deliberate learning activities rather than the byproduct of production. Firms that manage the learning process have an advantage over firms that simply manage learning through maximization of market share.

Firms earn a competitive advantage when they move down the learning curve more quickly than their rivals. Firms that consistently outperform their rivals through management of learning sustain their cost advantage over the long term (Dyer and Hatch, 2003). All semiconductor firms perform engineering analysis of production volume to improve yields, but some are consistently superior. Figure 2 shows reductions in a measure of yield losses for 30 semiconductor manufacturing processes in 16 firms. It is clear that the levels and rates of improvement in yield losses vary widely between the different processes. The main contribution of this study is to determine the degree to which these persistent differences in the rates of learning by doing are a result of differences in the management of human capital.

A mathematical model of knowledge and learning

While the traditional form of the learning curve, given in Equation 1, has been used extensively

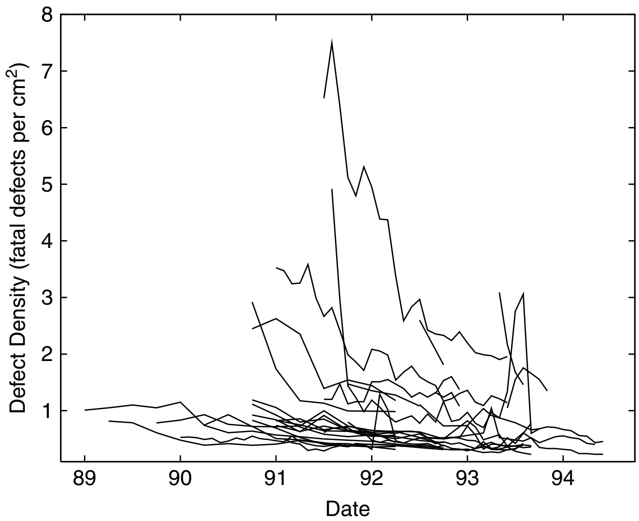

Figure 2. Defect density trends of semiconductor manufacturing processes

since it was first introduced, it has some well-known limitations. Several features of observed learning curves have been shown to fit poorly with the traditional learning geometry. For example, costs are sometimes observed to settle on a 'plateau level' that is not allowed with Equation 1, which falls asymptotically to zero (Carr, 1946; Asher, 1956; Conway and Schultz, 1959; Baloff, 1966, 1971; Hall and Howell, 1985; Muth, 1986). Similarly, the traditional model is not well suited to incorporate the possibility of non-linearities (Carlson, 1961, 1973; Yelle, 1979) or prior learning, the omission of which results in biased estimates (Montgomery and Day, 1985). These limitations have led to the proposal of alternative functional forms (Carlson, 1961, 1973; Yelle, 1979) such as the 'Stanford B' model, which explicitly controls for prior learning (Garg and Milliman, 1961). Use of the traditional form has persisted in spite of its limitations presumably because it is linear in logs and can be estimated easily with OLS.

The learning by doing model we use is based on the one used by Hatch and Mowery (1998). Cost is assumed to be a function of yields which are a function of learning by doing activities. A common assumption in the semiconductor industry is that the unit variable cost of manufacturing a chip is constant whether the die functions or not. Since the salable chips must bear the cost of scrapped output, the unit cost of producing good chips gets inflated by the yield losses:

$$AVC = \frac{u}{y} = \frac{u}{LY \cdot DY} \tag{2}$$

where u is the constant unit cost, y is net yield, LY is line yield, and DY is die yield. To estimate the learning curve for semiconductors, it is sufficient to estimate the line and die yield improvement curves as functions of the determinants of learning by doing, including human capital. Due to data limitations, only improvements in die yield will be analyzed in this study.

Consistent with the earlier discussion of yield loss and improvement, the accumulation of technology-specific knowledge is summarized by the cumulative number of wafers fabricated and the cumulative number of engineers devoted to process improvement. Let CV_t denote the number of wafers produced for a given process between time zero (the date of the first observation) and time t and CE_t denote the cumulative number of engineers for a process. Obviously, the level of process-specific knowledge is unobservable, but we can make use of it through the learning index L_t that is defined by the level of manufacturing experience:

$$L_t = a \cdot CV_t + b \cdot CE_t + L_0 \tag{3}$$

where $a \geq 0, b \geq 0$, and L_0 is the existing level of knowledge or experience in the first period. L_0 embodies the learning that has been accumulated prior to the first observation of the process.[6]

Before the learning index can be integrated into the yield-based learning curve, die yield must be normalized to correct for its dependence on the die size. To see the relationship between die yield and die size consider two wafers with identical defects scattered across the wafers. If the chips on one wafer are larger than on the other, die yield for the larger chips will be lower because the number of good chips will remain constant while the total number of chips falls. To standardize their measure of manufacturing performance, practitioners focus on the density of fatal defects per cm^2 of silicon rather than on die yield. The 'Murphy model' of defect density[7] defines the relationship between die yield and the average number of fatal defects per cm^2 as

$$DY = \left[\frac{1 - e^{-A \cdot DD}}{A \cdot DD}\right]^2 \tag{4}$$

where A is the die area and DD is the defect density parameter. An increase in the defect density causes an increase in defects. As engineers and operators acquire technology-specific knowledge, the density of defects declines and die yield rises. In this light, defect density is a good measure of

[6] It is difficult to imagine a situation where some manufacturing knowledge/experience does not exist before the first observations. Bahk and Gort (1993) study learning by doing in new plants; however, even for a new product and manufacturing process, previous manufacturing experience with related products is almost certainly embedded in the new product. Hatch and Reichelstein (2003) show how the learning curve and the cost elasticity of experience are influenced by the unobserved history.

[7] The list of commonly used models includes the Poisson model, the Murphy model (Murphy, 1964), and the negative binomial model (Okabe, Nagata, and Shimada, 1972; Stapper, 1973). Murphy extended the Poisson model to account for the observed clustering of defects on wafers. In particular, his model assumes a triangular approximation of the Gaussian distribution. See Stapper (1989) for an overview of the defect density literature.

learning by doing because it illuminates the relationship between knowledge and yield and because it maps directly to die yield and cost.

The objective is to identify and evaluate the factors that reduce the defect density parameter. To incorporate reductions of the defect density parameter into the learning curve, first assume that the learning curve is additively separable into a dynamic (learning by doing) component and a static component:

$$DD_t = h_1(L_t) + h_2(s_t) \tag{5}$$

where the learning by doing component $h_1(\cdot)$ depends on the unobservable learning index L_t defined in Equation 3. The static component $h_2(\cdot)$ includes the control variables s_t that do not directly affect the rate of learning by doing but still influence the defect density. A negative exponential functional form is chosen for $h_1(L_t)$, while $h_2(s_t)$ is assumed to be linear.[8] This gives

$$DD_t = \gamma + \psi \cdot e^{-(a \cdot CV_t + b \cdot CE_t + L_0)} + s_t$$

After some algebra to substitute the observable initial defect density value DD_0 for the unobservable level of starting knowledge, the specification of the basic learning curve is

$$DD_t = \gamma + e^{-(\alpha \cdot CV_t + \beta \cdot CE_t)} \cdot [DD_0 - \gamma - s_0] + s_t \tag{6}$$

where DD_0 is the starting defect density value and s_0 gives the starting values of the control variables.

To incorporate the influence of the human capital variables on learning performance it is only necessary to add the human capital variables to the learning index in Equation 3. The direct effect of human capital on knowledge and learning is given by the (direct) linear parameter, c_{hc}. Human capital is also expected to influence learning indirectly through its effect on the productivity of the basic learning drivers (cumulative volume and cumulative engineering) as human capital contributes more or less knowledge to learning activities. This indirect effect is specified through an interaction term between the human capital variable and the cumulative volume and cumulative engineering variables. Solving the model as described above, the learning curve as a function of human capital becomes

$$DD_t = \gamma + e^{-(\alpha CV_t + \beta CE_t + HC(\alpha_{hc} CV_t + \beta_{hc} CE_t + c_{hc}))} \times [DD_0 - \gamma - s_0] + s_t \tag{7}$$

where HC is a proxy for each of the hypothesized human capital variables. This specification of the learning curve is the basis for testing the hypothesized relationships between human capital and learning performance.

DATA AND METHODS

The data used to test the hypotheses described in the previous section were obtained through the Berkeley Competitive Semiconductor Manufacturing (CSM) Program.[9] The data were gathered through questionnaires sent to plant managers and follow-up interviews at fabrication facilities (fabs) of 25 semiconductor manufacturing facilities located in the United States, Asia, and Europe. Firms were initially selected from a list of 'world class' manufacturers and contacted to assess their willingness to participate. Once the firm agreed to participate, the questionnaire was sent to acquire fab-specific information on products, processes, and processing equipment. It also obtained the fab's history of monthly or quarterly wafer starts, yields, personnel histories, and major cost categories. Once the completed questionnaire was received, a team of researchers visited the fab for plant tours and interviews to identify the practices that generate the performance measured in the questionnaire data. Descriptive statistics and the Pearson correlation matrix for all variables are reported in Table 1.

Because the questionnaire was not sent to any firm unless they first agreed to participate in the study, the response rate was 100 percent. Every fab that was contacted and invited to participate agreed to participate in the study. The selection criteria of choosing world class manufacturers is not a random sample of the population of semiconductor

[8] The use of a negative exponential function for $h_1(\cdot)$ diverges from the more traditional specification in Equation 1. However, Levy (1965), Stata (1989), and Zangwill and Kantor (1998) have confirmed the appropriateness of an exponential functional form to model learning by doing.

[9] For a more detailed description of the Competitive Semiconductor Manufacturing project, see Leachman (1996).

Table 1. Descriptive statistics and correlation matrix for the sample

	Variable	Units	Mean	S.D.	Min.	Max.
(1)	Defect density	fatal defects/cm^2	1.01	1.06	0.11	7.49
(2)	Cumulative volume	1000 wafer starts	93.55	119.52	0.05	821.59
(3)	Cumulative engineers	allocated fte engineers	384.27	394.31	0.90	1938.20
(4)	Clean room grade	maximum particles/foot^3	1050.40	2918.20	1.00	10000.00
(5)	Mask layers	number of layers	13.15	5.81	5.00	29.00
(6)	Equipment vintage	ave. purchase date (year)	88.25	1.78	85.57	91.36
(7)	Technical education	High/Med/Low (2/1/0)	0.20	0.40	0.00	1.00
(8)	Experience required	H/M/L (2/1/0)	0.19	0.39	0.00	1.00
(9)	Screening test	Yes/No	0.73	0.44	0.00	1.00
(10)	SPC training	H/M/L (2/1/0)	1.11	0.92	0.00	2.00
(11)	Vendor training	Yes/No	0.22	0.37	0.00	1.00
(12)	Machine qualification	H/M/L (2/1/0)	1.06	0.64	0.00	2.00
(13)	Team involvement	H/M/L (2/1/0)	0.98	0.77	0.00	2.00
(14)	Troubleshooting	H/M/L (2/1/0)	0.96	0.92	0.00	2.00
(15)	Turnover	annual percentage	21.08	31.53	4.00	180.00

Number of observations = 702; Number of technologies = 49

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
(1)	1.00													
(2)	−0.34	1.00												
(3)	−0.32	0.40	1.00											
(4)	−0.11	−0.00	0.31	1.00										
(5)	0.15	0.12	−0.03	0.00	1.00									
(6)	−0.52	0.37	0.25	0.51	0.30	1.00								
(7)	−0.23	0.41	−0.10	−0.17	0.66	0.60	1.00							
(8)	0.66	−0.27	−0.31	−0.17	0.19	−0.58	−0.24	1.00						
(9)	−0.54	0.32	0.35	0.17	−0.13	0.46	0.30	−0.79	1.00					
(10)	−0.40	0.24	0.30	0.32	0.52	0.64	0.48	−0.53	0.54	1.00				
(11)	−0.31	0.15	−0.18	−0.20	0.19	0.43	0.62	−0.28	0.35	0.32	1.00			
(12)	−0.03	0.28	−0.12	−0.56	0.26	−0.15	0.43	−0.04	0.35	0.27	0.20	1.00		
(13)	−0.40	0.29	0.08	−0.43	0.32	0.27	0.66	−0.45	0.57	0.44	0.50	0.56	1.00	
(14)	−0.33	0.21	0.08	−0.32	0.53	0.30	0.57	−0.37	0.37	0.74	0.43	0.61	0.75	1.00
(15)	0.05	−0.15	0.11	0.56	−0.09	0.19	−0.25	−0.05	−0.21	−0.02	−0.25	−0.61	−0.34	−0.40

manufacturers but it does provide insights into the practices of the highest-performing firms.[10] The data employed in the empirical analysis are drawn primarily from the responses to the questionnaire and are frequently updated based on the follow-up interviews. Three firms did not provide all of the data necessary to construct the variables used in this study and had to be dropped.

Dependent variable

To control for the influence of die size on die yield, defect density is used as the dependent performance variable to measure learning. Defect density is an appealing measure of learning because virtually all defects are the result of some lack of knowledge and, as knowledge grows, defects fall resulting in direct reductions in manufacturing cost. The fabs in the sample reported either their monthly die yield or defect density.[11] When die

[10] The fact that the sample consists of largely high-performing firms means that we have minimized variance of the dependent (performance) variable. Thus, the tests of our hypotheses are actually conservative tests of the underlying theoretical constructs.

[11] The earliest participants in the CSM study were requested to report quarterly historic data on volume and yields. Subsequently the questionnaire was revised to request monthly data. This does

yield was reported, it was converted to the Murphy defect density using Equation 4. When fabs reported defect densities using a formula different from the Murphy model, the defect density was converted to die yield and then converted to the Murphy defect density.[12]

Independent variables

Production volume is measured by the number of wafers that enter the production process per period. The cumulative volume variable is the sum of wafer starts from the initial observation to the current period. These values come directly from the data reported by the fabs. For convenience in estimation, the cumulative volume variable is rescaled to represent units of 1000 wafers.

Unfortunately, unlike production volume, the number of full-time engineers devoted to the process during the period is not reported in the questionnaire. In fact, it is clear from follow-up interviews that this information is not recorded. The fabs invariably responded that they do not track the time that engineers spend on individual processes, but rather that engineers work on the most pressing problems. In order to estimate the influence of cumulative engineering on yields, we employ a rule to allocate the engineering staff to processes. If there are no new processes in the fab, each process is allocated a share of total engineering full-time equivalents (FTEs) that is proportional to the share of total volume accounted for by that process. If a new process has been introduced, we assume that the new process receives 75 percent of the engineering FTEs for the first year and then receives its portion of engineering according to its relative volume.

While this allocation scheme is arguably *ad hoc*, the fabs reported that this allocation was consistent with the time allocation of their engineers to problem-solving activities.[13] In the months required to 'characterize' and 'ramp-up' a new process, the most pressing problems arise with the new process and many of the fab's engineering resources are devoted to the effort. When there are no new processes in the fab, the allocation rule is conservative with respect to estimating the effect of engineering on learning because, in general, newer processes have relatively lower volumes but require more engineering effort in adjusting process specification limits.

Data for the human capital variables were obtained from both the mailed questionnaire and the on-site interviews conducted during visits to the fabs. Each visit included interviews with at least one employee in each job category as well as human resource managers. A survey guide was used during interviews to ensure that all of the topics were fully covered. Most of the variables are coded as yes/no or with a three-point ordinal scale typically expressed as high/medium/low. A description of the human capital variables and their coding is given in the Appendix.

Human resource selection

The human resource selection hypotheses are tested with data on education and screening exams for the hiring process. The technical education variable indicates whether a technical education (technical high school or technical associates degree) is required. It also reports the degree to which direct labor employees have technical degrees even if they are not required. The screening test variable is a simple binary variable that indicates whether the fab uses a test to screen for technical skills in the hiring process.

Human resource development

The human resource development hypothesis is operationalized through the use of three measures of human resource training: statistical process control, equipment vendor training, multiple machine

not cause a problem for estimating the learning curve as long as all the variables are defined by the appropriate period length.

[12] A data measurement problem has forced us to exclude line yield as a dependent variable in spite of its obvious impact on cost and performance. This omission is unfortunate but does not introduce a bias into our results. Line yield typically follows a learning curve that depends on the same factors as defect density, namely cumulative volume, engineering analysis, and human resources, In short, line yield typically increases as defects decrease. As long as the learning drivers that reduce defects are not also reducing line yields (and raising costs), there is no systematic bias introduced by employing defect density as the only dependent variable.

[13] While firms generally do not track the time engineers spend on various processes, in a recent site visit, one firm volunteered that on average a new manufacturing process takes about 75 percent of engineering resources during the initial stages. This unsolicited comment lends credence to the allocation scheme. To test the sensitivity of the estimates to the *ad hoc* 75 percent allocation rule, we varied the percentage rates allocated in the initial period and found the estimates to be stable.

qualification. The statistical process control (SPC) training variable refers to whether equipment operators are required to undergo on-the-job training in statistical process control procedures related to their job tasks. The SPC training variable also indicates the degree to which the fab considers SPC training to be a priority. The vendor training variable reports simply whether operators receive equipment-specific training from a vendor. The multiple machines qualification variable reports the average number of machines that an operator is qualified to operate within his or her area and is measured with a three-point scale.

Human resource deployment

Human resource deployment is operationalized as the proportion of operators that participate in problem-solving teams and the proportion of operator time spent troubleshooting process control problems (Arthur, 1994; Ichniowski and Shaw, 1999). When equipment operators acquire sufficient human capital to participate actively in problem-solving activities,[14] more information is available for analysis and decision-making and engineering resources are freed to focus on more difficult projects. The proportion of operators involved in teams is a reasonable measure of the amount of problem-solving that operators do. It also provides an estimate of the specific human capital in the fab because operators must have a minimum level of skills to participate meaningfully on troubleshooting teams. The troubleshooting measure of deployment reports the estimated average share of their time that equipment operators spend troubleshooting 'out-of control' situations with their equipment.[15]

Inimitability

Inimitability is tested with data on prior firm-specific experience and operator turnover. The prior experience variable measures whether firms require experience for hiring and the degree to which employees have previous experience in their production area, semiconductor manufacturing, and unrelated manufacturing. The operator turnover variable is the average annual percentage of full-time equivalent (FTE) operators that are replaced.

Control variables

The control variables are included in the static component of the model and influence the level of defects but not the rate of improvement in defects through learning. These variables include the cleanliness of the clean room *CR*, the number of mask layers *ML*, and the equipment vintage *Vin*. The clean room grade, measured by the maximum number of particles per cubic foot of clean room space, directly influences the incidence of fatal defects due to particulate contamination. The number of mask layers is a measure of the total number of steps in the process—more process steps increase the probability of errors and defects. The equipment vintage variable indicates the average installation date for processing equipment. Newer equipment, with a 'higher' vintage value, generally provides greater process control which reduces processing defects. As new equipment is installed the average vintage of equipment in the fab rises and overall process control is improved. Thus, the density of defects is expected to fall. In the few cases where fabs installed used equipment rather than new, the original purchase date (age) of the equipment was obtained.

The hypotheses are tested by estimating each specification of the learning curve using a nonlinear maximum likelihood estimator. The initial parameters for the maximum likelihood estimation were varied over a wide range to ensure that the estimates represent the global maximum of the likelihood function. To control for cross-sectional fixed effects in the panel data, we include a dummy variable for each process technology in the sample. To control for expected autocorrelation over time within panels, an autocorrelation correction is also employed.

RESULTS AND DISCUSSION

Results of the regressions to test the hypotheses are reported in Tables 2–4. In the tables, estimated coefficients and their asymptotic *t*-statistics are reported for each model of human capital and

[14] In many cases, these problem-solving opportunities focus on yield improvement but there are a number of other areas where operators are able to participate in solving problems, such as cycle time, on-time delivery performance, and equipment performance.

[15] Out-of-control events occur when SPC data indicate that processing parameters have fallen outside predetermined boundaries.

Table 2. Impact of human resource selection on learning performance

Coefficient	Basic model	Technical education	Screening tests
Basic learning effects			
γ	5.2967	8.3147	3.5874
$h_1(\cdot)$ constant	(1.7390)	(2.4353)	(1.1644)
α	0.00603	0.006785	0.006579
Cumulative volume	(2.0044)	(2.1007)	(2.2247)
β	0.00646	0.006354	0.007938
Cumulative engineers	(11.0910)	(10.636)	(8.6929)
Learning by doing × Human capital interaction effects			
α_{hc}		0.001746	−0.005435
Cumulative volume		(0.1802)	(−1.2701)
β_{hc}		0.001504	−0.005792
Cumulative engineers		(0.3716)	(−5.0515)
c_{hc}		0.46588	0.35209
Constant		(1.7882)	(3.0240)
Control variables			
Clean room	−0.000113	−0.000066	−0.000013
	(−1.2864)	(−0.7267)	(−0.2682)
Mask layers	−0.007627	−0.03284	−0.005355
	(−0.5592)	(−1.7764)	(−0.2963)
Equipment vintage	−0.05892	−0.09067	−0.042349
	(−1.6947)	(−2.3675)	(−1.2281)
R^2	0.9682	0.9684	0.9707
LR-test statistic	0.0000	3.6986	52.0484
ρ	0.6459	0.6270	0.5951

Number of observations = 702
Number of process technologies = 49
Values in parentheses are asymptotic t-statistics

learning by doing interactions. The number of observations n and the R^2 between the observed and predicted values are also reported. A likelihood ratio test was performed on each regression to test whether the three coefficients from each human capital variable significantly improve the model. The test verifies whether the log-likelihood value of the unrestricted model (with human capital coefficients) is significantly larger than log-likelihood value of the model where the human capital coefficients are restricted to be zero (basic model). The test statistic has a χ^2 distribution with three degrees of freedom. The estimated first-order autocorrelation coefficient, ρ, is reported with the estimates. Estimated coefficients for the 49 fixed-effect (dummy) variables are not reported to protect the proprietary nature of the data. Care must be taken in interpreting the levels and signs of the estimated coefficients due to the nature of the functional form in which they are estimated. A positive coefficient on variables included in the dynamic portion of the defect density specification, $h_1(L_t)$ (learning variables), indicates a reduction in defects (increase in yield) rather than an increase. However, for variables in the static portion of the learning curve $h_2(\cdot)$ (control variables), a positive coefficient indicates an increase in defects.

Results for the basic learning curve, Equation 6, are reported in the first column of Table 2 and verify the underlying learning curve hypothesis that cumulative volume and cumulative engineering together drive learning. Given the positive coefficient for the cumulative volume variable, we see that defect density is improving (falling) as cumulative volume increases. The coefficient is also statistically significant. The cumulative engineering variable is also significant in reducing defects. These coefficients define the rate of learning by doing for the fabs in the sample and underscore the importance of engineering analysis as a determinant of learning by doing in semiconductor manufacturing, reconfirming the idea that the benefits of learning come not only from repetition, but also from deliberate activities aimed at learning. Note that the estimated coefficients for cumulative

Table 3. Impact of human resource development on learning performance

Coefficient	SPC training	Vendor training	Mult. machine qualification
Basic learning effects			
γ	9.2455	7.8048	12.758
$h_1(\cdot)$ constant	(2.6605)	(2.3105)	(4.4690)
α	0.002098	0.006531	−0.014974
Cumulative volume	(0.7434)	(1.8789)	(−2.2021)
β	0.007199	0.006352	0.006224
Cumulative engineering	(8.6650)	(10.0460)	(4.3184)
Learning by doing × Human capital interaction effects			
α_{hc}	0.005743	−0.016614	0.019213
Cumulative volume	(1.2385)	(−2.3083)	(3.0847)
β_{hc}	−0.002727	0.002704	0.000465
Cumulative engineering	(−4.8009)	(0.6661)	(0.4282)
c_{hc}	0.43729	−0.40364	−0.2936
Constant	(4.9022)	(−0.7718)	(−5.5748)
Control variables			
Clean Room Grade	−0.000032	−0.000072	−0.000105
	(−0.4246)	(−0.7718)	(−1.2365)
Mask Layers	−0.049498	−0.02696	0.02399
	(−2.3151)	(−1.3192)	(2.3471)
Equipment Vintage	−0.10261	−0.08568	−0.14308
	(−2.6238)	(−2.2554)	(−4.3952)
R^2	0.9703	0.9684	0.9695
LR-test statistic	44.5780	2.8944	25.7854
ρ	0.6102	0.6341	0.5434

Number of observations = 702
Number of process technologies = 49
Values in parentheses are asymptotic t-statistics

volume and cumulative engineering are approximately equal implying that, at the sample mean, one full-time equivalent engineer per month is worth about 1000 wafers as a source of learning.

Results for the (static) control variables are mixed. Of the estimates of the three control variables, clean room grade (maximum number of particles), number of mask layers, and equipment vintage, only equipment vintage has a significant relationship with defects. Our results suggest that newer equipment provides superior process control and does significantly reduce defects. Contrary to expectations, clean room grade (maximum number of particles in the fab) does not have a significant relationship with defects, and in fact the sign is typically in the 'wrong' direction. However, our interviews suggest that this result should not be construed to suggest that cleanliness in the manufacturing environment is unimportant or deleterious. The great expense that firms incur to construct and maintain particle-free factories testifies to the importance of clean rooms. The sign and insignificance of this coefficient are more likely due to the coarseness of the cleanliness measure that indicates the *maximum* number of particles in the environment rather than the *actual* number of particles. Many firms have installed technologies that reduce the actual number of particles below the level reported in the clean room grade. We also found that the number of mask layers (process steps) does not reduce the likelihood of defects. Like clean room grade, the estimated coefficient is insignificant. The number of mask layers is an attempt to partially control for the inherent complexity and difficulty of the manufacturing process as it will contribute to defects. Unfortunately, our measure of this variable seems to be co-linear with the capability of the manufacturing site. Specifically, more difficult processes are done only in more technically advanced fabs such that, on average, they achieve higher yields. Our variable to control for the technical environment, the equipment vintage, has the expected sign and is only sometimes significant. These unexpected

Table 4. Impact of human resource deployment and inimitability on learning performance

Coefficient	Deployment		Inimitability	
	Team involvement	SPC troubleshooting	Experience required	Turnover
Basic learning effects				
γ	6.3281	9.3453	13.372	9.9084
$h_1(\cdot)$ constant	(1.8868)	(0.3913)	(4.5077)	(4.4468)
α	0.005272	0.002269	0.001226	0.005769
Cumulative volume	(1.6617)	(0.6879)	(0.5911)	(2.080)
β	0.007349	0.007017	0.003396	0.005306
Cumulative engineering	(9.3990)	(1.7008)	(5.7137)	(11.0020)
Learning by doing × *Human capital interaction effects*				
α_{hc}	−0.002393	0.006541	0.001767	0.000132
Cumulative volume	(−1.3682)	(0.6272)	(0.5764)	(0.0437)
β_{hc}	−0.002669	−0.002677	0.002701	−0.002796
Cumulative engineering	(−4.7936)	(−0.9919)	(2.5740)	(−10.3550)
c_{hc}	0.19483	0.47402	−0.3886	−1.0766
Constant	(1.7489)	(1.7794)	(−5.3850)	(−6.0381)
Control variables				
Clean room grade	−0.000088	−0.000099	−0.000023	0.000073
	(−0.8096)	(−0.1514)	(−0.5146)	(5.9162)
Mask layers	−0.024478	−0.05353	(0.01366)	0.009866
	(−1.4550)	(−0.5941)	(1.1314)	(1.1181)
Equipment vintage	−0.07007	−0.10412	−0.14966	−0.11007
	(−1.8450)	(−0.3988)	(−4.4273)	(−4.3180)
R^2	0.9695	0.9705	0.9720	0.9691
LR-test statistic	26.8448	48.1036	82.0694	25.0628
ρ	0.6005	0.6178	0.4829	0.5752

Number of observations = 702
Number of process technologies = 49
Values in parentheses are asymptotic t-statistics

results are likely the product of measuring opposite effects of the same force.

Table 2 also reports the results of regressions focusing on the impact of the human resource selection variables on the initial level and rate of improvement in defects. In the second column, the regression regarding technical education provides only limited support for Hypothesis 1a. The sign and value of the 'constant' coefficient c_{hc} indicates the direct effect of technical education requirements on the level of defects. In other words, it shifts the level or intercept of the learning curve up or down. The estimate indicates that requiring a technical education significantly reduces defects (shifts the learning curve down to lower levels of defects). However, requiring a technical education does not significantly influence the effectiveness of cumulative volume or cumulative engineering in moving along the learning curve to lower levels of defects. The increase in R^2 from adding the education variable coefficients to the basic model is quite small. Therefore, a likelihood ratio test was employed to verify additional explanatory power gained from adding education to the model. The likelihood ratio test statistic of 3.7 is well below the critical value (5.25) for a χ^2 one-tailed test with three degrees of freedom at 90 percent significance. Thus, while the direct learning effect is significant, adding education to the model does not significantly increase its explanatory power.

Results from the regression including the effect of human capital screening tests are consistent with Hypothesis 1b. The estimated 'constant' coefficient shows that defect density is significantly improved with increased screening in the hiring process. The regression also indicates that, while there is no significant impact on cumulative volume, screening significantly reduces the marginal productivity of engineering to reduce defects. This result confirms that effective screening places these firms on a different learning curve than their rivals. Firms that use screening tests in the hiring process are able to more effectively identify employees with the ability to learn, adapt to the new environment, and, depending on the quality of the screening test, identify candidates with skills that are conducive with those needed in the fab. The positive effect of screening tests moves firms so quickly down the learning curve that only the more difficult yield problems remain, rendering the engineering problem-solving activities relatively unproductive. The likelihood ratio test statistic is well above the critical value at the 99 percent confidence level (11.34), indicating that screening adds significant explanatory power to the model.

Estimates of the effect of human capital developed through investments in development and training are reported in Table 3. These results indicate that fabs with the greatest emphasis on statistical process control (SPC) training for equipment operators enjoy significantly fewer defects. SPC training seems to enable operators to solve relatively simple problems on their own, which significantly reduces defects. In turn, this reduces the productivity of engineers as they are left with the more difficult yield problems. Equipment-specific training by equipment vendors results in an insignificant increase in defects. Its impact on engineering productivity is also insignificant, while it has a significantly negative impact on the productivity of cumulative volume in reducing defects. The likelihood ratio test shows that SPC training adds significant value to the basic model while vendor training does not. The difference in effectiveness of SPC training compared to equipment training seems to suggest that training that strengthens problem-solving skills is most valuable.

Conceptually, training operators to work on multiple machines is effectively purchasing an option against being left without qualified operators. Empirically, we find that increasing the number of machines on which operators are qualified to work significantly increases defects. However, cumulative volume is made significantly more productive as operators are qualified to work on an increasing number of machines. The likelihood ratio test shows a significant difference between the restricted (basic) model and the multiple-machine qualification model. The significant negative impact of operators being qualified on multiple machines indicates that depth of human capital skills is more valuable than breadth of human capital skills in influencing learning performance. Having broad skills seems to sacrifice the depth of knowledge needed to improve learning performance.

Table 4 reports the estimates of the impact of human capital deployment on the level and rate of learning by doing performance. These regressions lend strong support to Hypothesis 3. As seen in the first column, the level of defect density is significantly reduced with increasing involvement of operators in problem-solving teams. The impact of team participation on the rate of learning from cumulative volume is not significant but the significant, negative coefficient on the interaction between cumulative engineering and team involvement indicates once again that the initial level of defects is reduced to such a degree by operators doing some of the work of engineers that there are diminishing marginal returns from engineering analysis. The impact of the amount of time that operators spend 'troubleshooting' out-of-control events is reported in the second column. Troubleshooting is the direct deployment of human capital development through SPC training. As with problem-solving team involvement, the direct effect of troubleshooting is a significant reduction in defects. Surprisingly, troubleshooting does not significantly affect the rate of learning through cumulative volume or cumulative engineering. The likelihood ratio test indicates significant explanatory power in both models.

Table 4 also reports results for the regressions that test the inimitability of human capital. Hypothesis 4 is strongly supported in these regressions. For example, the initial level of defects actually increases when fabs hire more employees with prior semiconductor experience. Increasing prior experience represents increasing human capital specificity in another firm and the negative impact on learning supports Hypothesis 4a that asserts that human capital is not easily transferable to a rival's manufacturing environment. These results corroborate the comments of one manager, who stated that he would rather not hire experienced operators because it took too long to help them overcome the habits they had learned at other firms. A fab cannot imitate the value of a rival's human capital simply by hiring away some of the rival's human resources, at least not without replicating the rival's manufacturing environment.

Finally, the regressions of turnover on defect density (column 4) provides even stronger evidence of the importance of firm-specific human capital on learning. This regression shows that defects increase significantly as the turnover rate increases. This validates the assertion that turnover represents knowledge leaving the firm. When experienced employees are replaced by new employees with less firm-specific human capital, the firm must work hard to develop and deploy them to the same effect within the firm's environment. As a result, the new employees require extra training and are more prone to making mistakes. A steady flow of new operators making the same old mistakes implies that permanent solutions are not being implemented and that learning by doing is slowed as learning resources are diverted to training.[16] Moreover, less knowledge is available to employ in problem-solving activities. In this situation, human capital becomes a source of yield losses rather than part of the solution. The regression also shows that high turnover makes engineers significantly less productive in reducing defect density. Through our interviews we learned that this is because with high turnover engineers must spend more of their time training new operators and continually solving the same repeated mistakes rather than implementing permanent solutions to yield problems. Thus, higher turnover both shifts the learning curve up and makes it flatter. This result reveals that, at least for some time, the value of experienced human resources can not be imitated and the dynamic adjustment costs of training and deploying new human resources can lead to persistent differences in performance. This result also indicates that in the semiconductor industry, increased equipment automation and engineering analysis can not fully substitute for the value of firm-specific human capital.

Our results strongly suggest that human capital holds great potential as a resource that can confer and sustain competitive advantage. While human resources are mobile, their firm-specific knowledge comprised of both codified and tacit knowledge acquired in a specific environment are often not fully mobile. The degree of firm specificity of human capital determines the degree to which it is protected from imitation through the socially complex environments where it is gained and used and through the time compression diseconomies that prevent rapid imitation. Thus, in this light, firm-specific human capital may earn rents in the form of superior performance in learning by doing. Differences in specialized human capital place firms on different learning curves that provide cost advantages for the superior firms. The findings of this study suggest that inimitable human capital allows some firms to remain on lower-cost learning curves even when they do not lead the industry in market share/volume.

Effective deployment of human capital integrates the entire manufacturing staff into one large problem-solving organization. In some fabs, equipment operators are expected only to push buttons and load wafers into machines. In other fabs, operators are given responsibility for equipment maintenance, repair, process control, and basic yield improvement. These fabs invest in the 'learning by doing' skills of their operators by training them in math, literacy, statistical process control, and detailed knowledge about their equipment and manufacturing processes. Over time, operators develop a stock of tacit knowledge related to the intricacies of their process steps and the idiosyncrasies of their machines. When fabs effectively include operators in yield improvement efforts, operators bring their specific tacit knowledge to bear on yield problems. These high-performance fabs expect their operators to solve some of the yield problems that would be left to engineers in other fabs. The benefit is that not only are these operators more efficient and less prone to making mistakes, but they also bring their tacit knowledge to learning (yield improvement) efforts. Consequently, the fabs are able to reduce defects, improve yields and lower costs at faster rates than rival fabs.

Our results also indicate that the cost advantages that can be attributed to human capital are sustainable because human capital is difficult (costly) to imitate. If human capital were perfectly mobile, imitation would require nothing more than hiring away experienced human resources. In that case, wages would adjust to match the productive value of the human resource and firms would earn no rents. In the semiconductor industry, firm-specific human capital is not mobile and does not deliver the same value in another firm that it did in the firm where it was developed. If new firm-specific human capital could be developed quickly, turnover would present no impediment to matching a rival's costs through learning because

[16] Argote, Beckman, and Epple (1990) found no significant evidence of turnover reducing learning rates. Their result is a puzzle because turnover should affect the stock and flows of knowledge as seen in the simulations of Carley (1992). The regression estimates reported here provide empirical verification of the disruptive effect of turnover on learning.

new human resources could be screened, trained, and deployed immediately. In fact, turnover is a double-edged impediment to imitating the value of a rival's human capital. First, knowledge leaves the firm with human resource turnover and then the rate of learning is slowed by the steady flow of new human resources. The inimitability tests reveal that human capital is also non-substitutable. Most fabs with high turnover rates (50% or more) find that they cannot utilize operators in their yield improvement efforts because they are not qualified. Instead, they must substitute some combination of engineers and automation to bypass the role of human capital. The results clearly show that while these substitute measures may help, these firms suffer inferior performance.

CONCLUSION

Despite the popularity of the resource-based view for explaining persistent heterogeneity in firm performance, empirical verification of the theory has lagged because many of the resources that generate sustainable advantages are either unobservable or extremely difficult to measure (Godfrey and Hill, 1995; Rouse and Daellenbach, 1999). This study seeks to overcome that limitation by utilizing proprietary, technology-specific data at the factory level in the semiconductor industry to study the impact of human resources on learning by doing performance.[17] We find that managing the selection, development, and deployment of human capital can significantly improve learning by doing and firm performance. Firms that use screening tests in the hiring process enjoy higher performance, presumably because they are able to identify employees with the aptitudes, attitudes, and skills that contribute to the stock of firm-specific human capital that serves the specialized needs of the company. Firms that emphasize human capital development through training in statistical process control find that their employees are more productive and can meaningfully participate in the learning activities of the firm.[18] We also find that the deployment of human capital to learning activities creates significant cost advantages. As equipment operators are integrated into the firm's problem-solving activities, their tacit knowledge is added to the effort and moves the technology to a significantly lower learning curve relative to firms that do not deploy operator knowledge in problem-solving. This use of operators as problem-solvers elevates their status from pushing buttons to generating new knowledge about the process technology and reducing costs. Transforming operators into quasi-engineers requires investments in human capital but pays big dividends in learning performance. In short, superior learning performance comes (at least in part) from better human resources and from better practices to develop firm-specific human capital and deploy it to learning activities.

Intel's knowledge management processes provide an excellent illustration of our findings. Most semiconductor industry analysts believe that 'Intel has the best chip yield in the industry' (Pfeiffer, 2003: 55). They attribute Intel's success to its 'copy exactly' manufacturing process which involves: (a) creating a prototype manufacturing process at Intel's R&D fab in Oregon and meticulously documenting each step, (b) transferring the process to a new plant with workers that have spent a year at the Oregon fab 'working side-by-side with R&D engineers learning everything they need to know,' and (c) allowing production engineers to improve the process, after extensive peer review, once chips are in production. For example, before Intel recently opened a new fab in New Mexico, it shipped 300 workers to Oregon for a year where it attempted to transfer 'tribal knowledge' to the workers. New Mexico plant manager Bruce Sohn says that tribal knowledge is information that Intel's most experienced employees know but may not have written down. He states, 'We want to copy everything—even the subtle things we may not even acknowledge that we do' (Pfeiffer, 2003: 55). When one worker was found to be polishing the inside of an etching machine by wiping across the grain, he was asked to do it in the approved circular pattern instead (It is less likely to drop specks of debris into the grooves.) Intel's attention to developing specialized human resources with tacit knowledge that aids 'learning

[17] This effort to engage in 'inquiry from the inside' complements research conducted through 'inquiry from the outside.' Adapting the traditional theories of economics to address the questions discussed by managers follows in the tradition of Penrose (1959) in the resource-based view of the firm (Kor and Mahoney, 2000).

[18] Not all investments in training pay equal dividends. Equipment-specific (but not firm-specific) training provided by equipment vendors does not contribute to superior performance, while training operators to work with multiple types of equipment results in significant performance losses.

by doing' is critical to their cost advantage in semiconductors.

The competitive advantage of Intel and other high-performing fabs gained through the role of human capital in learning is protected by the inimitability of human capital. We find that firms that attempt to obtain human capital by hiring operators with experience in rival firms suffer significant performance losses. To the degree that experience builds firm-specific human capital, it is less productive in another firm and requires dynamic adjustment costs to evaluate, retrain, and deploy the human capital to productive tasks in the new environment. Similarly, the impact of turnover on learning performance reveals the challenges of imitating the value of human capital without taking time to develop it. Turnover results in a loss of knowledge and training that leads to significant increases in defects. On top of that, the rate of learning is slowed as turnover disrupts the basic learning process and human resources are focused on training (relearning) rather than new learning. This result is consistent with Penrose's (1959) observation that the time and attention required for existing personnel to train new personnel leads to dynamic adjustment costs.

There are several questions that remain for future research on the role of human capital in generating and sustaining competitive advantage. For example, what is the nature (what are the specific attributes) of firm-specific knowledge? Future research might more explicitly explore the attributes of knowledge that are truly firm-specific vs. those that are redeployable to other firm settings. Moreover, are there optimal ways to target and develop firm-specific human capital? Along a similar vein, future research could explore in greater detail the conditions under which prior industry experience helps, or hurts, an employee's performance. While our research suggests that prior industry experience hurts performance, there are likely to be industry contexts within which prior experience improves performance. In addition, future research might address some important questions with regard to human resource training, such as: Which training methods and topics are most important for learning by doing? How is the product of training transformed into tacit knowledge and how is it integrated into the broader problem-solving activities in the firm? Finally, future research might seek to develop deeper insights into the workings of social complexity and time compression diseconomies and the role they play in protecting human capital from imitation.

In summary, our research clearly shows that human resources are strategically important in semiconductor manufacturing because they embody firm-specific tacit knowledge. This knowledge is difficult for competitors to imitate even when employees are hired away because the knowledge is specific to the original work environment and therefore cannot add similar value in a different work environment. Thus, firms that employ effective human resource selection, training, and deployment processes that facilitate learning by doing may enjoy the only truly sustainable advantage—the ability to learn (and improve) faster than competitors.

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APPENDIX: CODING OF HUMAN CAPITAL VARIABLES

Hypothesis	Variable	Variable values		
		High (value = 2)	Med. (value = 1)	Low (value = 0)
Selection	Technical education required	Required	Not required but almost all have	Many do not have
	Screening test		Used	Not used
Development	Statistical process control training	Yes, considered very important	Yes, but not a priority	None
	Vendor training		Used	Not used
	Multiple machine qualification	Qualified to run all machines in area	Qualified on 3 or more machines	Qualified on 1–2 machines
Deployment	Team involvement	All employees involved	'Significant number' involved	Few to none involved
	Troubleshooting	Almost always involved	Sometimes involved	No involvement
Inimitability	Prior experience required	Prior experience in specific process area in semiconductor manufacturing	Prior experience in semiconductor manufacturing	Unrelated or no prior experience in semiconductor manufacturing
	Turnover	Percentage per year (including temporary workers)		