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Learning, Knowledge Transfer, and Technology Implementation Performance: A Study of Time-to-Build in the Global Semiconductor Industry

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Organizational growth and performance hinge upon the effective deployment of productive knowledge in new facilities. However, getting those facilities fully operational can be difficult and time consuming. Interestingly, we understand little about what determines the performance of that process. In this paper we help fill this gap by analyzing multiple determinants of time-to-build—i.e., the time it takes a firm to build and ramp up operations at a new manufacturing facility. Theoretically, we develop predictions regarding the effects of competitive, firm, and technology characteristics on time-to-build. Empirically, we test our predictions on a sample of plant construction projects in the memory segment of the global semiconductor industry. We find that competition from rivals with superior technology is associated with shorter time-to-build, at least up to a point. Firm and industry experience are associated with shorter time-to-build. International projects, and those that push the technological frontier, take longer. Findings from this study enrich the literatures on corporate growth, international expansion, and technology strategy. We discuss implications for research and practice.

Key words: time-to-build; international knowledge transfer; organizational learning
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Introduction

To develop and sustain competitive advantage, a firm must do more than simply create distinctive knowledge-based assets; it must also exploit the resulting advantage efficiently (Nelson and Winter 1982). To leverage its advantage, a multiplant firm must effectively extend that advantage to new facilities across various locations. However, making technologies viable in new facilities is often a difficult and time-consuming process (e.g., Kogut and Zander 1992, Hatch and Mowery 1998, Martin and Salomon 2003a). Moreover, the success of that process stands to substantially affect firm performance.

Although scholars from various disciplines recognize the potential impact of knowledge transfer, deployment, and implementation on organizational success and viability (e.g., Teece 1977, Galbraith 1990, Winter and Szulanski 2001), little attention has been devoted to how such effects manifest in the time it takes to make new facilities viable. In this paper we fill this gap by analyzing how competitive, firm, and technology characteristics combine to affect the time it takes firms to get their facilities fully operational. As such, the dependent variable of interest is "time-to-build"—i.e., the time it takes a firm to build and ramp up operations at a new manufacturing facility (Koeva 2000, Pacheco-de-Almeida 2003).

This study makes several contributions to the strategy and technology literatures. First, it explicitly recognizes and examines the time to build manufacturing facilities as an endogenously determined outcome. The literature has long recognized time-to-build as an important strategic consideration (e.g., Ghemawat 1984, Majd and Pindyck 1986, Pacheco-de-Almeida and Zemsky 2003, Pacheco-de-Almeida 2003), yet no study that we know of addresses how competitive, organizational, and technology characteristics jointly influence it. Second, we argue that time-to-build is a novel indicator of performance. Studying it, and its determinants, adds to our understanding of firm growth and operational performance. Finally, we recognize that substantial heterogeneity in time-to-build exists across firms. This heterogeneity stands to form the basis for lasting competitive advantage (Winter and Szulanski 2001, Martin and Salomon 2003a), and we examine its strategic determinants.

Theory

Literature Review

Knowledge transfer has long occupied a prominent, if not always explicit, place in research on strategic management and corporate expansion. Deploying and extending productive knowledge to new facilities is inherent in corporate growth. The speed and effectiveness of that process can determine a firm's ability to penetrate new markets, preempt and respond to rivals, and adapt to market changes. Scholars have examined how knowledge transfer influences firm performance (e.g., Teece 1977, Argote 1999, Levin 2000, Winter and Szulanski 2001), how technology transfer considerations affect governance (e.g., Martin and Salomon 2003a, Mayer and Salomon 2006), and under what conditions firms exploit knowledge across organizational and national boundaries (e.g., Galbraith 1990, Szulanski 1996, Ingram and Simons 2002, Martin and Salomon 2003b, Edmondson et al. 2004). However, little attention has been given to the process of deploying knowledge-based assets in new facilities, and how knowledge transfer impacts operational performance.

With respect to corporate growth, early work from an economics perspective emphasized how macroeconomic fluctuations influenced whether firms would expand by investing in new plants. Received wisdom suggested that expansion follows general economic business cycles, and that firms build new plants when demand warrants it (see Koeva 2000 for a review). In general, this literature examines firm expansion in the context of real business cycle theory, with research by Kydland and Prescott (1982) highlighting the role of time-to-build.

Scholars in the industrial organization (IO) economic tradition have focused on the effects that the time it takes to make technologies viable in new facilities (i.e., time-to-build) have on production and profit at the industry level. Early empirical work examined time-to-build to assess performance differences across industries rather than firms (e.g., Mayer and Sonenblum 1955, Mayer 1960, Ghemawat 1984, Lieberman 1987a, Koeva 2000). Studies conclude that heterogeneity exists across industries in the time it takes to build plants. In this tradition, research generally models such heterogeneity as an exogenous, industry-specific constraint that impacts some outcome of interest. For instance, Pacheco-de-Almeida and Zemsky (2003) examined how firms choose to invest in production capacity given a delay in the time it takes to get production facilities online. They analyzed how time-to-build influences industry structure, profits in a duopoly, and social welfare. However, given its industry-level focus, the IO literature leaves little room for firm heterogeneity in time-to-build.

In the strategic management literature, the primary outcome of interest is firm rather than industry heterogeneity. Scholars in this literature recognize that technology deployment and knowledge transfer are central to firm growth, and impact firm performance. Consistent with this conjecture, a stream of studies going back at least to Argote and Epple (1990) and Argote et al. (1990) has shown that experience with knowledge transfer results in learning that can improve productivity and quality (Szulanski 1996, Bohn and Terwiesch 1999, Terwiesch and Bohn 2001, Hatch and Dyer 2004), decrease production costs (Darr et al. 1995, Darr and Kurtzberg 2000), increase innovative output (Hatch and Mowery 1998, Salomon and Shaver 2005, Salomon 2006), improve profitability (Ingram and Simons 2002), and enhance survival (Ingram and Baum 1997, Baum and Ingram 1998).

With respect to the deployment and transfer of knowledge to new facilities, scholars have focused on how characteristics of the technology to be employed constrain or encourage expansion. Work from an evolutionary, knowledge-based perspective highlights that the complexity and tacitness of the knowledge to be deployed in a facility stand to impede knowledge transfer (see Teece 1977; Kogut and Zander 1992, 1993; Simonin 1999a, b; Martin and Salomon 2003a, b). Complex knowledge is inherently difficult to convey (Teece 1977, Mansfield et al. 1982). Teece (1977), for example, found that complexity increased the costs of implementing productive knowledge. In the same vein, Simonin (1999b) showed a negative relationship between complexity (and tacitness) and the ease of transferring marketing know-how. Szulanski (1996) studied how characteristics of the knowledge and the parties involved influence perceptions of transfer and implementation efficacy. He found that knowledge stickiness increased the difficulty of the transfer of best practices within organizations. Firms, however, can fruitfully develop strategies to address these challenges (Galbraith 1990). For instance, Winter and Szulanski (2001) argue for replication as strategy. They maintain that firms may develop capabilities to routinize knowledge deployment. Intel's "Copy Exactly!" approach to building semiconductor plants stands as an example of such (McDonald 1998): Every facet of existing productive knowledge should be replicated down to the finest detail when deploying technologies in new facilities. Further, Martin and Salomon (2003a) argue that competitive heterogeneity exists among firms in their abilities to transfer knowledge efficiently, with predictable governance and performance consequences.

In sum, existing research from various perspectives underscores the importance of knowledge implementation and transfer to firm growth and performance. However, the application of knowledge in new facilities remains relatively understudied. To our knowledge, no study explicitly examines firm heterogeneity in time-to-build, or how knowledge transfer conditions impact time-to-build performance. Furthermore, none has jointly and comprehensively tested industry, firm, and technology effects on this important firm-level performance metric.

Hypotheses

To remain consistent with the extant strategy and economics literatures, we examine time-to-build as our dependent variable. Previous studies have employed various performance variables, including estimated transfer costs, ease of transfer, satisfaction with implementation, and time-to-build. Although each of these variables is amenable to analyzing operational performance, we focus on time-to-build as an objective measure that can be readily compared across firms.

With regard to independent variables, we focus our analysis on competitive, organization, and technology characteristics. Specifically, we consider competitive dynamics, foreignness, organizational learning, and the impact of technology complexity.

Competition. Business actions do not occur in a void. Firms are constantly vying for position, trying to beat competitors to market (Chen et al. 1992). Competitive dynamics and interfirm rivalry focus firm attention and motivate responses to other firms' actions (Chen 1996). Whenever actions taken by incumbents or entrants are perceived as threatening in nature (e.g., threatening a firm's market position or its potential to earn above normal returns), the focal firm will generally respond vigorously (Schumpeter 1934, Chen et al. 1992). In the context of time-to-build, when faced with competitors making large resource commitments to build similar (or more advanced) facilities, the focal firm has incentives to beat its competitors to market in order to preserve its position. We therefore expect firms to strategically speed their plant investments in an attempt to make their facilities viable sooner when more rival facilities with similar, or superior technology, are being built. Formally stated:

Hypothesis 1. *Time-to-build will decrease with the number of similar, or superior, facilities being built by competitors.*

Organization. Organizational factors relevant to time-to-build include the domestic/foreign status of the parent firm and a firm's ability to benefit from various sources of experience. Through their impact on the process of knowledge deployment, these factors can significantly influence the time it takes a firm to build its facilities.

Scholars in the international business literature argue that foreign firms face disadvantages relative to domestic firms operating in their home environment. This is referred to as the "liability of foreignness" (Hymer 1960). Foreign investors bear additional costs due to information asymmetries, cultural differences, coordination difficulties, and local biases (Zaheer 1995, Caves 1996, Martin and Salomon 2003a). Empirical results consistent with this theory show that foreign firms generally have higher labor costs (Mincer and Higuchi 1988, Lipsey 1994), are subject to more lawsuits (Mezias 2002), take longer to achieve economies of scale in production (Galbraith 1990), suffer from lower profitability (Zaheer 1995), and experience a higher probability of failure (Zaheer and Mosakowski 1997). Moreover, physical distance compounds the costs of deploying knowledge, and learning can be impeded when the source and recipient of the knowledge are not collocated—especially when they are in different countries (Teece 1977, 1981; Galbraith 1990; Kogut and Zander 1992; Hatch and Mowery 1998). For these reasons, we expect foreign plant investments to be subject to higher coordination and communication costs, which will translate into greater time-to-build. We therefore hypothesize:

Hypothesis 2. *Time-to-build will be greater for foreign-owned, versus domestic-owned, plants.*

Another organizational factor relevant for time-to-build is organizational learning. In this study we view learning as a process of accumulating, encoding, and leveraging insights gleaned through experience (Fiol and Lyles 1985, Levitt and March 1988, Huber 1991, Argote 1999). Two forms of learning can be helpful. The first is experiential learning. This form of learning-by-doing accrues as a firm repeatedly engages in an activity (for a review see Argote 1999). In this context, the relevant experience is that which accrues from prior deployments (e.g., building previous plants). The second form of learning is based on industry-level experience. This type of learning refers to the insight that a firm gains as other firms "do"—i.e., by encoding the experience of others within the industry (Ghemawat and Spence 1985, Lieberman 1987b, Argote et al. 1990, Ingram and Baum 1997).

With respect to learning from one's own experience, past deployments develop a "discipline of practice" that creates more efficient replication routines (Nelson and Winter 1982, p. 77). This provides the opportunity for firms to encode experiences into routines that they may exploit when engaging in future deployments (Nelson and Winter 1982, Levitt and March 1988, Martin and Salomon 2003b). Consistent with this intuition, Teece (1977) showed that the costs of transferring technological know-how across plants decreased in firm experience. Likewise, Galbraith (1990) found that prior experience resulted in greater productivity when transferring technology to new plants. More generally, we expect a firm's experience to translate into enhanced efficiency when building new plants.

Hypothesis 3. *Time-to-build will decrease with cumulative firm experience (i.e., with the number of times that a firm has previously built production facilities).*

Besides learning from their own experiences, firms also learn from others (Argote et al. 1990, Ingram and Baum 1997, Baum and Ingram 1998). They benefit from accumulated industry expertise, in this case, the cumulative experience of those that have come before them (Ghemawat and Spence 1985, Lieberman 1987b, Argote et al. 1990, Argote 1999). Firms may learn by benchmarking competitors, hiring employees with an in-depth knowledge of industry practice, contracting with suppliers who have a long industry history, or via more informal channels such as trade associations, industry conferences, and networking among scientists, managers, and engineers (Huber 1991, Ingram and Baum 1997, Baum and Ingram 1998, Darr et al. 1995, Darr and Kurtzberg 2000).

The greater the level of prior industry experience, the more any firm within the industry stands to benefit from a deeper understanding of the underlying technologies and the conditions for their use (Nelson and Winter 1982, Argote et al. 1990). This familiarity can facilitate knowledge implementation in new facilities by mitigating the coordination and troubleshooting difficulties inherent in such deployments (Bohn and Terwiesch 1999, Terwiesch and Bohn 2001). Although industry-level learning has been connected to increased survival (Baum and Ingram 1998, Ingram and Baum 1997), decreased costs (Darr et al. 1995, Darr and Kurtzberg 2000), and profitability (Ingram and Simons 2002), to our knowledge, no study has examined its influence on efficiency in establishing new facilities. We therefore expect that industry-level experience will benefit firms and manifest as decreased time-to-build.

Hypothesis 4. *Time-to-build will decrease with cumulative industry experience (i.e., with the number of times that other firms within the industry have previously built production facilities).*

Technology. In addition to the aforementioned competitive and organizational factors, the nature of the technology being deployed in a new facility stands to have a substantial impact on time-to-build. Technology complexity plays a critical role (Teece 1977; Galbraith 1990; Kogut and Zander 1992, 1993). Complexity increases with the number, variety, sophistication, and interactions among components, especially when the know-how represents an advance relative to the state of the art (Scuricini 1988).

Firms that implement complex, state-of-the-art technologies often deal with less codified knowledge for which they lack requisite process understanding—the "know why" and the "know how"—to produce reliably, and at high volume (Bohn 1994). To put complex technologies to productive use, firms must first gain an understanding of those technologies (Edmondson et al. 2004). Because complex knowledge is difficult to understand, express, and replicate accurately (Nelson and Winter 1982, Argote 1999), the need for coordination is greater (Teece 1977), greater ex ante experimentation is required (Bohn and Terwiesch 1999, Terwiesch and Bohn 2001), and troubleshooting is often more difficult (Hatch and Dyer 2004). In fact, Terwiesch and Bohn (2001) document ramp-up problems at semiconductor plants associated with the launch of new products and production processes. Likewise, Galbraith (1990) found that complex technologies are associated with greater productivity loss after plants are opened, and a longer time to recover from such loss. For these reasons, we expect complexity to increase the time it takes to effectively implement technologies in new production facilities, thus increasing time-to-build.

Hypothesis 5. *Time-to-build will increase with technology complexity.*

Research Design

Sample

To test our hypotheses, we study the global semiconductor manufacturing industry. This industry possesses several advantages for our purpose. First, the industry is characterized by frequent innovations and intense competition over knowledge-based assets (Eisenhardt and Schoonhoven 1996, Hatch and Mowery 1998, Henisz and Macher 2004). Second, the industry is global in scope, allowing us to observe a wide range of investments and locations. Finally, plant investments can be reliably documented and compared. All of this provides the opportunity to study time-to-build across facilities in various locations, across technologies with varied complexity, and in an industry well documented over time.

Our initial data set comes from the *International Fabs on Disk* (IFOD) database. This source contains information on 1,630 semiconductor plant investments as of fall 2001. It provides information on the type of semiconductor facility, the year the plant became operational, the end products produced (and their features), and the nationality of the parent firm(s). We limit our sample to plants that manufacture memory products (e.g., RAM). This subset is a homogeneous market amenable to rigorous technology comparisons (e.g., Malerba 1985, Eisenhardt and Schoonhoven 1996). This yielded a list of 571 facilities.

After an extensive electronic search of standard sources, published industry reports, and press refleases in the Lexis/Nexis database (e.g., *Electronic News*, *Engineering News*, *Asia Business News*, and *The Wall Street Journal*), we were able to gather time-to-build data on 265 of the 571 plants.[1] Our final sample thus includes 265 plant investments from 66 unique parent companies over the period 1982–2001.[2]

Measures

Time-to-Build (*Dependent Variable*). The economics literature has identified the time-to-build manufacturing facilities as an important strategic consideration for firms (e.g., Pacheco-de-Almeida and Zemsky 2003, Pacheco-de-Almeida 2003). New manufacturing facilities represent substantial and lasting investments for firms. In fact, the average cost of a new, full-scale semiconductor plant has been estimated at upwards of $1 billion (IC Knowledge 2001). Not surprisingly, commitments to new facilities with such high stakes can have a substantial impact on firm performance.

Building a new plant is a long and carefully planned process.[3] The figure in the online appendix (provided in the e-companion)[4] depicts this process. The process usually begins with a forecast of demand conditions, wafer start requirements, and the firm's ability to meet demand. If the firm determines that it cannot adequately meet demand without constructing a new facility, it then determines its equipment needs, the projected budget, the capacity, and considers possible locations for the plant. This takes several weeks to complete.

After the firm has determined that it should build a plant, it will generally announce publicly its intentions to do so.[5] Concurrently, or soon thereafter, the firm orders all necessary equipment, begins to design the layout of the plant, and develops an overall project plan and schedule. The firm breaks ground a few months later and the physical construction begins. During the basebuild the foundation gets laid, the plumbing is installed, and the physical structure goes up. The firm then installs the production machinery and a long ensuing stage of equipment testing begins. Testing continues until the firm is satisfied that the equipment works properly and that it thoroughly understands how to use the equipment. Although there are still some kinks left to work out, the firm now officially opens its doors for production and begins its ramp-up. During the ramp-up phase the firm produces salable product, but production is not yet perfected. Yield (the proportion of output that is of sufficient quality to sell) is generally low. The ramp-up phase continues until the plant reaches its target yield and intended capacity, a milestone marking the completion of the implementation process (Hatch and Mowery 1998).

The plant construction process forms the basis of our time-to-build measure. Although firms subcontract various portions of the activity to construction firms and equipment manufacturers, they generally manage and coordinate the entire project, and perform many of the tasks involved, including technical tasks. Moreover, there exists substantial heterogeneity across companies in how they manage and coordinate the activities, and how effectively they implement their technologies (McDonald 1998).[6]

Following Koeva (2000) and Pacheco-de-Almeida (2003), we define *time-to-build* as the time it takes to complete a manufacturing facility. To gauge this outcome, we compiled plant-level statistics from standard industry sources found in the Lexis/Nexis database. Because national, local, and industry trade publications closely monitor events in the industry, we were able to collect detailed data on the progress of various plants. We collected information on the date a firm first announced it would build a new plant, the date construction began, the date operations

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[1] We conducted *t*-tests and tests of proportions to ascertain how representative the 265 plants are of the population of 571 memory plants. We found no significant differences in general indicators such as plant size; in our predictive indicators of technology and competition (described below); or in our indicators of organizational strategy, except that joint venture plants represent a higher proportion of the sample than of the rest of the population. We attribute this one difference to the fact that time-to-build information is more likely to become publicly available for plants with more than one parent. Follow-up χ^2 tests showed that the parent companies in our sample do not substantially differ from the rest in their propensity to report time-to-build information. Thus, the caveat regarding joint ventures notwithstanding, our sample is broadly representative of the underlying population.

[2] Although we were only able to compile time-to-build data for 265 plant investments, we use the full sample of 571 plants to compute measures such as firm experience, industry experience, and the number of rival plants built.

[3] Information on the process was compiled from interviews with engineers and managers at two large semiconductor firms.

[4] An electronic companion to this paper is available as part of the online version that can be found at http://mansci.journal.informs.org/.

[5] A firm may try to strategically delay this announcement; however, once it begins to order equipment, it becomes all but impossible for the firm to veil its investment decision. Equipment suppliers generally report such large orders to shareholders and analysts. Also, because there are so few players in the industry, and each plant requires extraordinary capital investment and often the acquisition of large tracts of land, word of the new plant travels fast.

[6] The quality and/or availability of subcontractors and equipment manufacturers may also impact time-to-build. We address this point further in the discussion and conclusion section.

began, and the date the plant finally achieved full-scale production with the requisite yield.[7] We then calculated *time-to-build* as the time (in months) from the announcement date until the plant achieved full capacity.[8, 9]

Competitive Rivalry. To test Hypothesis 1, we include a measure of competitive rivalry. The competitive pressures will be greater when more plants are scheduled to come online concurrently. Firms are likely to respond aggressively to plants with similar or superior technology. We therefore define *rival plants with superior technology* as the number of memory plants (other than the focal plant) built contemporaneously and with a feature size less than, or equal to, that of the focal plant. Smaller feature sizes indicate more advanced products resulting from more complex production processes, such that the output will sell at a premium and depress demand for products with larger feature sizes (see Malerba 1985, Martin and Salomon 2003b). The conjecture in Hypothesis 1, therefore, is that the firm has a strong incentive to adjust its construction schedule to beat competitors with superior technology to market. To control for the effect of plants with weaker competitive potential, we define *rival plants with inferior technology* as the number of memory plants (other than the focal plant) that were completed (came online) in the same year as the plant in question, but with a larger feature size.

Foreign Direct Investment. Foreign direct investment occurs when a substantive operating investment is made in a foreign location. The standard used by academic researchers and governments is that foreign direct investment occurs when a firm takes an equity stake of at least 10% in a facility abroad (Caves 1996). Thus, we coded as foreign investments those where a firm held a share of at least 10% in a plant in another country. Practically, if a plant had a foreign owner in these data, that owner always held at least 50% of the equity in the plant.[10]

Learning Variables. We measure two forms of learning: learning from the firm's own experience and learning from the industry's experience. Own-firm learning accumulates as a firm builds successive facilities. To measure this, we counted the number of memory plants previously built by the parent company (see Teece 1977). Because research shows that domestic expansion generates a different experience base than foreign expansion (e.g., Martin and Salomon 2003b), we computed two experience variables. The first represents a count of the number of previous memory investments made by the firm in its home country. The second measures the number of previous memory investments made by the firm abroad. We refer to these measures as *domestic firm experience and foreign firm experience*.

Firms can also learn from the plant-building experiences of rivals. We therefore define *cumulative industry experience* as a count of the number of memory plant investments made by other firms in the industry, in the same country, before the focal plant. This measure is at the country level because prior research shows that experience in a given country has a substantial impact on subsequent investments in that country, and that industry-level learning of this sort can help compensate for the firm's lack of experience in a particular country (Henisz and Delios 2001, Chung and Song 2004).[11]

Technological Complexity. Because we seek to understand the effects of complexity as it varies in a single precisely defined industry, we use an industry-specific measure that can be reliably tracked over time and across firms. The most widely accepted indicator of technological complexity in the industry is feature size (see Eisenhardt and Schoonhoven 1996, Martin and Salomon 2003b, Hatch and Mowery

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[7] Although our *time-to-build* data came from various media sources, our data collection was systematic. We recorded the exact day of each event, and barring that, the month. We applied the 15th of the month to those records without an exact day. To the extent that dates are inaccurate, this may introduce some bias into the results. However, we believe this bias to be small. Moreover, when we randomly assigned missing days, the results did not change.

[8] In some instances where the announcement date or the date when a plant achieved full-scale production was unavailable, we estimated the missing data using means for similar plants. We successfully replicated all main results when eliminating such observations from the sample. As a further robustness check, we ran the results solely on the time between groundbreaking and ramp-up ($n = 265$). Results did not change. Finally, we ran specifications on intermediate phases separately—e.g., the time between announcement and groundbreaking ($n = 175$), and the time between ramp-up and full capacity ($n = 105$). Although some results differed slightly across these specifications, the main conclusions did not change. For these reasons we believe our results to be robust to the limitations of the data and the specification of time-to-build.

[9] We also collected information on plant delays. We recorded the date on which the company announced that it was delaying construction of the plant, and the date on which it began construction again. Our dependent variable captures the total time-to-build without subtracting any delays. We do this to accurately capture firm responses to the economic cycle. Only 8 of 265 plants experienced construction delays. Results were similar when delays were subtracted from the dependent variable, or when observations of plants with delays were removed from the sample.

[10] We explored the robustness of our results excluding plants in which a foreign firm owned less than 100% of the equity. The results were largely consistent with those presented here.

[11] In robustness analyses we found that broader measures of learning based on plants built by other firms in other countries were not significant predictors of time-to-build. Although we follow recent studies that focus on the country level of analysis (e.g., Ingram and Simons 2002), others have focused on more localized effects (e.g., Baum and Ingram 1998). We therefore also examined specifications with measures based on other firms' plants in the same city. The results were consistent with those reported below.

1998, Henisz and Macher 2004). This measures the width of the conducting channels in a semiconductor chip, expressed in microns. The narrower the feature size, the greater the storage capacity as more circuits fit on one chip. Firms compete to produce semiconductors with ever thinner features (Malerba 1985, Schoonhoven et al. 1990). Reducing feature size requires the development of ever more sophisticated manufacturing procedures, increases the number and variety of manufacturing steps, requires extensive product and process development efforts, and renders the interaction among design and process elements more difficult to comprehend. Thus, smaller feature sizes require more complex and tacit organizational knowledge (Malerba 1985, Hatch and Mowery 1998, Martin and Salomon 2003b, Hatch and Dyer 2004).

The feature size of the semiconductors manufactured at a plant therefore serves as the basis for our measure of complexity. This information is reported in the IFOD database. Because a given absolute feature size may represent more of an obstacle if it is substantially smaller than the industry state of the art, we computed a relative measure of feature size. This reflects the fact that novel technologies, those that depart substantially from the industry norm, present a greater challenge to implement. We define *relative feature size* as the ratio of the focal facility's feature size to the average for all facilities built in the industry in the previous three years (see Henisz and Macher 2004). The three-year window allows the technological frontier to evolve with contemporaneous practice (see Leiblein et al. 2002, Henisz and Macher 2004).[12] Because complexity increases with miniaturization, decreasing *relative feature size* indicates increasing complexity (Henderson 1995, Eisenhardt and Schoonhoven 1996).

Control Variables

We control for several other variables that might influence time-to-build. First, we control for the size of the plant, measured as its monthly wafer fabrication capacity (expressed in thousands), with the supposition that larger plants take longer to build. We label this measure *facility capacity*. Second, we control for the overall cost of the plant, using detailed cost information obtained from Lexis/Nexis. We label this variable *facility cost*. It represents the inflation-adjusted cost to build the plant, in hundreds of millions of U.S. dollars. As a correlate of plant size and scope, we might expect facility cost to be positively related to time-to-build; however, to the extent that facility cost proxies for the time-cost trade-off when building a plant (Mansfield et al. 1982, Pacheco-de-Almeida and Zemsky 2003), it might be negatively associated with time-to-build. Third, we include a dummy variable to control for whether the plant is a full-fledged fab (0) or an *R&D/pilot facility* (1). Controlling for plant capacity, *R&D/pilot* facilities might take longer to build because firms take greater care to implement experimental processes. Fourth, we control for whether the plant investment is a foundry. Foundries are subcontracting facilities that manufacture other firms' designs. This may affect implementation. The variable *foundry* was coded as one if the plant in question is a foundry facility, zero otherwise. Fifth, we control for whether the plant is a joint venture. Relative to wholly owned plants, joint ventures are likely to suffer from communication and knowledge-sharing difficulties across partners, which should increase time-to-build (Kogut and Zander 1992, 1993). However, a joint venture may also allow partners to pool complementary resources and thus ease facility construction (Mitchell 1989). Thus, although the direction of the effect is ambiguous, building a plant as a joint venture may affect time-to-build. We code the variable *joint venture* as one if the plant has two or more substantive corporate parents, and zero (indicating a wholly owned facility) otherwise.[13] Finally, to control for firms' responsiveness to fluctuations in the industry business cycle, we add a measure of growth in demand. The "Global Shipments Report" published by the Semiconductor Industry Association reports detailed, worldwide semiconductor memory sales. We convert the raw measure into annual growth rates to remove the effects of calendar time. Because firms are forward looking and plan capital investments in advance (Koeva 2000), we operationalize *demand growth* as a two-year average of future demand growth (i.e., the geometric average of the growth from time (t) to time $(t+2)$).[14]

Statistical Method

We specify a plant's time-to-build as a linear function of the explanatory variables. However, given the panel data structure with multiple firm observations over time, the possibility arises that the errors will not be independent across time or within firms (Greene

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[12] To assess the sensitivity of our results with respect to complexity, we ran specifications using alternative definitions of relative feature size including different year windows, as well as absolute feature size and absolute difference in feature size. The results were consistent with those reported below.

[13] Our ownership data came from various sources. For most joint ventures, ownership data came from International Fabs on Disk. Otherwise, data were compiled from Lexis/Nexis searches and the Directory of Corporate Affiliations.

[14] Although using a two-year window for demand growth is somewhat arbitrary, it matches the plausible horizon for demand and competitive forecasts in the industry. We explored combinations and permutations of various demand leads and lags, using windows of up to three years. Regardless of the leads or lags used, the results were robust.

Table 1 Descriptive Statistics and Product Moment Correlations

	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1. *Time-to-build*	1.00													
2. *Facility cost*	0.29*	1.00												
3. *Capacity*	0.21*	0.33*	1.00											
4. *Foundry*	0.17*	0.14*	0.42*	1.00										
5. *R&D/pilot facility*	0.03	−0.04	−0.41*	−0.02	1.00									
6. *Joint venture facility*	0.10	0.17*	0.15*	0.35*	−0.15*	1.00								
7. *Demand growth*	−0.10	−0.10	0.02	0.02	−0.10	0.01	1.00							
8. *Rival plants with inferior technology*	0.13*	0.16*	0.07	0.07	0.18*	−0.02	−0.13*	1.00						
9. *Rival plants with superior technology*	−0.13*	−0.10	−0.07	0.02	−0.19*	−0.04	−0.56*	0.19*	1.00					
10. *Foreign facility*	0.12	0.03	0.05	0.05	−0.13*	0.06	−0.18*	0.36*	0.20*	1.00				
11. *Relative feature size*	−0.21*	−0.20*	−0.07	0.03	−0.13*	0.08	−0.66*	0.04	0.59*	0.07	1.00			
12. *Domestic firm experience*	−0.07	0.26*	0.03	−0.19*	−0.06	−0.09	0.06	−0.01	−0.01	0.03	−0.05	1.00		
13. *Foreign firm experience*	−0.01	0.19*	0.01	−0.07	−0.01	−0.03	−0.05	0.13*	0.07	0.22*	0.04	0.56*	1.00	
14. *Cumulative industry experience*	−0.06	0.19*	−0.11	−0.21*	−0.04	−0.15*	0.10	0.01	0.01	−0.22*	−0.12	0.37*	0.17*	1.00
Mean	28.07	5.93	19.04	0.14	0.16	0.11	12.01	0.36	16.47	0.33	0.78	5.92	2.13	52.34
Standard deviation	7.80	4.44	10.12	0.34	0.37	0.20	8.85	0.48	10.25	0.47	0.33	6.38	2.95	52.12
Minimum	9.00	0.25	0.40	0.00	0.00	−0.32	0.00	0.00	0.00	0.00	0.15	0.00	0.00	0.00
Maximum	54.83	27.48	45.00	1.00	1.00	0.46	41.00	1.00	38.00	1.00	2.23	30.00	13.00	198.00

*Indicates p-value < 0.05.

2000). There are many potential time-dependent, macrolevel factors that could affect time-to-build, such as an increase in efficient scale and the trend toward disaggregating value chain activities. Likewise, because several firms in the sample have more than one plant, the errors could be correlated within firms if some firms perform differently than others due to systematically better management of the process. Moreover, some factors plausibly associated with time-to-build, such as firm size, are not directly measured here.[15]

Because we are unable to identify and measure the effects described above, there exists the potential for a systematic component to be embedded in the error term, which violates OLS assumptions (Kennedy 1998). Fixed or random effects may be used to correct for violations of this sort (Greene 2000). We therefore include a vector of fixed time effects and random firm effects into the specification.[16] After we control for such heterogeneity, we can more confidently assume that the error term is i.i.d. normal. The efficient estimator is generalized least squares, and nested models can be compared via adjusted R^2. Greater detail regarding the empirical specification can be found in the online appendix.

Results

Descriptive statistics and pairwise correlations are presented in Table 1. The average *time-to-build* is nearly 28 months, with a minimum of 9 and a maximum of 55. Correlations are generally as expected and moderate in magnitude. Influence tests did not show any evidence of multicollinearity. Examinations of the Durbin-Watson statistic and within-firm residuals did not indicate serial correlation.

The multivariate regression results are presented in Table 2. Although not presented, the time dummies were significant as a set ($p < 0.05$), and suggest that *time-to-build* increased with the passage of time in this industry. Likewise, the firm random effects were significant as a set ($p < 0.01$). This suggests that there are lasting, systematic differences across firms in technology implementation performance. Although not a direct test of the phenomenon, this result is consistent with heterogeneous knowledge transfer capacity across firms (Martin and Salomon 2003a).

In column 1 we present base results with control variables. *Facility cost* is positive and significantly related to *time-to-build*. The economic significance of this effect is small. A $100 million increase in the cost of a facility increases time-to-build only by about

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[15] Ideally, we would have liked to include more direct firm-level controls. However, many of these firms are private; thus, firm-level data are not readily available. For firms that are diversified into unrelated businesses and industries, it is difficult to extract relevant business unit data. Finally, the sample firms are from many countries (and some government owned), making reliable information all the more difficult to collect, validate, and compare.

[16] We use random firm effects because some parent firms exhibit no variance in the dependent variable (including, necessarily, firms with a single plant). Under this condition, and because we have few observations per firm on average, random effects are preferred (Kennedy 1998). Hausman tests confirmed that random firm effects describe the data better than fixed firm effects. Robustness checks with fixed effects were satisfactory (see the online appendix).

Table 2 Regression Results for *Time-to-Build*

	1	2	3	4	5	6	7	8	9
Constant	21.97***	21.64***	24.48***	24.19***	27.13***	27.53***	27.49***	28.25***	27.56***
	(15.36)	(14.58)	(12.23)	(12.14)	(10.44)	(10.77)	(10.72)	(10.81)	(10.55)
Facility cost	0.28***	0.27**	0.24**	0.24**	0.22**	0.28***	0.28***	0.29***	0.27**
	(2.36)	(2.28)	(2.01)	(2.05)	(1.86)	(2.41)	(2.41)	(2.47)	(2.31)
Facility capacity	0.14***	0.14***	0.13**	0.13**	0.12**	0.12**	0.12**	0.12**	0.13**
	(2.45)	(2.33)	(2.22)	(2.17)	(2.02)	(2.10)	(2.11)	(2.02)	(2.23)
Foundry	0.43	0.43	0.43	0.67	1.28	0.15	0.13	−0.59	−0.12
	(0.26)	(0.27)	(0.26)	(0.41)	(0.79)	(0.09)	(0.02)	(−0.35)	(−0.07)
R&D/pilot facility	2.28*	2.06*	1.68	1.79	1.74	1.57	1.61	1.42	1.45
	(1.62)	(1.44)	(1.18)	(1.26)	(1.23)	(1.12)	(1.14)	(1.01)	(1.04)
Joint venture	−0.18	−0.01	−0.07	−0.69	−0.82	−0.82	−0.80	−0.64	−0.91
	(−0.17)	(−0.01)	(−0.07)	(−0.62)	(−0.74)	(−0.75)	(−0.73)	(−0.58)	(−0.82)
Demand growth	−2.29	−2.37	−2.65	−2.94*	−2.56	−3.03*	−3.00*	−3.26*	−2.67
	(−0.99)	(−1.03)	(−1.15)	(−1.28)	(−1.11)	(−1.33)	(−1.32)	(−1.43)	(−1.17)
Rival plants with inferior technology		0.04	−0.03	−0.02	−0.09	−0.08	−0.08	−0.08	−0.08
		(0.80)	(−0.48)	(−0.35)	(−1.17)	(−1.13)	(−1.14)	(−1.13)	(−1.05)
Rival plants with superior technology			−0.12**	−0.13**	−0.09*	−0.09*	−0.09*	−0.09*	−0.09*
			(−2.11)	(−2.30)	(−1.48)	(−1.57)	(−1.58)	(−1.56)	(−1.47)
Foreign facility				2.28**	2.13**	2.23**	2.29**	1.71*	2.98***
				(2.17)	(2.04)	(2.19)	(2.21)	(1.57)	(2.33)
Relative feature size					−3.51**	−3.36**	−3.33**	−3.54**	−3.62**
					(−1.80)	(−1.75)	(−1.72)	(−1.84)	(−1.88)
Domestic firm experience						−0.24***	−0.22***	−0.18**	−0.20**
						(−3.05)	(−2.40)	(−1.82)	(−2.03)
Foreign firm experience							−0.07	−0.07	0.13
							(−0.35)	(−0.37)	(0.57)
Cumulative industry experience								−0.02**	−0.01
								(−1.69)	(−1.19)
Foreign facility $*$ country-specific foreign experience									−0.92**
									(−2.07)
Foreign facility $*$ third-country foreign experience									−0.22
									(−0.61)
Firm effects	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year effects	YES	YES	YES	YES	YES	YES	YES	YES	YES
N	265	265	265	265	265	265	265	265	265
Adjusted R^2	0.139	0.142	0.155	0.171	0.184	0.215	0.215	0.223	0.240

Note. t-statistics are in parentheses.
*Indicates p-value < 0.10; **indicates p-value < 0.05; ***indicates p-value < 0.01 (one-tailed tests).

8.4 days. The effect of *facility capacity* is positive and significant, and its economic significance is likewise small. The effect of foundry is not statistically different from zero. By contrast, controlling for cost and capacity, *R&D/pilot* facilities take 2.28 more months to build than full-fledged fabs. However, this effect disappears in later models when we include information about the specific technology to be used in the facility.

The *joint venture* variable is statistically insignificant. Notwithstanding knowledge-based arguments about the challenges of sharing knowledge and coordinating activities across firm boundaries, the result suggests that intrafirm transfers might be equally difficult to coordinate (Lapré and Van Wassenhove 2001, Hatch and Dyer 2004). However, the fact that the estimate is negative (albeit insignificant) favors a complementarity interpretation whereby access to the partners' respective capabilities offsets communication and coordination difficulties (Mitchell 1989).

The marginal effect of *demand growth* is directionally correct. It is not significantly different from zero in column 1, but statistically significant in some later models. There are several plausible interpretations. First, if firms make accurate ex ante analyses before they commit to such large-scale projects, they do not need to vastly alter their construction projects based on unfolding demand. Second, because we do not observe plants that firms decide ex ante not to build, we may not observe the full effect of demand growth. Third, because our demand growth measure was calculated using actual rather than forecasted demand, the measure may be noisy. Finally, we cannot rule out that once a firm decides to build a plant, the commitment binds it to continue the project regardless of external demand conditions.

In columns 2 and 3 we include measures of competitive pressures. The results in column 2 suggest that firms do not pay much attention to rivals with inferior technologies. However, firms respond to rivals with similar or more sophisticated technologies by speeding *time-to-build* (column 3). Hypothesis 1 is therefore supported. Each memory plant built contemporaneously by rivals with equivalent or more advanced technology encourages firms to speed deployment by 3.60 days. A one-standard-deviation (10.25 plants) increase in the number of rival plants therefore translates into nearly 37 days by which the typical firm speeds its build time. This finding is even more striking to the extent that rival plants tax industrywide resources, reducing subcontractor slack. That is, we might plausibly expect time-to-build to increase in competitor plants. The result therefore represents a conservative estimate of the impact of competition absent such resource constraints.[17]

In column 4 we include a measure of foreignness. Consistent with Hypothesis 2, plants owned by foreign parents take longer to build than their domestically owned counterparts. On average, it takes firms about 2.28 months longer to get plants operational in foreign locations. This result corroborates existing findings that demonstrate the substantial constraints that national differences place on knowledge implementation in new facilities (Teece 1977, 1981; Galbraith 1990; Martin and Salomon 2003b). Furthermore, it provides additional empirical substantiation (and a precise estimate) of the liability of foreignness (e.g., Hymer 1960, Zaheer 1995).

In column 5 we add our measure of technological complexity. The results show that decreasing relative feature size increases *time-to-build*. The marginal effect indicates that a 10% decline in feature size (relative to the state of the art) adds about 11.86 days. Therefore, consistent with Hypothesis 5, we find that the more complex the technology, the longer it takes to get new plants up and running.

In columns 6, 7, and 8 we incorporate our measures of organizational learning. Adding domestic transfer experience (in column 6) and cumulative industry experience (in column 8) provides strong support for Hypothesis 3 and partial support for Hypothesis 4. Specifically, a firm's domestic experience decreases the time-to-build subsequent facilities (as per Hypothesis 3). Each prior domestic plant built by the firm prior to the focal investment decreases *time-to-build* by 7.2 days. Given that the sample average is almost 6, this equates to more than one month saved for a typical firm relative to an inexperienced firm building the same plant. This implies that domestic experience can provide the firm with a set of routines and/or templates that it may meaningfully employ in future projects (e.g., Szulanski and Jensen 2006, Jensen and Szulanski 2007).

We find beneficial but less consistent effects of the accumulated stock of experience within the industry (Hypothesis 4). From column 8, each additional plant built before the firm builds its plant decreases *time-to-build* by about 0.6 days. With respect to magnitude, a one-standard-deviation increase in prior industry experience expedites the *time-to-build* of future plants by about one month. However, we are careful not to draw strong inferences because the effect becomes insignificant in column 9 with the inclusion of the foreign experience interactions.

In contrast to the above findings, foreign transfer experience (in column 7), although directionally correct, neither adds to model fit nor generates statistically significant results. A likely explanation is that the benefits of foreign experience apply to subsequent foreign investments rather than to ones made in the domestic market. That is, prior foreign experience may reduce the liability of foreignness (Martin and Salomon 2003b). Accordingly, we test the interaction of *foreign facility* by *foreign firm experience*. However, among previous foreign expansions, a distinction can be made between experience in a given host country and experience in other foreign countries (Henisz and Delios 2001). We thus disaggregate the *foreign experience* measure into two components: *country-specific foreign experience* (the cumulative number of plants built by the firm in the same foreign country as the current plant) and *third-country foreign experience* (the cumulative number of plants built by the firm in other foreign countries). This allows us to gauge whether foreign experience provides general benefits that firms can leverage across all foreign markets, or if learning is localized to a given country environment. We find (in column 9) that foreign experience helps decrease *time-to-build* for foreign plants, but only for those plants built in the same foreign country. The results across both interaction terms imply that learning is localized and not applicable across various country contexts. Interpreting the main effect in conjunction with the interactions suggests that first-time foreign implementations in a given country take

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[17] To test for the possibility that many plants being built at the same time tax industry resources, we ran results including the quadratic of rival plants with superior technology. We found a negative and significant main effect ($\beta = -0.32$) and a positive and significant quadratic effect ($\beta = 0.01$). The inflection point is at 16 plants and the effect reaches zero at 32 plants—the upper end of the observed range. This suggests that although firms have an incentive to speed implementation to match rivals, scarce industry resources may have prevented them from doing so when the number of rival plants was in the upper end of its range.

nearly 3 months longer (versus 2.28 months longer for the entire sample). This time-to-build penalty can be overcome, but only in the upper range of observed foreign country-specific transfer experience (3–4 plants).

Overall, the effect of foreign experience is complementary to that of domestic experience; however, insofar as investments in foreign plants replace equivalent domestic investments, the firm foregoes benefits of accumulating domestic experience, and a net liability of foreignness remains (at least in the ranges of experience observed in our data).

Sensitivity and Robustness

As described further in the online appendix, we tested several variants of the above models. First, we assessed the potential for an endogeneity bias via fixed firm effects. We also estimated simultaneous equations to account for the potential endogeneity of facility cost. The results were largely consistent with those presented herein, so our inferences do not change. Second, we examined power-law (ln-ln) and exponential (ln-transformed dependent variable only) specifications, finding slight differences (see the online appendix for details). Third, we discounted the learning measures to assess whether learning was subject to depreciation. Our results were consistent with those presented herein although stronger in economic magnitude, indicating that recent experience provides greater benefits. Finally, we explored model 6 from Table 2 with a quadratic experience effect. We found a U-shaped effect consistent with decreasing returns to experience and, potentially, learning detriments. However, no firm in our sample had invested in enough plants to result in a net performance decrement (i.e., sample firms with many plants still had shorter time-to-build than similar firms absent experience).

Discussion and Conclusions

We find support for hypotheses pertaining to competitive, organizational, and technological determinants of time-to-build. We show that firms indeed build plants faster as the threat of entry by rivals increases (Hypothesis 1). We demonstrate that time-to-build is greater for plants located abroad, indicative of a liability of foreignness (Hypothesis 2). We find that domestic experience can facilitate subsequent foreign and domestic investments, whereas foreign experience can be meaningfully leveraged for subsequent expansions in a given foreign country (both confirming and extending Hypothesis 3). Finally, complex, state-of-the-art technologies take longer to implement (Hypothesis 5), even after controlling for multiple firm, industry, and facility features.

Not all our hypotheses received full support. Although firms seemingly benefit from the collective experience of other industry participants, as time-to-build decreased in the number of plants previously built by other firms in a given country, this effect was not robust across specifications. Hypothesis 4 therefore receives only mixed support.

The findings from this study hold several important implications for management scholars and practitioners. First, this paper makes a contribution to a relatively understudied research area. Although the extant economics, strategy, and knowledge management literatures imply that time-to-build plays a role in overall firm performance, we have little systematic understanding of the factors that affect time-to-build. The results confirm that competitive, organizational, and technological factors all stand to affect the time-to-build fabrication facilities, and it is important to take these effects jointly into account.

Second, our results extend the knowledge transfer literature. Knowledge transfer, deployment, and implementation are integral to getting a facility fully operational, and their role extends beyond the simple construction of a physical facility. Knowledge transfer activities are especially critical during the planning, testing, and ramp-up phases, and in the overall management of the time-to-build process. Moreover, because knowledge transfer is inherent in firm growth and can strongly affect profitability, time-to-build represents a construct of considerable interest to strategy and technology scholars alike.

Third, this study sheds light on the factors that influence speed to market in the semiconductor industry. The context is representative of fast-changing industries where time to market is critical (Schoonhoven et al. 1990). The quicker firms get their plants online, the greater the revenue stream that they are able to generate, and the better they are able to defend competitive positions (McDonald 1998). Consistent with this intuition, we find evidence of significant competitive rivalry. After controlling for the size and cost of the plant, we find that firms build plants faster when more rival plants are coming online with similar, or better, technologies. Ultimately, the time that a firm takes to implement its knowledge will determine its relative speed in exploiting new technologies, penetrating new markets, and countering competition (Chen 1996, Martin and Salomon 2003a).

Finally, the results highlight an important contingency with regard to domestic, versus international, expansion. A significant penalty arises from building facilities in foreign countries. Firms can compensate for this penalty through experience in a given foreign country. However, it is important to recognize that to the extent that building a foreign plant precludes the erection of a similar domestic plant, firms make an important trade-off. Firms may pursue a predominantly domestic strategy and thereby benefit from experience that they can leverage across future investments, domestic or foreign; or a strategy with a substantial country-specific foreign component, gaining compensating advantages for subsequent expansions in that country. This highlights the pros and cons of domestic versus international strategies, and among the latter, of focused versus dispersed foreign expansion (see also Zaheer and Mosakowski 1997). Thus, for international business and international management scholars, estimating time-to-build represents a novel approach to measuring the additional costs associated with international expansion, and highlights the trade-offs that firms face when making such decisions.

For managers, our findings underscore the importance of strategically managing time-to-build, and highlight the potential for firms to develop lasting competitive advantage through time-to-build. Variance in time-to-build translates into real economic consequences for firms. Not only does bringing a plant online faster help preempt competitors, but because the semiconductor industry is characterized by steady product price declines averaging about 30% per year (Smith and Reinertsen 1991, Grimm 1998), each month's delay translates into a ceteris paribus decrement in total revenue over the life of a plant. The exact amount of lost revenue depends on whether the delay occurs during the plant construction (build) stage—thus precluding any sales—or during the ramp-up stage—in which case some compensating sales may occur, albeit subject to the capacity and yield obtained during the additional ramp-up time. Based on the Smith and Reinersten (1991) and Grimm (1998) calculations, and assuming a typical five-year operating life, we estimate a one-month delay at approximately 2.2% of a plant's lifetime revenue.[18]

Using this estimate, and the $1 billion cost of a typical plant, we can predict the economic sensitivity of plant projects to various drivers of time-to-build.[19] The above implies nearly $22 million in lost revenue for each month's delay, or $733,000 per day. These costs are not inconsequential, because by these estimates a firm's first foreign plant results in $65 million in forgone revenue. A 10% deviation in relative feature size results in $8.7 million in forgone revenue. These stylized facts, however, do not imply that firms should avoid building foreign plants or making investments in complex technologies. Rather, firms should factor time-to-build implications into their calculus when making such investments with the understanding that offsetting revenues or cost reductions elsewhere (e.g., from foreign labor and other inputs) will be required to make the investment worthwhile. Firms may also enhance revenues by speeding the process through the pursuit of specific strategies. For example, each plant's worth of domestic transfer experience translates into $5.3 million worth of benefits to subsequent plant investments. Each investment by a firm in a given foreign country results in $20.2 million worth of savings for its subsequent investments in that country, and a firm saves $880,000 with each plant built by other firms in the same country prior to its investment. In addition, each rival plant spurs a firm building a plant simultaneously to speed time-to-build so as to capture $2.7 million in additional revenues. Calculations of this sort are sorely needed, because very few studies address the precise economic impact of strategic factors in this, or other, knowledge-intensive industries (see Bohn and Terwiesch 1999).

This study also highlights a complexity versus yield trade-off specific to the semiconductor industry. Because achieving full-scale production, and thereby yield, is the mandate in this industry, our study underscores the importance of the trade-offs that firms make between implementing more complex technologies and achieving yield targets. Semiconductor firms seemingly trade off greater revenues they may generate by adopting complex technologies for additional costs incurred in the time that it takes to implement those technologies. Our findings for feature size coupled with the average industry price declines suggest instances in which achieving higher yields and ramping up facilities more quickly with a less sophisticated technology might be more profitable than taking a longer time to achieve yield with more sophisticated technologies. The prescription then would be that when making ex ante plant-related decisions, firms should maximize a combination of yield and feature size with time-to-build factored in, rather than considering targets for absolute yield independent of feature size, or feature size independent of time-to-build. These trade-offs augment others identified in the semiconductor production literature (e.g., Terwiesch and Bohn 2001). Whereas the standard problem involves increasing wafer start capacity and ramp-up speed at the expense of yields and vice versa, our results highlight how decisions regarding technological complexity ex ante impose constraints upon the firm ex post—i.e., increase (decrease) the costs (revenues) associated with achieving yield targets.

Limitations and Future Research

At this point, we draw several caveats. First, in this study we discuss the learning benefits associated with

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[18] This estimate allocates a one-month delay equally across building and ramp-up stages, and assumes output during the ramp-up phase to be half of the plant's full capacity. Further details are available from the authors.

[19] These calculations use the following assumptions: The net present value of the plant construction project is $0 (future revenues equal expected costs), the discount rate is 0%, and the plant has a five-year life with no residual value.

time-to-build. Learning, however, is a complex construct. It could simply be that events missing from the analysis that take place concurrently with our measures of learning could be driving the time-to-build results. We have taken steps in the empirical specification to mitigate the possibility that some underlying latent effect of this sort leads firms to both build successive plants and decrease time-to-build. However, we cannot fully rule out that possibility. Thus, although we present evidence consistent with learning, we cannot be sure that these results are a de facto outcome of learning.

Second, with respect to the ramp-up of plants in these data, we record the date on which firms announce that the plant has achieved its stated capacity and target yield. However, yields are not static, and firms may improve yields long after the plant has achieved its stated capacity. Moreover, firms may differ in what they consider "optimal" yield. Because we only observe the date on which the firm announces it has achieved its target yield, and not the actual yield percentage achieved, we are not able to control for such heterogeneity. We therefore acknowledge that our model may not adequately control for yield expectation dynamics. However, when we ran results for time-to-build excluding the ramp-up period (e.g., from announcement to the date operations first began, ignoring the subsequent yield phase), the results did not differ substantially. Therefore, we believe that any error induced with respect to target yield is small. Furthermore, to the extent that firms differ systematically in setting their yield targets, the firm effects help control for that heterogeneity.

Third, as we mentioned earlier, firms subcontract various portions of facility development to construction firms, equipment manufacturers, and other industry suppliers. This raises the possibility that heterogeneity in the extent to which firms rely on subcontractors, and in the performance of those subcontractors, stands to influence time-to-build. Ideally, we would have liked to include information on firm subcontracting behavior; unfortunately, we could find neither detailed nor reliable subcontractor data. To the extent that the number of facilities built proxies for the availability of subcontracting resources, that may help control for this concern. In addition, if firms subcontract consistently to a subset of suppliers over time, the firm effect should control for this unobservable. Still, we acknowledge that it would be relevant to study the role of suppliers and subcontractors in more detail, data permitting.

The aforementioned caveats notwithstanding, our results suggest several additional research extensions. For example, because firm factors systematically influence the implementation process, we may plausibly conclude that firms differ in their capacity to transfer and implement knowledge (Martin and Salomon 2003a). Future research may address to what extent heterogeneous capabilities of this sort affect the time-cost trade-off in deploying new technologies (Mansfield et al. 1982, Dierickx and Cool 1989).

Likewise, because time-to-build encompasses discrete stages (planning, construction, ramp-up), future work could examine the differential impacts on the intervening stages. In addition, because the stages may be sequentially dependent, a fruitful extension could assess the impact of one stage on others. For example, we might plausibly expect thorough implementation during the construction phase to increase efficiency during the ramp-up phase.

Although we did not find any impact of joint ventures on time-to-build, future research should revisit the impact of partner selection. To the extent that there are strong complementarities among joint venture partners, we might expect to find a strong selection effect. Joint venture benefits may also be contingent on a communication-enhancing relationship history and on stable operating conditions (Kotabe et al. 2003, Krishnan et al. 2006). Therefore, joint ventures deserve ongoing attention with respect to knowledge transfer and firm strategy (Martin and Salomon 2003b, Ingram and Simons 2002).

Finally, future research could examine how time-to-build affects corporate-level performance. Because plant investments represent substantial capital outlays, effectiveness in knowledge transfer is likely to have a significant impact on overall performance. On the whole, given the operational and strategic importance of time-to-build in many industries, further research in this area is well warranted.

Electronic Companion

An electronic companion to this paper is available as part of the online version that can be found at http://mansci.journal.informs.org/.

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