Tacitness, Learning, and International Expansion: A Study of Foreign Direct Investment in a Knowledge-Intensive Industry

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Abstract

This paper examines the impact of knowledge tacitness on a firm's propensity to establish plants in foreign rather than domestic locations. Our predictions build on knowledge-based, internalization, and evolutionary theories of foreign direct investment. We argue that the tacitness of technology has an inverted-U effect on the propensity to undertake foreign investment. We also expect that as a firm learns about a technology, it will become more likely to make foreign investments. We examine two forms of learning: that which accumulates as a function of the number of plants previously built by the firm (transfer-based learning), and that which accumulates as a function of time since the firm started using a technology (time-based learning). We investigate empirical effects in a sample of investments in the memory segment of the semiconductor industry. Our predictions about the curvilinear effect of tacitness are supported. The results also suggest that learning is a matter of taking time to become acquainted with the use of the technology, and of gaining experience through successive foreign plant investments. The study adds to the understanding of the effects of knowledge on corporate expansion.

(*Knowledge-Based*; *Foreign Direct Investment*; *Tacit Knowledge*; *Learning*; *Experience*; *Corporate Expansion*; *International*)

Research in international management emphasizes that the characteristics of the knowledge employed by a firm play a crucial role in its foreign expansion. However, some ambiguity remains as to the conditions under which knowledge-based assets should encourage a firm to invest abroad. One widely held perspective, internalization theory, holds that knowledge-based assets possess the greatest potential to support investments abroad because, relative to other assets, a firm's knowledge can be replicated easily in multiple locations (Buckley and Casson 1976, Caves 1996). However, the possession of knowledge-based assets does not by itself guarantee that a firm will be able to exploit these assets in foreign operations. Before knowledge can be exploited abroad, firms must overcome the obstacles to its transfer. Recent work from an evolutionary perspective suggests that the tacitness of knowledge places major constraints on the extent to which it can be transferred abroad (Kogut and Zander 1993, 1995). Interestingly, we know little about how tacit knowledge influences a firm's propensity to make foreign investments.

Prior literature also points out that organizational learning can affect a firm's propensity to transfer knowledge abroad (Teece 1977, Nelson and Winter 1982). As a firm learns about a given technology over time, and with repeated transfers of the technology, it should become more likely to leverage that knowledge abroad. However, research has yet to comprehensively examine how these forms of learning affect foreign investment.

To fill these gaps, this paper develops and tests theory about the effects of a firm's knowledge on its propensity to invest abroad rather than domestically. Accordingly, the dependent variable of interest is the establishment of a wholly or partly owned production facility by a firm in a foreign location (rather than a domestic location). This outcome represents foreign direct investment.[1] We seek (1) to examine the effects of knowledge tacitness on foreign direct investment and thereby to resolve some ambiguity in the existing literature as to the extent to which tacit knowledge encourages and/or discourages foreign direct investment, and (2) to examine what forms of organizational learning promote foreign direct investment. The analysis focuses on technology, but is generally applicable to other types of knowledge-based assets.

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Knowledge and Foreign Direct Investment

Knowledge is a fundamental concern to researchers investigating how firms (and national economies) grow. International growth requires not only the accumulation and creation of new knowledge, but also the replication of existing knowledge in multiple locations (Penrose 1959, Rugman and Verbeke 2002). Building on that idea, the internalization theory of international investment argues that firms can undertake foreign direct investment by exploiting the knowledge-based assets available to them (Buckley and Casson 1976, Caves 1996). That is because knowledge-based assets, unlike physical or financial assets, have a public-good characteristic such that they can be replicated and shared among several facilities without incurring the full costs of recreating the asset with every transfer. Successful multinational corporations expand by replicating accumulated knowledge-based assets in foreign locations, using these assets to outcompete rivals in successive locations (Mitchell et al. 1992, Morck and Yeung 1992). From this perspective then, accumulated knowledge-based assets increase the likelihood of foreign direct investment.

However, scholars have pointed out that replication in foreign locations cannot be taken for granted, even for firms whose domestic operations have accumulated significant knowledge-based assets (see Hennart 1982). Specifically, Teece (1977, 1981) and Kogut and Zander (1992, 1993, 1995) have advanced an "evolutionary" perspective of the multinational firm. They posited that the extent and manner in which a firm may expand internationally depends upon the tacitness of its knowledge-based assets. Tacitness is a feature of knowledge that requires "the observance of a set of rules which are not known as such" to those following them (Polanyi 1958, p. 49). Tacit knowledge is that which is not amenable to well-articulated representation (Winter 1987, Wright 1997).

Tacitness, it turns out, makes knowledge both particularly suitable and particularly problematic for international investment. On the one hand, the buildup of tacitness is inherent in the accumulation of the organizational know-how that underpins technology and other knowledge-based assets (Nelson and Winter 1982, Cowan and Foray 1997, Dosi 1988). Furthermore, tacitness protects knowledge against imitation by rival firms and therefore ensures that it remains effective against rivals in various locations (e.g., Dierickx and Cool 1989, Saviotti 1998). Thus, in accordance with internalization logic, the tacitness of technological knowledge should be positively associated with the propensity for a firm to expand abroad (Teece 1981, Martin and Salomon 2003).

Yet knowledge, when not embodied in well-defined physical artifacts, can be very difficult to replicate accurately (Nelson and Winter 1982). At a certain point, tacitness stands to substantially increase the difficulty of transferring technology, especially across national boundaries. The initial fixed cost of transfer rises with tacitness (Teece 1977, Argote 1999). Furthermore, the obstacles to transfer increase more than proportionately as tacitness increases and its sources get compounded (Dosi 1988, Simonin 1999).

This stands to affect the desirability of transferring a given production technology to a foreign facility. The more tacit the technology, the greater the additional costs incurred in a foreign location relative to a domestic location (Teece 1977, 1981). Under these conditions, exporting the output of domestic plants becomes more attractive relative to transferring the production technology across borders. Thus, high levels of tacitness encourage domestic rather than foreign investment.

Taken together, the aforementioned arguments suggest that the aggregate relationship between tacitness and a firm's propensity to engage in foreign direct investment will be nonmonotonic. There is a positive relationship between tacitness and foreign direct investment at relatively low levels of tacitness. However, if tacitness is above some level, it renders international technology transfer uneconomical and thus discourages foreign direct investment in a marginally increasing way. Therefore, we predict that the impact of technology tacitness on foreign direct investment will have an inverted-U shape.

HYPOTHESIS 1. *The likelihood that a firm will select a foreign rather than a domestic location for a new investment has an inverted-*U *shaped relationship with the tacitness of the technology.*

Another knowledge factor relevant to foreign direct investment is organizational learning. Broadly defined, "organizational learning means the process of improving actions through better knowledge and understanding" (Fiol and Lyles 1985, p. 803). While past foreign direct investment research has suggested that learning may matter, it has not comprehensively examined the range of learning effects that is relevant to effective knowledge transfer. We propose that two forms of learning can be helpful in harnessing technologies and other types of knowledge-based assets (see Nelson and Winter 1982, Levin 2000). The first is experiential learning that accrues as firms repeatedly engage in an activity. In our setting, the relevant experience is with prior technology transfers; therefore, we refer to this as transfer-based learning. The second form of learning is time-based.

This pertains to the fact that, as a firm uses a technology over time (even absent repeated transfers), it may gain insight into how to deploy and transfer the technology.

While both forms of learning may occur simultaneously, they represent conceptually separate effects. Transfer-based experience is a matter of learning-by-doing that develops routines for transfer, while time-based learning is a matter of gaining an introspective understanding of the technology in a process akin to learning-before-doing (Nelson and Winter 1982, Argote 1999).[2] Empirical studies have also shown these effects to be separate (see Argote 1999). For example, a recent study by Levin (2000) showed that time and experience have independent effects on quality improvement in the automotive industry.

Of the two forms of learning, transfer-based has received more attention. Past transfers develop a "discipline of practice" that creates more efficient replication routines (Nelson and Winter 1982, p. 77). This lowers the cost of transferring technology and renders foreign investment more suitable relative to domestic investment (Teece 1981, Martin and Salomon 2003). Experience acquired from previous transfers may thus be associated with a greater propensity to locate investments abroad (Yu 1990).

HYPOTHESIS 2. *The likelihood that a firm will select a foreign rather than a domestic location for a new investment increases with the number of times that the firm has made an investment using similar technology in the past.*

Time-based learning also stands to affect foreign direct investment. Practically, organizations learn by turning inferences from history into routines that guide future behavior (Levitt and March 1988). Thus, "a firm with an established routine possesses resources on which it can draw very helpfully in the difficult task of attempting to apply that routine on a larger scale" (Nelson and Winter 1982, p. 119). The longer a firm employs a technology, the more familiar it stands to become with the conditions for its use (Cowan and Foray 1997). Empirically, Teece (1977) and Galbraith (1990) reported that the costs of technology transfer decreased as a function of the time elapsed since the transferor started using a technology. This, in turn, should encourage foreign direct investment (Teece 1981, Martin and Salomon 2003).

HYPOTHESIS 3. *The likelihood that a firm will select a foreign rather than a domestic location for a new investment increases with time since the firm first implemented a similar technology.*

Research Design

Sample

An industry characterized by knowledge-intensive processes is most suitable for testing our hypotheses. We study the semiconductor manufacturing industry, as it possesses several advantages toward that purpose. First, there is intense competition over knowledge-based proprietary assets (Eisenhardt and Schoonhoven 1996, Wright 1997). Second, it is a fast-paced industry with frequent innovations (Methé 1992). Third, the industry has a global scope. Products are easily exported across borders and plant location is not tied to a local product market. Third, products, processes, and plant investments can be reliably documented and compared. Consistent with the industry's high technological intensity, we focus the analysis on the technological knowledge associated with semiconductor production processes.[3]

To collect data about individual investments in the semiconductor manufacturing industry, we started with the list of plants in the *International Fabs on Disk* database. This authoritative source of plant-level data provides information from primary sources on facility purpose, year the plant became operational, end product features, manufacturing processes employed, and nationality of the principal parent firm(s). The database includes information on 920 semiconductor plants as of Fall 1999. We limited our sample to plants that manufacture memory products, commonly called RAM. Previous studies have identified this subset as a homogeneous product-market amenable to rigorous technology comparisons (e.g., Eisenhardt and Schoonhoven 1996, Malerba 1985). The restriction to memory plants yielded a list of 385 facilities. From this list we excluded 35 Taiwanese plants that are part of a unique government-sponsored system of industrial parks. The foreign direct investment status of those facilities exhibited no variance due to their ownership. Seven cases were lost due to missing data. The resulting intermediate list included 346 plants, all built since 1970.

The learning-related variables of interest in this paper are features of parent companies rather than individual plants. Therefore, we identified and coded each plant's parent(s) and levels of ownership. An extensive electronic search of standard sources, published industry reports, and press releases was conducted to identify each plant's corporate affiliation (e.g., *Directory of Corporate Affiliations, Electronic News, Asia Business News*, and *The Wall Street Journal)*. Of the plants in the sample, 308 have a single owner. There are 38 joint ventures; of these, 36 have exactly two parent firms and two have three separate parents. In joint ventures, the dependent variable (foreign direct investment) and some of the independent variables of interest (accumulated learning) may differ across parents. Therefore, we created distinct records for each parent.[4] This yielded our final sample of 386 observations $(308+36*2+2*3)$ from 84 unique parents. Characteristics of the 84 parents stand to affect the decision to locate a plant domestically or abroad. Thus, we use these parent company identities as the basis for measures of learning and as a locus of statistical control.

Measures

Foreign Direct Investment (Dependent Variable). Our dependent variable measures whether a substantive investment is made in a foreign location (foreign direct investment) or in the parent company's home country (domestic investment). The accepted 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, Graham and Krugman 1995, Vukmanic et al. 1985). For consistency, we used the same 10% cutoff to identify domestic investments. Thus, we coded as domestic investments those instances where a firm held a share of at least 10% in a plant in its home country, and as foreign investments those where a firm held a share of at least 10% in a plant in another country.[5] Out of the 386 observations in the sample, 102 are foreign direct investments. The dependent variable Foreign Direct Investment takes a value of 1, while it takes a value of 0 for the 284 domestic direct investments.[6]

Tacitness

Kogut and Zander (1993) identified noncodifiability, complexity, and nonteachability as determinants of tacitness. For variance, their empirical research relied on a cross-sectional sample from a variety of industries. By contrast, we seek to understand the effect of tacitness as it varies in a single, precisely defined industry. Accordingly, we use an industry-specific measure of tacitness that can be reliably tracked over time.

The most commonly used technological indicator in the industry is feature size. 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. Accordingly, firms compete on the basis of their ability to produce semiconductors with ever-thinner features (Eisenhardt and Schoonhoven 1996, Malerba 1985, Schoonhoven et al. 1990). To do so, they must regularly develop ever more sophisticated manufacturing procedures and invest in ever more expensive equipment. That is because with each reduction in feature size, a new set of tools must be used to etch the chips. Most importantly, at certain break points associated with the wavelength of the light used to do the etching, new equipment must be added and new combinations of technical solutions must be implemented.

Reducing feature size requires extensive product and process development efforts (Malerba 1985, United Nations 1986, Wright 1997). As feature size decreases, increasingly more sophisticated printing processes become required (Henderson and Clark 1990). As the industry evolves, progress in miniaturization relies on the accumulation of tacit organization-level knowledge (Balconi 2002, Malerba 1985). Based on interviews of senior executives, Eisenhardt and Schoonhoven (1996, p. 143) identify feature size reduction as "the fundamental technical challenge within the industry." Table 1 shows how four successive generations of technologies were developed during the study period, allowing industry leaders to shrink feature size from 3 microns to 0.12 micron. With each new technology the combination of mask design, light source, optical device, and aligner becomes more complex and the underlying integrative know-how becomes less widely articulated (Henderson 1993, 1995).

In general, as firms push the frontiers of the technology within and across successive product generations, the knowledge they develop becomes more abstract and more difficult to convey (Nelson and Winter 1982). Codifiability and teachability decrease while complexity

Table 1 Generations of Semiconductor Technology

Lithography Technique (Generation)*	Feature Size Range (in microns)*	Year First Introduced	Median Introduction Year
Photo Contact and Projection Printing (1)	10–2	1970	1984
Direct Step-On-Wafer (2)	2–1	1976	1989
Mid Ultraviolet Stepper (3)	1–0.5	1981	1994**
Deep Ultraviolet Stepper (4)	0.5–0.1	1984	1996***

Note.

*Source: Adapted from United Nations 1986, Malerba 1985, Henderson 1993, and Quirk and Serda 2001. The feature sizes indicated reflect typical manufacturing practice. Our research design allows for the decline in feature size as process improvements move the technology closer to the theoretically feasible minimum.

**A few plants incorporating this generation of technology were still being built as of the end of the study period.

***Many plants incorporating this generation of technology were still being built as of the end of the study period.

increases. Tacitness that spills from product specifications to process requirements creates particularly strong obstacles to intrafirm transmission (Grant 1996). This is precisely what has been happening in the semiconductor industry (see Eisenhardt and Schoonhoven 1996, Malerba 1985, Methé 1992, Wright 1997).

Furthermore, as feature size approaches but cannot reach zero, achieving a given absolute reduction in feature size requires ever more knowledge. The sophistication and replication difficulty of the knowledge employed in the semiconductor industry increases more than proportionately to the reductions in feature size that the knowledge allows (Malerba 1985, United Nations 1986, Wright 1997). MacDonald (1998) describes how the cost and difficulty of transferring the underlying know-how between plants rose dramatically due to the complication and multiplicity of system interactions with smaller feature sizes. Moore (1997) reports that as feature size decreases, the depth and diversity of knowledge required overtake the ability of individuals and even entire teams to master and communicate basic know-how. Sweeney (1999) shows that the number of checks and trials required before a process becomes operational increases at least proportionately to the decrease in feature size because "knowability" of the process declines. Henderson (1995) describes how increasingly tacit knowledge accumulated among manufacturers as overall technology advanced, sometimes hindering further improvement.

The feature size of the semiconductors to be manufactured at a plant therefore serves as the basis for developing a measure of knowledge tacitness in the industry. This information is reported in *International Fabs on Disk*. Two issues arise in coding our tacitness measure, however. First, we need to transform this variable to acknowledge that tacitness varies more than proportionately with feature size. Second, an increase in tacitness corresponds to a *decrease* in feature size. Given that we predict a nonmonotonic effect of tacitness on foreign direct investment, we need to recode our measure so that increases in our measure can be interpreted as increases in tacitness. We address both issues by taking the inverse of the feature size of a plant's output. This transformation is consistent with the convergence of feature size towards an asymptotic minimum, with each absolute increment requiring ever more knowledge accumulation (Henderson 1993, Sweeney 1999). We refer to this measure of knowledge tacitness as feature-size-based and label it Feature Size Index.[7]

Learning Variables

Consistent with our hypotheses, we measure two forms of firm-level learning: transfer-based learning and time-based learning. An assessment of either form must take into account the extent to which past learning will be relevant to a current project (Argote 1999). This will depend on the comparability of the knowledge being deployed in current and past projects. Because successive generations of technology bring about additional knowledge requirements, learning may occur primarily by reference to generations of technology, rather than to the product-market as a whole (Henderson and Clark 1990, Martin and Mitchell 1998, Cabral and Leiblein 2001).

The four generations of technologies described in Table 1 serve as the basis for measuring learning. Henderson (1993, 1995) argues that each generation brings about new combinations of component techniques and suppliers (e.g., mask design, light source, optical device, alignment mechanism) that render prior learning insufficient and thus require new learning. The learning process effectively restarts with each generation (Crawford 1997, Henderson and Clark 1990). Thus, we classified each plant into one of the four categories. We used plant information published in the trade press in conjunction with feature-size data from our main data source and the sources cited in Table 1 to identify the generation of process technology employed by each plant.[8]

Transfer-based learning accumulates as a firm builds successive facilities. This form of learning-by-doing allows the parent firm to gain experience with the issues involved in transferring the manufacturing technology. Thus, we counted the number of plants previously built by the parent company using the same generation of technology as the investment of interest (see Teece 1977). Because domestic and foreign experience may influence foreign expansion differently, we computed two experience variables. The first counts previous investments made by the firm in its home country. The second counts the firm's previous investments abroad. We refer to these measures as Number of Prior Domestic Transfers and Number of Prior Foreign Transfers, respectively.

By contrast, time-based learning refers to the opportunities to explore and assimilate the knowledge that develops as the firm continuously employs a given technology. This form of learning pertains to opportunities to experiment with the technology and its uses over time, independent of the number of facilities in which it is implemented. We measure this as the number of years that have elapsed since the parent firm first built a plant using the same generation of technology. For the first plant of a given generation, a value of 0 is assigned. This specification is the same as in Teece (1977) and Galbraith (1990). We label this measure Years Since First Use.[9]

Control Variables

Although this paper focuses on the effects of knowledge characteristics on foreign investment, we control for other variables that have the potential to influence the foreign direct investment decision. Following the international business literature, we control for two important factor conditions and for market size (Barrell and Pain 1996, Caves 1996). Among input factors, one possible influence is labor costs. We measure labor costs using hourly manufacturing compensation costs in the firm's home country, measured in real U.S. dollars (from Bureau of Labor Statistics, "International Comparisons of Hourly Compensation Costs for Production Workers in Manufacturing"). All else equal, high labor-cost countries may be less attractive for investment. Thus, if labor costs influence the foreign direct investment decision in our sample, this variable should be positive as high domestic labor costs encourage foreign investment over domestic investment.

Another potential input-factor effect pertains to the capital requirements associated with plant scale. All else equal, an increase in the size (and cost) of efficient plants reduces the number of plants that get built. Brainard (1997) suggested that this could reduce foreign direct investment. We measure changing scale requirements in the industry by the average size of plants built in an observation year (other than the focal plant), expressed in thousands of wafers per month. We label this as the Average New-Plant Scale. Meanwhile, everything else equal, growth in demand creates room for new plants, which may favor foreign direct investment. We measure Market Demand as annual worldwide sales, in billions of real dollars (from the Semiconductor Industry Association, "Global Shipments Report").[10]

We also include controls that are particularly applicable to this industry. We control for whether a firm is based in one of the three dominant countries in the industry: the United States, Japan, and South Korea. Most investments are made in these three countries (25%, 47%, and 9%, respectively). Firms in these industry-leading countries may be comparatively less prone to invest abroad.[11] Thus, we created three country-of-origin dummy variables to indicate United States, Japanese, and Korean firms. In addition, we control for whether the plant investment is a foundry. Foundries are specialized plants that manufacture other firms' designs. This arrangement may facilitate foreign direct investment. The variable Foundry was coded as 1 if the plant in question was a foundry facility, and 0 otherwise.

Statistical Methods

In addition to the above control variables, we use statistical means to address potential unobserved firm effects that may affect foreign direct investment decisions. Each parent company, for reasons not fully observable, may have a different propensity toward foreign direct investment. If a firm has several plants, it is possible that the error term will not be independent across these observations. In theory, either a fixed-effects or a random-effects model may be used to correct for this (Greene 2000). However, in our data, 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, a random-effects model is preferred (Kennedy 1998). Furthermore, a Hausman test conducted on the subset where fixed effects can be estimated (see Greene 1995) unambiguously shows that random effects describe the data better than fixed effects ($\chi^2 = 7.70, p = 0.36$). Accordingly, and given that our dependent variable is binary, we employ a random-effects probit. The random-effects specification effectively controls for a full range of unobserved parent-company effects and is appropriate when studying foreign direct investment (Caves 1996, Greene 2000).

Estimates resulting from the random-effects probit model are a direct monotonic but nonlinear function of the underlying variables. A positive coefficient indicates that the variable in question has a positive effect on a parent firm's propensity to make foreign rather than domestic investments. Nested models can be compared by the χ^2 test.

Results

Descriptive statistics and pairwise correlations are presented in Table 2. The positive correlations between Foreign Direct Investment and Number of Prior Foreign Transfers, and between Foreign Direct Investment and Years Since First Use, are consistent with our hypotheses. However, Number of Prior Domestic Transfers is negatively correlated with Foreign Direct Investment. Other correlations are generally as expected. The correlations between Year Since First Use and Number of Prior Domestic Transfers, and to a lesser extent Number of Prior Foreign Transfers, follow from the fact that these learning mechanisms unfold in parallel. Multicollinearity statistics for these variables, and for the

Table 2 Descriptive Statistics and Product Moment Correlations ($N = 386$)

	Mean	Std. error	1	2	3	4	5	6	7	8	9	10	11	12
1. Foreign Direct Investment (dependent variable)	0.26	0.44	1.000											
2. Feature Size Index (tacitness)	2.53	1.46	0.027	1.000										
3. No. of Prior Domestic Transfers (domestic transfer-based learning)	2.48	3.26	−0.051	0.182	1.000									
4. No. of Prior Foreign Transfers (foreign transfer-based learning)	0.81	1.70	0.240	0.074	0.205	1.000								
5. Years Since First Use (time-based learning)	3.88	4.66	0.136	0.134	0.532	0.387	1.000							
6. U.S. Parent	0.28	0.45	0.128	0.031	−0.103	0.197	−0.057	1.000						
7. Japanese Parent	0.48	0.50	−0.290	−0.017	0.260	−0.202	0.170	−0.591	1.000					
8. Korean Parent	0.09	0.29	−0.107	0.057	−0.008	−0.115	−0.085	−0.196	−0.301	1.000				
9. Foundry	0.08	0.26	0.230	0.019	−0.127	0.087	−0.088	0.065	−0.233	−0.090	1.000			
10. Labor Costs	13.60	6.13	0.138	0.199	0.256	0.152	0.287	0.182	0.170	−0.334	−0.160	1.000		
11. Average New-Plant Scale	16.5	2.13	0.032	0.065	0.121	0.068	0.119	−0.031	−0.003	0.025	0.025	0.045	1.000	
12. Market Demand	80.55	54.38	0.133	0.304	0.218	0.213	0.267	0.001	0.183	0.304	0.318	0.249	0.246	1.000

Table 3 Effects of Tacitness and Learning on Foreign Direct Investment Propensity: Probit Regression Estimates with Parent-Firm Random Effects

Model	1	2	3	4	5	6	7	8	Prediction
Feature Size Index		−0.027	0.577**	0.551**	0.532**	0.528**	0.646***	0.573**	+ (H1)
		(0.078)	(0.236)	(0.243)	(0.258)	(0.260)	(0.247)	(0.272)	
Feature Size Index, Squared			−0.090***	−0.085***	−0.087***	−0.076***	−0.091***	−0.085***	− (H1)
			(0.030)	(0.031)	(0.032)	(0.033)	(0.030)	(0.033)	
No. of Prior Domestic Transfers				0.081		0.020		−0.073	+ (H2)
				(0.068)		(0.079)		(0.051)	
No. of Prior Foreign Transfers					0.302***	0.292***		0.234**	+ (H2)
					(0.083)	(0.111)		(0.118)	
Years Since First Use							0.070***	0.073**	+ (H3)
							(0.021)	(0.033)	
U.S. Parent	−0.929***	−0.942***	−0.922***	−0.973***	−0.861***	−0.873***	−0.955***	−0.844***	
	(0.334)	(0.343)	(0.321)	(0.342)	(0.288)	(0.294)	(0.329)	(0.289)	
Japanese Parent	−1.58***	−1.59***	−1.61***	−1.71***	−1.47***	−1.50***	−1.72***	−1.49***	
	(0.467)	(0.476)	(0.472)	(0.506)	(0.406)	(0.427)	(0.487)	(0.424)	
Korean Parent	−1.42	−1.40	−1.52	−1.61	−1.36	−1.39	−1.57	−1.35	
	(3.33)	(3.61)	(3.94)	(5.40)	(2.64)	(3.10)	(6.86)	(3.80)	
Foundry	0.525	0.531	0.444	0.463	0.428	0.430	0.556	0.524	
	(0.351)	(0.358)	(0.362)	(0.388)	(0.349)	(0.355)	(0.375)	(0.366)	
Labor Costs in Home Country	0.005	0.006	0.004	0.002	0.006	0.006	0.005	0.008	
	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	
Average New-Plant Scale	0.005	0.004	0.023	0.023	0.018	0.018	0.024	0.020	
	(0.064)	(0.065)	(0.069)	(0.079)	(0.063)	(0.066)	(0.075)	(0.063)	
Market Demand	0.024	0.027	0.016	0.010	0.001	0.000	−0.010	−0.011	
	(0.017)	(0.020)	(0.021)	(0.023)	(0.020)	(0.021)	(0.023)	(0.021)	
Constant	−1.94	−2.10	−2.22	−1.74	−1.07	−0.991	−0.567	−0.392	
	(1.37)	(1.65)	(1.71)	(1.72)	(1.50)	(1.51)	(1.79)	(1.57)	
Rho	0.399***	0.415***	0.371***	0.408***	0.245*	0.257*	0.359***	0.234*	
	(0.115)	(0.123)	(0.122)	(0.126)	(0.135)	(0.137)	(0.126)	(0.138)	
N	386	386	386	386	386	386	386	386	
Model χ^2	80.05***	80.17***	87.37***	89.47***	98.34***	98.46***	98.31***	103.66***	
(d.f.)	(8)	(9)	(10)	(11)	(11)	(12)	(11)	(13)	

Choice between foreign and domestic investment: Dependent variable = 1 if Foreign Direct Investment.
Values in parentheses are standard errors; *p*-values: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.10$ (all two-tailed).

model as a whole, were satisfactory. Nevertheless, we include the learning variables hierarchically to verify that our regression results are robust.

The multivariate regression results are presented in Table 3. All eight models have highly significant χ^2 statistics, showing that the sets of variables included have strong explanatory power relative to a model limited to the intercept. The rho statistic, an indicator of the existence of parent-firm effects, is significant. This further validates that a random-effects specification is proper for our data (Greene 1995).

Model 1 reports a base model of control variables. These results confirm the value of controlling for country of origin among firms with the largest home industries, especially the United States and Japan, whose firms are less prone to undertake foreign direct investment. The other controls exhibit positive but nonsignificant effects. This suggests that labor costs, scale requirements, and market demand do not much affect the likelihood that a plant will be located abroad. Such results are consistent with prior findings that exogenous market factors make relatively little difference to the foreign direct investment decision once firm effects are taken into account (e.g., Buckley and Casson 1976, Caves 1996).

Models 2 and 3 incorporate the Feature Size Index measuring tacitness. Model 2 includes a main effect only, while Model 3 adds a quadratic term to test the nonmonotonic pattern predicted in Hypothesis 1. Model 2 allows us to test for the monotonicity that might arise if the feature size index were spuriously associated with effects implied by models of the one-way transition from domestic to international production such as Vernon's (1966) product life cycle. In Model 2, the main effect of the feature size index alone is small and statistically insignificant. This is compatible with our expectation that the effect of the Feature Size Index is nonmonotonic. Indeed, when we add a quadratic term in Model 3, the model fit improves substantially; the χ^2 increment of 7.32 for two additional variables is significant at $p < 0.05$ relative to Model 1. The significant positive main effect and negative quadratic indicate that the propensity of a firm to locate a plant abroad increases up to a point, and then decreases as a function of the tacitness of the technology that the plant will use. It is consistent with Hypothesis 1.

Model 4 incorporates the effect of Number of Previous Domestic Transfers. That effect is not statistically significant. By contrast, the effect of Number of Previous Foreign Transfers, as reported in Model 5, is significant and positive. This pattern is confirmed in Model 6, where only Number of Previous Foreign Transfers is significant when the variables are included together. Thus, Hypothesis 2 is supported for foreign transfer experience only. Furthermore, adding the foreign transfer-based learning variable improves the model χ^2 significantly (increment of 8.99 relative to Model 4), but adding the domestic variable does not (increment of 0.12 relative to Model 5).

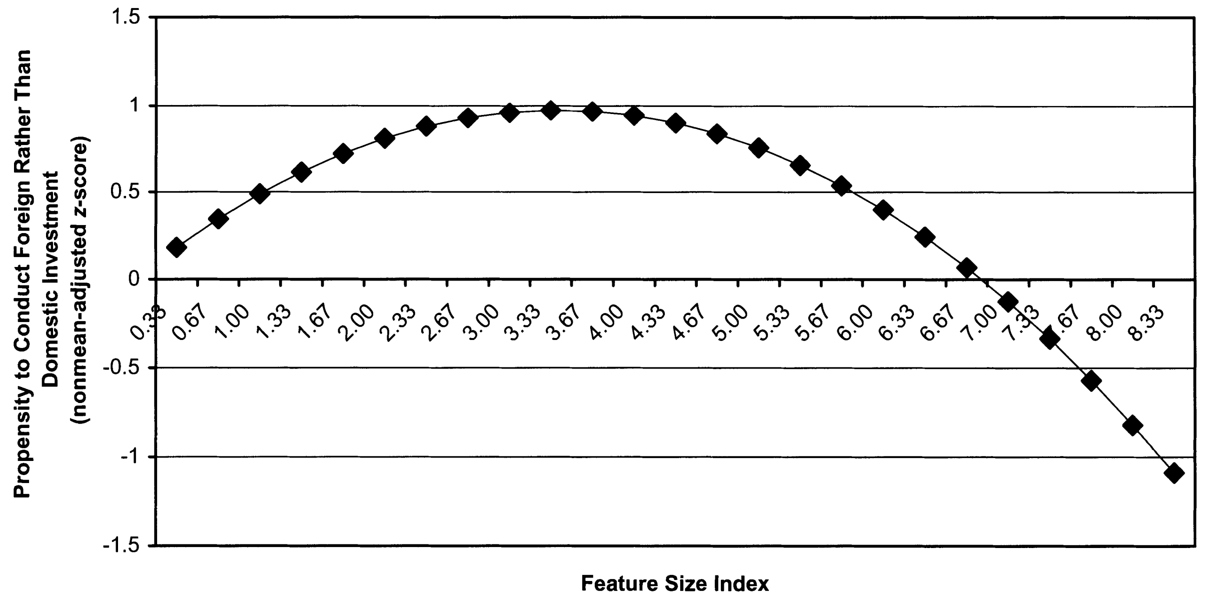
In Model 7, the measure of time-based learning is added to the equation. Years Since First Use has a positive and significant effect on Foreign Direct Investment. This effect remains, as does that of Number of Previous Foreign Transfers, when the three learning variables are included together in Model 8. Thus, Hypothesis 3 is supported. The hierarchical analysis shows that time- and transfer-based learning have separate effects. Years Since First Use adds significantly to the model fit when it is added to the measures of transfer-based learning (χ^2 increment of 5.19 relative to Model 6), and Number of Previous Foreign Transfers significantly increases the χ^2 even after controlling for Years Since First Use (increment of 4.64 relative to a model including the other two learning variables). Computation of the marginal effects shows that adding one plant's worth of experience with foreign direct investment increases the probability of a future foreign direct investment by 4.79%, and adding one year to the firm's familiarity with the technology increases the probability of foreign direct investment by 1.44%.

Figure 1 provides a graphical representation of the nonmonotonic effect of the Feature Size Index based on the coefficients of Model 8. Foreign direct investment propensity is quite low at the lowest levels of the Feature Size Index and increases up to a certain level of tacitness. It decreases beyond that level, reaching its lowest value at the highest index levels observed in our data. This suggests that the most tacit technology raises the strongest obstacles to foreign direct investment.

Additional Analysis and Robustness

We investigated several variants of the models described above to assess the robustness of our results. First, we

Figure 1 Effect of Feature-Size-Based Index of Tacitness on Foreign Direct Investment Propensity



replicated the analyses while limiting the data to the first 14 years of each generation of technology. By truncating of each generation in the same way as the most recently introduced, this approach addresses the possibility that our results are an artifact of some propensity to build domestic plants of each generation before foreign ones. The reanalysis confirmed the inverted-U effect of the feature size index, thus showing that our results are not due to uneven truncation and that a monotonic specification does not properly represent the foreign direct investment behavior in our sample. We also confirmed Hypothesis 1 when splitting the sample at the median of the feature size index, and again while splitting at the maximum value of the observed effect reported in Figure 1. We found the effect of Feature Size Index to be positive below the median, and negative above it.

Second, we replaced the measures of transfer- and time-based learning with measures that incorporate the firm's entire history in the industry, regardless of technology generation. The results were consistent with those reported above but slightly weaker, suggesting that our specification of the learning variables is more suitable in this industry. Other effects remained similar to those reported above.

Third, we subjected our tacitness measure to further examination. We replicated our results with various versions of the feature size variable, including some without inversion and some with logarithmic or reverse-logarithmic transformation. While significance levels dropped slightly in some cases, the results were qualitatively similar.

Finally, we examined interaction effects that would occur if learning were to moderate the effects of tacitness. We used linear, curvilinear, and split-sample approaches consistent with the nonmonotonic effect of the feature size index. We found no significant interaction effect in this analysis, regardless of the learning variable used. These results are consistent with earlier findings whereby learning acts independently of tacitness (see Simonin 1999).

Discussion

We find consistent support for our prediction of an inverted-U relationship between tacitness and foreign direct investment. Our measure of tacitness, while relatively simple, conforms to widely accepted notions of how knowledge has evolved in the industry we study. One might ask whether our feature-size-based variable incidentally captures the overall knowledge intensity associated with the technology, rather than its tacitness. If that were the case, however, we would not find a nonmonotonic pattern whereby foreign direct investment relates negatively with the index beyond some level (see Caves 1996, Morck and Yeung 1992). Indeed, herein lies one of the main implications of our results.

Our results extend existing research on the multinational corporation by describing how tacitness can limit a firm's ability to leverage knowledge-based assets. Because tacitness raises transfer costs, it may render the international implementation of some knowledge-based assets uneconomical. These results are broadly consistent with one of the fundamental ideas advanced by Kogut and Zander (1992, 1993, 1995): If multinational corporations are devices for the creation and replication of knowledge-based assets across national boundaries, then it is important to recognize that tacitness places a constraint on their scope. Practically, our results imply that opportunities for capturing foreign markets (Buckley and Casson 1976) must be tempered by tacitness considerations and their impacts on knowledge transfer.

We also examined how transfer- and time-based forms of organizational learning affect foreign direct investment. We found that experience with prior foreign transfers significantly promotes foreign direct investment. However, experience with domestic transfers did not make a substantial difference. Decomposing transfer experience this way is informative because foreign transfer-based learning pertains jointly to the process of technology transfer and to the challenges of operating in a foreign environment (Yu 1990), while domestic transfer-based learning is limited to deploying the technology in a constant home environment. From this standpoint, the results show that learning about the foreign dimension of transfer matters more than learning solely about the domestic process of technology transfer.

The results also suggest that time-based learning about the technology matters, even after controlling for transfer-based experience. This points to the relevance of introspective learning as it pertains to knowledge transfer (Nelson and Winter 1982). This effect had not received attention in the previous literature on foreign direct investment, even though previous studies recognize that mechanisms for learning about particular technologies represent an important avenue for international research (Teece 1981; Kogut and Zander 1993, 1995). Generally, our result is consistent with arguments that emphasize the time-bound nature of learning about technology (e.g., Cowan and Foray 1997, Dasgupta and David 1994, Mansfield et al. 1982, Nelson and Winter 1982).

Our results can also be examined in the context of Vernon's (1966) product-life-cycle hypothesis. Vernon argued that firms from innovative countries would tend to manufacture domestically at first, and to wait to conduct foreign direct investment until the market grew sufficiently. Assuming steady growth in international demand, the resulting delay of foreign, relative to domestic, investment may suggest a pattern similar to that found for our time-based learning variable. However, closer examination shows that a learning explanation better describes our empirical results than the product-life-cycle hypothesis does. The measure of market demand is nonsignificant, disconfirming Vernon's (1966) main prediction. By contrast, the variable more directly associated with time-based learning, Years Since First Use, is significant. This suggests that learning is a more suitable interpretation of our results than is the demand explanation associated with the product-life-cycle model—at least in our empirical context.[12]

Nevertheless, Vernon (1966, 1979) provided a relevant insight in stating that an important assumption of the product-life-cycle model is that a domestic location is preferred at first when a project entails substantial communication difficulties. Vernon surmised that operating in a foreign location would compound difficulties by making communications more difficult. Since then, research has established the widespread importance of information constraints to foreign direct investment (see Martin et al. 1998). This study informs that line of research by arguing that tacitness shapes the relative attractiveness of domestic and foreign locations.

More generally, our results describe conditions under which firms not only transition from domestic to foreign investment, but also revert to preferring domestic over foreign locations. By contrast, most international research has focused on the one-way transition from domestic to multinational strategy. Our research suggests the possibility of the reverse transition as an industry evolves. This reversal pattern has received little attention in the foreign direct investment literature. Although we find in further analysis that one cycle of increasing and decreasing foreign direct investment describes our sample, the results suggest the possibility elsewhere of cyclical patterns in which firms expand abroad, revert back to domestic investment, and then subsequently expand abroad anew.[13] This makes it all the more relevant for researchers to examine how and under what conditions tacitness can impede knowledge transfer, and to pursue analyses of the dynamics of technology and learning in corporate and international expansion.

The study also suggests several other directions for future research. First, the effects we describe could affect the performance of foreign investments. Specifically, investments that involve overly tacit knowledge should exhibit difficulties in transfer and startup.[14] This should also affect the overall financial performance and survival of parent corporations. Second, firm-level effects on foreign direct investment in the presence of tacit technology invite further scrutiny. Several firm-level variables not directly measured in our study would plausibly affect foreign direct investment. They include the parent firm's nontacit technology, managerial resources, and brand strength in industries where it is applicable. In addressing the study's research question, we sought to obtain a thorough understanding of foreign direct investment in one industry. The sample provides useful insights into firms from multiple countries over a relatively long time period. However, one limitation of the study is that the sample did not allow the systematic collection of the aforementioned firm-level data. Fortunately, the data setup allowed us to compensate statistically for these omissions by including random firm effects. Nevertheless, the study of how specific corporate effects vary with technology tacitness would be worthwhile.

Third, the search for firm-level effects should extend to variables that specifically affect corporate behavior and efficiency in dealing with tacit knowledge. Our results suggest that firms will not all respond alike in the presence of tacitness. Research has highlighted how firms differ in their ability to absorb technology from the outside, whether through imitation or through formal transfer (Cohen and Levinthal 1990, Teece 1981). It is just as plausible that firms differ systematically in their ability to transfer technology outward from an internal source, whether to foreign subsidiaries or to nonsubsidiary recipients (Martin and Salomon 2003). Research that conceptualizes and measures this source of heterogeneity could expand existing findings about the impact of tacitness on technology transfer.[15]

Finally, various location effects would be worth examining, if only as controls. For example, in less global industries and where buyer tastes and sophistication differ markedly across countries, firms may invest where demanding customers operate (see Martin et al. 1995, von Krogh et al. 2000). More generally, it would be interesting to examine institutional and other environmental factors that could affect firm expansion, especially if these factors stand to moderate the effects of tacitness and time-based learning.

Conclusion

This paper examined the effects of knowledge tacitness and organization-level learning on corporate international expansion. We found that as the tacitness of a firm's technology increases, its propensity to produce in foreign locations increases up to a point, and then decreases. This finding is consistent with one of the main tenets of the internalization theory of foreign direct investment (Buckley and Casson 1976) and of related models of business and corporate strategy (e.g., Penrose 1959, Teece 1980): Knowledge-based assets determine firm scope. Our findings also highlight the relevance of an evolutionary or knowledge-based perspective that acknowledges the importance of tacitness (Kogut and Zander 1992, 1993). Thus emerges a perspective of the multinational corporation as simultaneously leveraging knowledge-based assets to expand, and constrained in its expansion by knowledge tacitness.

This research also examines the effects of two forms of organization-level learning on expansion. We find that time-based learning matters, as does foreign transfer-based learning. While the latter has typically received more attention in the literature, our results suggest that some learning mechanisms are inherently time bound. Together, these findings further confirm the relevance of knowledge to corporate expansion. It remains to be seen whether other organization-level features, including differences in technology transfer capacity, (Martin and Salomon 2003), moderate the relationships between knowledge accumulation, tacitness, and corporate expansion. Further conceptual and empirical research in this area appears well warranted.

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Endnotes

[1]International business research addresses the decision to expand abroad as well as related issues, such as the choice among modes of entry. Regarding the expansion decision, studies commonly look at cross sections of industries or firms to determine how likely they will be to establish their own production operations abroad (e.g., Buckley and Casson 1976, Dunning 1993). Our research design builds on that tradition by asking whether, given that a firm makes an investment (i.e., a plant is built), the investment will be made domestically or abroad (Barrell and Pain 1996).

[2]Rosenberg (1982) also refers to learning-by-using, whereby insight into a production technology may be obtained by observing its ongoing output, even if the technology itself is not being transferred.

[3]Other types of intangible assets such as marketing and managerial knowledge could also favor foreign direct investement, though evidence on those provides less empirical support (Caves 1996, Grubaugh 1987, Morck and Yeung 1992). The empirical analysis is designed to control for such nontechnological intangibles and other unobserved firm characteristics.

[4]Because this research design includes joint venture observations more than once, it is important to ensure that the results are robust to inadvertent correlation among same-plant residuals in joint venture cases. We conducted several sensitivity tests. First, we replicated the results for joint ventures and wholly owned subsidiaries separately. Second, we ran a probit specification with random effects for joint ventures. Third, we replicated the analyses while randomly eliminating all but one parent per joint venture. We found the results reported below to be stable, with no evidence of group effects biasing our analyses. Overall, we are confident that the pooling of plant observations is appropriate for this statistical analysis.

[5]We replicated the results with equity thresholds of 50%, 50.1% (limiting the observations to absolute majority ownership), and 100% (limiting the observations to wholly owned subsidiaries). The results were similar to those reported below, further validating the legal 10% threshold (Graham and Krugman 1995).

[6]A possible alternative to foreign direct investment is licensing. However, licensing cannot be used as reliable evidence of foreign expansion in the semiconductor industry because licensing in this specific industry commonly serves to equilibrate property rights claims (i.e., patents), and not to transfer manufacturing knowledge or initiate foreign production (Hall and Ham Ziedonis 2001, Teece 2000). Licensing may nevertheless be an outcome of interest for studies in other industries or for research addressing mode of entry outcomes rather than the foreign direct investment question addressed here.

[7]A potential issue with this measure is that it tends to increase over time and may therefore be spuriously confounded with time-based factors such as the aging of technology. To address this we replicated the analysis while including year effects that control for any time-related artifacts in a comprehensive and flexible manner. We found the results reported below to be robust, while the year effects as a set did not contribute substantial explanatory power. Thus, we conclude that the effects of the feature size index are not spurious.

[8]Specifically, we used specialized industry publications together with general sources found in the Lexis/Nexis database to collect information about which process technology the plant used. We cross-referenced this information with feature size data that is reported in our main data source. In the few instances where additional information was not available, we assigned the plant to the technology generation found in confirmed cases of plants using the same feature sizes. We interviewed engineers in the semiconductor industry who confirmed the suitability of this inference and of our overall classification approach.

[9]Our secondary data search allowed us to confirm the ownership and technology history of the plants of interest and to ascertain whether and when the parent firms had built any plants earlier. In general, while we cannot eliminate altogether the possibility of minor residual left censoring, we are confident that our measures of learning accurately capture the experience accumulated by the parent firms included in the study.

[10]Correlation statistics indicate that the demand variable is also a suitable instrument for the volume of industry output. Controlling for scale and demand is important because their combination could generate an inverted-U pattern, with market demand encouraging investment and scale limiting the number of plants built. Like the feature

size index, both scale and demand trended upwards in the semiconductor industry during the study period. Thus, adding both controls helps ensure that we do not spuriously attribute results to tacitness.

[11]These country dummies also address the possibility that some investments would be made for knowledge-seeking purposes. While perhaps unlikely in the context of the fabrication plants that we study (as opposed to research and development facilities), the knowledge-seeking argument holds that the propensity of a firm to invest abroad (domestically) is a function of the technological weakness (strength) of its home-country industry. Between them, the United States, Korea, and Japan account for 91.5% of the industry patents granted in the sample countries in the industry. This confirms the strength of these three countries, potentially making foreign direct investment from these countries less likely. The corresponding dummies would control for any such effect, among other things.

[12]The extant literature also suggests that the product life cycle is an unlikely explanation in our context for at least three reasons. First, the product-life-cycle model is predicated on comparative advantage considerations that make it primarily applicable to markets where a country exhibits distinctive demand or the product addresses a unique factor disadvantage (high-priced consumer goods and labor-saving producer goods in Vernon 1966). It is least likely to characterize industries that make standardized goods, where technology changes rapidly, or where technological leadership is dispersed internationally (Vernon 1966, Giddy 1978). The memory segment of the semiconductor industry is more closely associated with the latter characteristics (e.g., Méthé 1992). Second, the product-life-cycle model is least applicable to industries where demand and competition are global, with more than one country home to large buyers and competitors (Vernon 1979, Harrigan 1985). Again, this puts semiconductors in the less applicable category. Third, the product-life-cycle model, in general, has been found to be more useful in describing data through the 1960s, and less applicable from the 1970s onwards, due to widespread economic development and advances in telecommunication technology and managerial capabilities (Giddy 1978, Vernon 1979, Harrigan 1985). Our study covers the latter period. On these counts, the existing literature would fail to support a product-life-cycle explanation for the context we study.

[13]If they occur, such cycles might punctuate forms of organizational learning that complement the time- and transfer-based learning effects we found.

[14]It would also be interesting to examine the effects of learning on transfer costs proper. Given our learning results and the prior evidence (Teece 1977, Galbraith 1990), we would expect transfer costs to decrease with learning. Likewise, learning should affect the time required to transfer knowledge.

[15]Among the challenges for such research, depending on industry context, would be to obtain measures of tacitness that describe precisely how each firm handles tacit knowledge. We thank an anonymous reviewer for pointing this out. In industry contexts where there are multiple and radically different technological solutions to a given problem (unlike in semiconductor manufacturing), it would also be interesting to appraise whether knowledge tacitness is, or could be, determined endogenously in firms.

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