Technological Resources and the Direction of Corporate Diversification: Toward an Integration of the Resource-Based View and Transaction Cost Economics

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This study considers how a firm's resource base affects the choice of industries into which the firm diversifies. It offers two main extensions of prior research. First, it operationalizes technological resources at a more detailed level than in prior studies, thereby enabling a more stringent analysis of the direction of diversification. This analysis shows that the predictive power of the "resource-based view of the firm" is greatly improved when resources are measured at a finer level. Second, the study integrates principles from transaction cost economics into resource-based predictions concerning diversification. In particular, it tests the common assumption that rent-generating resources are too asset specific to allow contracting. The findings point to circumstances where resources can be and are exploited through contracting rather than through diversification.
(*Diversification; Resource-Based View; Transaction Cost Economics; Patents*)

1. Introduction

Despite recent reports to the contrary, corporate diversification remains a ubiquitous feature of the modern economic landscape (Montgomery 1994). In the last decade, the resource-based view of the firm has been touted as particularly well suited to understanding diversification. Nevertheless, the operationalization of this framework has been limited to broad characterization of resources and the industries in which they might be fruitfully applied. For example, empirical studies have focused on proxies such as R&D spending to measure technological resources, finding that firms that exhibit high R&D intensities tend to diversify into industries that also exhibit high R&D intensities. While informative, this is substantially different from theoretical expositions of the resource-based view (e.g., Wernerfelt 1984, Barney 1986) and related research into "technological competence" (e.g., Patel and Pavitt 1994), which suggest that a particular technological resource is useful in only a narrow range of applications. Put another way, the empirical research on the resource-based view can not predict whether a pharmaceutical firm is more likely to enter biotechnology or electronic data processing, both of which exhibit similar R&D intensities.

In addition, the resource-based approach to diversification has generally under emphasized the possibility that firms can exploit resources through market arrangements rather than through expansion of corporate boundaries (exceptions include Teece 1980, 1982). Transaction cost economics suggests that managers (and scholars) should consider alternate contractual methods by which a firm can exploit its resources. While many resource-based scholars have acknowl-

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edged theoretically that resources might be exploited through contracts, the empirical approaches to the question of diversification have implicitly or explicitly assumed that any resource valuable, rare, and inimitable enough to generate sustainable rents is too asset specific (in the sense of Williamson 1985) to be contracted out.

This study extends previous research in two ways. Empirically, it operationalizes technological resources at a more fine-grained level than has been done in prior resource-based research. This facilitates the integration of elements of the technological competence and resource-based literatures to shed additional light on firms' diversifying behavior, and supports more stringent testing of diversification directionality than in previous research. Theoretically, by stressing the links between transaction cost economics and the resource-based view, it examines and tests the assumption that rent-generating resources are necessarily too asset specific to allow contracting.

2. The Resource-Based View of Diversification

During the last fifteen years, scholars have developed a resource-based framework for analyzing business strategy. Drawing heavily on Penrose (1959), the resource-based framework suggests that the firm is best viewed as a collection of sticky and imperfectly imitable resources or capabilities that enable it to successfully compete against other firms (Wernerfelt 1984, Barney 1986). These resources can be physical, such as unique equipment or innovations protected by patents, or intangible, such as brand equity or operating routines. Of particular importance is the application-specificity inherent in such resources. The same characteristics that enable a firm to extract a sustainable rent stream from these assets often make it nearly impossible for the firm to "transplant" them or utilize them effectively in a new context. Thus, a firm that has developed an advantageous resource position is protected to the extent that its resources are specific to certain applications; at the same time, this specificity constrains the firm's ability to transfer these resources to new applications (Montgomery and Wernerfelt 1988).

Operationalization of Resources

Empirical research on diversification has typically followed one of two paths to operationalize resources. The first avenue rests on the assumption that more "related" diversification supports more extensive exploitation of application-specific resources than does unrelated diversification. Most studies in this vein have relied on proximity within the SIC system to measure the degree of relatedness between two industries (e.g., Montgomery and Wernerfelt 1988). The second avenue relies on R&D intensity, advertising intensity, and other such investments as proxies for underlying resources. Montgomery and Hariharan (1991) find that firms tend to diversify into industries that have R&D intensities, advertising intensities, and capital expenditure intensities similar to those of the firms' existing businesses. They also find that higher R&D intensities and advertising intensities are associated with more diversification, and interpret this as evidence that R&D and marketing activity creates transferable resources that provide competitive advantage.[1]

Each of these constructs is subject to criticism. Any measure of industry relatedness that relies on proximity among SIC codes necessarily rests on strong assumptions about the ordering of the SIC system. SIC-based constructs typically rely on categorical decision rules (such as "1 if in same 2-digit industry, 0 otherwise") that assume that each SIC code is equidistant from all other codes—in other words, as Gollop and Monahan (1991) note, the chemical industry (SIC 28) is equally "distant" from petroleum (SIC 29) and nonelectrical machinery (SIC 35). Such measures also assume that 3- or 4-digit industries within a single 2-digit SIC are equally "similar" to each other. The use of such measures for a resource-based test are of particular concern, because the SIC system is based on product (output) characteristics rather than on resource (input) characteristics. It is therefore unclear whether proximate 3- or 4-digit SIC codes actually share common or similar resource use patterns.

A corollary concern exists regarding the fungibility

[1] The Montgomery and Hariharan study builds on a long tradition in the economics and management literature (e.g., Gort 1962, Lemelin 1982).

of R&D and advertising intensity. The theoretical development of the resource-based view has explicitly emphasized the specificity of application of rent-generating resources. Montgomery and Wernerfelt (1988) argue that a resource's rent-generating capacity should be inversely related to its range of useful applications, suggesting that potentially valuable resources can realize this value in only a few applications. This view is echoed by research into "technological competence," which has found evidence of stable and highly focused areas of corporate technological strength (Pavitt et al. 1989) and high correlation between the primary business in which a firm operates and the set of technological areas in which it patents (Patel and Pavitt 1994).[2] Yet the proxies used in the resource-based empirical research do not capture these constraints.

Three recent studies have focused explicitly on underlying resource requirements across industries to examine diversification patterns. Farjoun (1994) uses census data to operationalize industry relatedness as the degree to which two industries use the same types and proportions of human expertise. He finds that a firm tends to diversify into industries that rely on patterns of expertise similar to those required in its extant industries. Coff and Hatfield (1995) use similar data in a study of acquisition announcements, finding evidence of higher returns for acquisitions that are more "related" in terms of human expertise. Robins and Wiersema (1995) use Scherer's technology inflow-outflow matrix to operationalize industry relatedness as the degree to which two industries rely on the same inflows of technology, finding that corporate performance is higher for firms that have diversified into technologically related industries than those that have diversified into technologically unrelated industries.

However, these three studies characterize resources only at the industry level; they do not have information on firms' repositories of expertise or technology. Focusing on industry aggregate data precludes the analysis of interfirm differences in resource pools and diversification patterns. This in turn limits these studies' ability to address issues relating to heterogeneity in firms' resource bases. As shown below, identification of individual firms' resource portfolios allows development of more nuanced insights into the role of resources in diversification, and more fully-developed integration of resource-based insights with those of other approaches.

Below I construct a measure of corporate technological resources, based on patent data, that arguably captures more effectively than R&D intensity the narrow range of businesses in which a firm's technological resources can be profitably applied. Following the logic of the resource-based theorists, I expect that a firm will more readily diversify into industries in which its portfolio of technological resources will confer competitive advantage.

HYPOTHESIS 1. *Ceteris paribus, a firm is more likely to diversify into a business the more applicable its existing technological resources are to that business (in absolute terms).*

This hypothesis differs from those tested in the above-cited empirical tests of diversification, which have hypothesized that a firm will be more likely to diversify into a business the more similar its R&D intensity is to the R&D intensity of the business. In effect, I expect that addition of more accurate measures of technical resources and the businesses in which they provide value will significantly improve the explanation of corporate diversification patterns.

A firm is constrained in the amount of entry it can pursue in a given time period due to limitations on managerial time (Penrose 1959). In the face of such constraint, it will select among its potential viable entries according to the degree to which its resources provide advantage in each industry (Montgomery and Wernerfelt 1988). A higher applicability of a firm's technological resources to a given business, *relative* to the applicability of its technological strengths to other businesses, should increase the likelihood that the firm enters the given business.

[2] Jaffe's research into "technological position" (1986, 1989) similarly suggests that firms are able to alter the direction of their technological strengths only gradually. Jaffe also finds that firms benefit from "nearby" R&D far more than from "distant" R&D, suggesting severe limits on the fungibility of technological knowledge—an implication that is consistent with Scott and Pascoe's (1987) study of "purposive diversification" in R&D.

HYPOTHESIS 2. *Ceteris paribus, a firm is more likely to diversify into a business the more applicable its existing technological resources are to that business, relative to other opportunities facing the firm.*

Hypothesis 2 differs from Hypothesis 1 in its focus on relative as opposed to absolute applicability of technological resources. Put another way, while Hypothesis 1 only considers the applicability of a firm's resources to a focal industry, Hypothesis 2 introduces into the decision calculus the applicability of a firm's resources to other industries that the firm might enter.

Diversification vs. Contracting Out Resources: The Role of Appropriability

As stated above, the resource-based view is based heavily on Penrose's theory of firm growth (1959). The Penrosian framework is usefully informed by transaction cost economics. Penrose implicitly assumes that exploitation of excess resources necessitates their use within the firm. As a logical consequence, her framework is unidirectional—firms grow, but never shrink; firms acquire, but never divest.[3] The transaction cost perspective asks whether there are alternate ways to utilize these assets, including outside contracting and spinoffs (Teece 1980). Transaction cost economics also offers a rationale for the potential benefits of contracting out excess resources (incentive intensity) and suggests circumstances in which such resources will be better spun off from the company (Teece 1982, Williamson 1985).

Resource-based theorists have traditionally acknowledged some insights of transaction cost economics, but have not tested their implications. Montgomery and Hariharan (1991) explicitly assume that the resources they investigate—technical and marketing skills—are difficult to transfer, and Montgomery (1994) contends that resources to which rent accrues are likely to be difficult to contract out. Chatterjee and Wernerfelt (1991) implicitly assume that the technological and marketing resources for which R&D intensity and advertising intensity are proxies can not be exploited through contracting out.

[3] Mahoney and Pandian (1992, p. 367, fn. 7) note that while the resource-based view predicts growth and diversification, "a 'resource-based theory of divestment' is clearly lacking."

Yet it is not clear that this assumption is valid. Several empirical and theoretical studies have identified conditions under which technological resources can be exploited through contractual means. Teece (1986) proposes that licensing is a feasible alternative to diversification unless technological knowledge is either highly tacit—in which case contracts calling for effort associated with knowledge transfer are difficult to monitor and enforce—or easily transferable *and* weakly protected—in which case attempts to negotiate a license are fraught with problems associated with the paradox of information and secrecy is required to appropriate returns to technology. Levin et al. (1987) find wide variation in the efficacy of licensing technological innovations across industries, which they cite as evidence of varying levels of transaction costs across these industries. To the extent that licensing is a feasible alternative to diversification for a given technology in a given business, the likelihood of diversification into that business should be moderated.

HYPOTHESIS 3. *Ceteris paribus, a firm is more likely to diversify into a business the more likely that contracting out its technological resources in that business is subject to high contractual hazards.*

a: Ceteris paribus, a firm is more likely to diversify into a business as the feasibility of licensing its technological resources in that business <u>decreases</u>.

b: Ceteris paribus, a firm is more likely to diversify into a business as the need for secrecy to appropriate returns to its technological resources in that business <u>increases</u>.

c: Ceteris paribus, a firm is more likely to diversify into a business as the degree of tacit knowledge associated with its technological resources in that business <u>increases</u>.

3. Data and Specification of the Model

The empirical test of the above hypotheses entailed estimating the entry of existing firms into new SICs during the three-year window 1982–1985 as a function of firm, industry, and resource characteristics in 1981. While study of a more recent time period would be desirable, focusing on the early- to mid-1980s allows me to integrate information from several previously unlinked data sources. My sample of firms is largely a subset of the database compiled by Jaffe (1986) for his research into "technological position." Jaffe's database, which is itself a subset of the NBER R&D Master File, includes 573 U.S. firms existing between 1973 and 1980. Of these, 479 firms continued to appear in the Compustat database through 1985. I generated my sample by selecting randomly (using Excel's random number generator) 344 of these 479 firms.[4] To reduce the emphasis on large, technology-intensive firms inherent in the Jaffe database, I then selected randomly 68 firms from the population of firms that 1) appeared in the 1981 and 1985 Compustat and 2) did not appear in Jaffe's database.[5] The resulting sample encompassed a wide range of U.S. economic activity: Of the 449 four-digit manufacturing industries, 433 were represented by at least one firm in the sample in 1981. Sample firms participated in anywhere from one SIC (several firms) to 84 SICs (ITT), with a median of 10 SICs.

I relied on patent data to identify each firm's technological resource base. In recent years, patent data has been increasingly used as an indicator of corporate technological capabilities in management research (Jaffe 1986, Patel and Pavitt 1994, Mowery et al. 1996). Detailed information exists concerning every patented innovation, whether assigned to a public or private firm. Among the data available is a classification code that identifies the type of technology embodied in the patent. Thus, compared to R&D expenditures, patents offer richer information on the particular range of technological strengths possessed by a firm.

[4] Although inclusion of all 479 Jaffe firms would raise fewer concerns about my sample, time and resource constraints precluded this. My reliance on a randomly selected 344-firm subset should yield unbiased results; a difference of means test between my sample and the Jaffe firms that I excluded indicates no significant difference between the two sets of firms except for R&D intensity (my sample has a lower R&D intensity than the set of excluded firms).

[5] I selected 68 "non-Jaffe" firms because this provides a sample of minimum sufficient size to estimate state-based logit models on the non-Jaffe-only subset. I estimated such models in my dissertation (Silverman 1996).

At the same time, patent data have limitations of their own. Much of a firm's technical knowledge may remain unpatented either because it is unpatentable (e.g. an algorithm) or because a firm may choose not to patent a patentable innovation. Differences in the comprehensiveness of patenting may exist across firms, industries, and time. In addition, there is variation in the technological and economic value embodied in individual patents.

In response to these concerns, Patel and Pavitt (1994) argue that codified (patented) knowledge and uncodified knowledge are highly complementary. They point out that other measures of technological competence that incorporate tacit knowledge, such as peer review judgments, have been shown to yield similar results to those of patent measures (Narin et al. 1987). While patents do not directly measure a firm's noncodifiable knowledge, they should function as a partial, noisy indicator of its unpatented technological resources. To the extent that patents do not accurately measure corporate technological capabilities, the coefficients for the technological resource variables in this study will be biased downward (toward insignificance).

I used the MicroPatent database, which includes the front page of every patent granted by the U.S. Patent and Trademark Office (USPTO) since 1975, to construct each firm's "patent portfolio." For each firm in my sample, I identified all patents in the MicroPatent database for which applications were filed before December 31, 1981 (the patent literature typically uses date of application, rather than date of granting, as the date on which a firm has access to a patented technology). These patents comprise the firm's patent portfolio, and hence provide one measure of its existing technical resources, as of 1981. Since large multiunit firms frequently assign patents to subsidiaries, I used the 1981 *Who Owns Whom* reference book to identify every subsidiary—domestic and foreign—of each firm in the sample. I was thus able to search the MicroPatent database for patents assigned to any of these parent or subsidiary names, and aggregate all patents at the parent level. The firms in this sample accounted for more than 70,000 patents—well over 50% of all U.S. patents assigned to U.S. firms during this period—assigned to more than 1,500 patenting entities.[6]

In addition to patent data, I used Compustat and the AGSM/Trinet Large Establishment Database (Trinet) to compile data on other firm characteristics, discussed below. I also used the *Annual Survey of Manufactures* and the *FTC Line of Business Data* to compile information on all four-digit SIC manufacturing industries—that is, all 449 four-digit SIC industries between SIC 2000 and SIC 3999. Lack of data (usually R&D or advertising intensity) necessitated the elimination of 20 industries, yielding a final set of 429 potential destination industries.

Dependent Variable

The dependent variable, Div_{ij}, is derived from the Trinet database and is coded as a categorical variable:

$\text{Div}_{ij} = 1$ if firm i enters industry j between 1981 and 1985, and 0 otherwise.

The Trinet database, which was compiled every other year between 1979 and 1989, includes information on corporate ownership and four-digit SIC scope of operations for every establishment with twenty or more employees in the United States. Comparison with the Census of Manufactures indicates that Trinet encompasses roughly 95% of all establishments that it should; most of the omissions are likely to be of smaller firms, rather than the large corporations in my sample (Voigt 1993). By aggregating the Trinet establishment data at the firm level, I determined all four-digit SICs in which my sample firms participated in 1981 and in 1985. Any industry j in which firm i does not participate in 1981 is a potential destination industry in 1985. Those potential destination industries in which firm i does participate in 1985 are entries, and are coded as 1. Such entry can occur through either acquisition or internal expansion; this study does not distinguish between the two modes (see Silverman 1996, Chapter 6 for an analysis of entry mode choice). Those potential destination industries in which firm i does not participate in 1985 are non-entries, and are coded as 0. Entry occurred in 1,023 of the 170,721 potential entries in my sample (0.5%), and nonentry occurred in 169,698 (99.5%) of the potential entries.[7] Sample firms' diversifying entry ranged from zero SICs entered (approximately 25% of the firms) to 37 SICs entered (Cooper Industries), with a median of two entered SICs.

Independent Variables—Measures of Technological Resource Applicability

$AbsTech_{ij}$ is defined as the absolute level of firm i's patent portfolio that is likely to be applicable to industry j. It is derived from firm i's patent portfolio as follows. First, I used the U.S. Patent Class—U.S. SIC concordance developed in Silverman (1996) to derive probability-weighted assignments to four-digit SICs for each patent in firm i's portfolio. This concordance takes advantage of the fact that the Canadian Patent Office (CPO) assigns each granted patent to both a patent class and to SICs in which the patented innovation is likely to be manufactured and used. It uses the frequency with which Canadian patents in each patent class are assigned to each SIC to create a probability distribution relating U.S. patent classes to U.S. SIC codes. For example, suppose that the CPO has granted 376 patents assigned to patent class i, and has assigned 138 of these patents to SIC j as the SIC of Use. Then any single patent assigned to patent class i

[6] The MicroPatent database, like other sources of patent data, is noisy in the coding of assignees. This is driven by two elements: First, there is no standard format to which an assignee's name must conform; second, there are inevitably typographical errors and misspellings in the transcription of this information into the USPTO's files and into the Micropatent database. I searched for variations of all names, and for key character substrings, in an attempt to reduce the resulting noise. I also visually scanned all patent assignments to catch incorrect assignments. Nevertheless, some errors of both exclusion of relevant patents and inclusion of irrelevant ones may have occurred.

[7] Potential entries = 412 firms × 429 industries − the 6,027 firm-industry pairs in which firms already participated in 1981 = 170,721. I also re-estimated all results in this paper using a 3-digit definition of industry. About $\frac{1}{3}$ of my observations are eliminated during this reestimation, either because a firm may diversify into multiple 4-digit SICs that fall within a single 3-digit SIC, or because a potential entry at the 4-digit level may not be a potential entry at the 3-digit level. The results for 3-digit SICs are virtually identical to the 4-digit results presented in this paper, with the exception of the loss of significance for the appropriability variables. These results are available upon request.

during this period has probability 0.37 (138/376) of being assigned to SIC of Use j.[8]

Second, I aggregated these probability-weighted SIC assignments over firm i's entire patent portfolio to determine the total strength of firm i's technological resources, as measured by its patents, in each SIC. Formally, $\mathrm{AbsTech}_{ij}$ is a measure of application-specific technological strength:

$$\mathrm{AbsTech}_{ij} = \sum_{c} \mathrm{Prob}(\mathrm{industry} = j \mid \mathrm{patent} = c) * N_{ic},$$

where N_{ic} equals the number of patents in firm i's portfolio assigned to U.S. Patent Class c.

Hypothesis 1 proposes that a firm is more likely to diversify into a business as its technical strength applicable to that business increases. The coefficient for $\mathrm{AbsTech}_{ij}$ is therefore expected to be positive.

RelTech$_{ij}$ is defined as the applicability of firm i's patent portfolio to industry j, relative to the applicability of firm i's patent portfolio to other industries. It is derived from $\mathrm{AbsTech}_{ij}$ as follows:

$$\mathrm{RelTech}_{ij} = \mathrm{AbsTech}_{ij} / \max_{j}\{\mathrm{AbsTech}_{ij}\}$$

It was argued above that a firm faces constraints on the amount of entry it can pursue in a given time period. If this is true, then, as Hypothesis 2 proposes, the firm will select among its potential viable entries according to the degree to which its resources provide advantage in each industry. I therefore expect that higher *relative* applicability of firm i's patent portfolio to industry j should increase the likelihood that firm i enters industry j, independent of the effects of *absolute* levels of applicability. The coefficient for $\mathrm{RelTech}_{ij}$ is therefore predicted to be positive. It is worth noting that while many resource-based theorists have hypothesized variations on Hypothesis 2, the hypothesis has previously remained untested due to the difficulty of constructing sufficiently detailed empirical constructs.

Independent Variables—Measures of Contractual Hazards

Proxies for transaction cost-related hazards associated with contracting out innovations are derived from the Yale survey on research and development. In their survey of senior R&D executives at several hundred large U.S. firms in the early 1980s, Levin et al. (1987) asked each respondent to rate on a seven-point scale, for his/her line of business, the importance of several mechanisms for appropriating returns to innovation including licensing royalties, secrecy, and learning-curve advantages. Several scholars have used these to proxy for the overall strength of a given industry's appropriability regime, usually by taking the highest rating from across all mechanisms. In this study I use them individually to proxy for contracting hazards associated with exploiting innovation in a given industry.

Royalty$_j$ is defined as the feasibility of licensing innovations in industry j. I assume that the more important license royalties are as a method of appropriating returns to innovation in industry j, the lower the hazards and, hence, transaction costs associated with contracting for technology in industry j (Levin et al. 1987). Hypothesis 3a proposes that, in such industries, firms will prefer to exploit their technical resources through contractual means rather than through expansion of their boundaries. Conversely, in industries where license royalties are not effective for appropriating returns, firms will have little alternative but to diversify if they are to exploit their technical resources. Thus, the coefficient for $\mathrm{Royalty}_j$ is expected to be negative.

Secrecy$_j$ is defined as the importance of secrecy to appropriating returns to innovation in industry j. I assume that in industries where secrecy is important, contracting for technology is subject to hazards associated with concern about information leakage. Hypothesis 3b proposes that, in such industries, firms will rely on diversification rather than contracting to exploit their technological resources. The

[8] This concordance assumes that patents are assigned and exploited according to similar processes in the U.S. and Canada—not an unreasonable assumption, since more than 50% of patents in Canada are assigned to U.S. firms. Full details as to the construction and testing of this concordance are available in Silverman (1996) or from the author upon request. Additional information also appears in the appendix of the working paper version of this article, which can be downloaded from *http://www.ssrn.com.* Note that this concordance is similar to the work of Evenson, Kortum, and Putnam at the two-digit SIC level in Canada (e.g., Kortum and Putnam 1989).

Table 1 Control Variables: Definition, Data Source, and Predicted Signs

Variable	Definition	Data Source	Expected Sign
IGrowth_j (%)	CAGR of sales in industry j between 1978 and 1981	Annual Survey of Manufactures	+
IConc_j (%)	4-firm concentration ratio in industry j in 1982	Census of Manufactures	−
$\text{IR\&DInt}_j$ (%)	Industry-wide ratio of R&D expenditure to revenue in 1977	FTC Line of Business Data	?
IAdvInt_j (%)	Industry-wide ratio of advertising expenditure to revenue in 1977	FTC Line of Business Data	?
FSales_i ($billion)	Sales for firm i in 1981	Compustat	+
FGrowth_i (%)*	CAGR of sales by firm i between 1978 and 1981	Compustat	+
$\text{FR\&DInt}_i$ (%)	Weighted average of the ratio of R&D expenditure to revenue for firm i in 1978–1981	Compustat	+
FAdvInt_i (%)	Weighted average of the ratio of advertising expenditure to revenue for firm i in 1978–1981	Compustat	+
$\text{DiffR\&D}_{ij}$	Absolute value of the difference between industry R&D intensity and firm R&D intensity	$\lvert\text{IR\&DInt}_j - \text{FR\&DInt}_i\rvert$	−
DiffAdv_{ij}	Absolute value of the difference between industry advertising intensity and firm advertising intensity	$\lvert\text{IAdvInt}_j - \text{FAdvInt}_i\rvert$	−

* All models were also specified using $\ln(\text{FSales}_i)$, with no change in results.

coefficient for Secrecy_j is therefore expected to be positive.

$\textit{Learning}_j$ is defined as the importance of learning curve advantages to appropriating returns to innovation in industry j. I assume that in industries where learning curve advantages are efficacious, knowledge is sufficiently tacit that it does not leak out of the learning firm. Grindley and Teece (1997) have noted the hazards associated with contracting for technology when licensees will subsequently generate tacit knowledge concerning the licensed technology—for example, by making more difficult the monitoring and enforcement of "grant-back" provisions in which the licensee must transfer to the licensor all improvements to the licensed technology.[9] Hypothesis 3c proposes that, in such industries, firms will rely on diversification rather than contracting to exploit their technological resources. The coefficient for Learning_j is therefore expected to be positive.

[9] In addition, much of the transaction cost literature on licensing discusses the hazards associated with a licensor's tacit knowledge. The current study does not directly address such hazards due to the difficulty of parameterizing tacit knowledge in a firm's existing businesses, as opposed to the industry of potential entry.

Control Variables

A number of control variables are included in the model. In addition to controlling for various firm, industry, and firm-industry relatedness characteristics that both theory and prior empirical research suggest will affect diversification behavior, inclusion of these variables facilitates the comparison of this study's results to those of prior resource-based research on diversification. Firm-level variables include firm size, growth, R&D intensity, and advertising intensity. Industry-level variables include industry size, growth, R&D intensity, and advertising intensity. Firm-industry relatedness measures include the difference between firm i's R&D intensity and industry j's R&D intensity, and the difference between firm i's advertising intensity and industry j's advertising intensity. Table 1 identifies the data source, measurement, and expected sign of each of these variables. As Table 1 indicates, the data for industry R&D and advertising intensities are taken from 1976–1977, while all other data comes from 1981–1982. The FTC Line of Business database is generally accepted as an unusually accurate source of information on U.S. industry characteristics. However, the FTC ceased production of this database after 1977. I thus faced a choice between using a second-best source of industry data—such as attempting to construct industry averages from firm-level Compustat data—and using accurate industry data from a slightly different time frame than my other data. I opted for the latter; thus an implicit assumption in this study is that industry-level R&D and advertising intensities did not change dramatically between 1978 and 1981.

The hypotheses enumerated in §2 can be tested in a model of entry into new markets. My model borrows from Montgomery and Hariharan (1991). As did they, I look at changes in firm-level diversification as a function of firm characteristics, destination industry characteristics, and the relationship between firm and industry characteristics. I extend the model by including direct measures of the applicability of a firm's technical resource base to potential destination industries as well as measures of the transaction cost hazards associated with contracting out vs. in-house exploitation of technical resources.[10] The resulting model is:

$$
\begin{aligned}
P(\text{Div}_{ij} = 1) \\
&= \beta_0 + \beta_1 \text{AbsTech}_{ij} + \beta_2 \text{RelTech}_{ij} \\
&\quad + \beta_3 \text{Royalty}_j + \beta_4 \text{Secrecy}_J + \beta_5 \text{Learning}_j \\
&\quad + \beta_6 \text{IGrowth}_j + \beta_7 \text{IConc}_j + \beta_8 \text{IR\&DInt}_j \\
&\quad + \beta_9 \text{IAdvInt}_j + \beta_{10} \text{FSales}_i + \beta_{11} \text{FGrowth}_i \\
&\quad + \beta_{12} \text{FR\&DInt}_i + \beta_{13} \text{FAdvInt}_i \\
&\quad + \beta_{14} \text{DiffR\&D}_{ij} + \beta_{15} \text{DiffAdvInt}_{ij} + e_{ij}.
\end{aligned}
$$

[10] I do not include a direct measure of industry profitability as did Montgomery and Hariharan because reliable data on industry profitability is not available for the time period covered by my data. However, this is not as severe a lack as it first appears. Most studies of diversification have not included an industry profit measure. More important, the two that have (Montgomery and Hariharan 1991, Orr 1974) both found that industry profitability has an insignificant effect on diversification entry when factors that are hypothesized to affect industry profitability (industry concentration, growth, R&D intensity, and advertising intensity) are included as variables. I include these factors in my model.

Table 2 presents the mean, standard deviation, minimum value, and maximum value of each variable. The values for AbsTech and RelTech indicate that both are highly skewed, which underscores the fact that there are many instances in which a firm has no technical resources (as measured by patents) that are applicable to a particular industry. Table 3 presents the correlation matrix for the variables.

4. Logit Estimation: Results and Discussion

The phenomenon under study is best described by a categorical variable—either entry takes place or it does not. Rather than use all 169,698 nonentries in my analysis, I used state-based sampling techniques to construct a sample of entries and nonentries. I derived a sample consisting of all entries and slightly less than one percent of nonentries (the latter were selected using SAS's random number generator). Manski and McFadden (1981) have demonstrated that state-based sampling provides more efficient generation of information than does a purely random sample when a population is overwhelmingly characterized by one state, and that logit estimation using data derived

Table 2 **Descriptive Statistics of the Independent Variables**
[a]$n = 2514$; [b]$n = 1380$

Variable (units)	Mean	Std. Dev.	Minimum	Maximum
Entry (0–1)[a]	0.407	0.491	0.000	1.000
IGrowth (%)[a]	10.011	6.084	−10.440	87.630
IConc (%)[a]	37.465	20.715	3.000	99.000
IR&DS (%)[a]	1.662	1.948	0.000	10.920
IAdvS (%)[a]	1.555	2.313	0.010	19.500
FSales ($B)[a]	3.737	10.710	0.008	65.564
FGrowth (%)[a]	4.191	11.116	−38.728	63.027
FR&DS (%)[a]	1.762	1.756	0.000	9.912
FAdvS (%)[a]	1.227	2.410	0.000	15.642
DiffR&D (%)[a]	1.665	1.835	0.000	10.920
DiffAdv (%)[a]	1.860	2.655	0.003	19.500
AbsTech (pats)[a]	3.020	19.259	0.000	489.132
RelTech (pats)[a]	0.038	0.107	0.000	1.000
Royalty (7-pt scale)[b]	3.134	1.157	1.000	7.000
Secrecy (7-pt scale)[b]	3.639	1.008	0.665	6.500
Learning (7-pt. scale)[b]	5.054	0.779	2.000	7.000

Table 3 Correlation Matrix of the Independent Variables [a]$n = 2514$; [b]$n = 1380$

Variable	IGrowth	IConc	IR&DS	IAdvS	FSales	FGrowth	FR&DS	FAdvS	Diff R&D	Diff Adv	Abs Tech	Rel Tech	Royalty	Secrecy	Learning
IGrowth[a]															
IConc[a]	−.046														
IR&DS[a]	.344	.173													
IAdvS[a]	−.080	.132	−.008												
FSales[a]	.043	.009	.024	−.018											
FGrowth[a]	.025	.020	.016	−.028	.052										
FR&DS[a]	.062	.020	.110	.003	.008	.149									
FAdvs[a]	−.011	.006	−.004	.068	−.063	.010	.105								
DiffR&D[a]	.172	.077	.531	.016	.013	.123	.539	.030							
DiffAdv[a]	−.045	.082	−.029	.664	−.049	.002	.049	.601	.014						
AbsTech[a]	.087	−.003	.136	−.019	.158	−.000	.113	−.033	.018	−.033					
RelTech[a]	.115	−.095	.198	−.063	−.011	.039	−.017	−.014	.033	−.060	.320				
Royalty[b]	−.099	.128	−.147	−.095	.024	.003	−.029	.005	−.127	−.057	−.027	−.017			
Secrecy[b]	−.029	.155	.049	.151	−.060	.030	−.015	−.015	−.001	.088	−.030	.017	.003		
Learning[b]	.108	.023	.110	−.048	.019	.033	.006	−.022	.066	−.059	.016	.032	.022	.013	

$|\rho| > .039$ is significant at $p < .05$ for $n = 2514$; $|\rho| > .051$ is significant at $p < .05$ for $n = 1380$.

from state-based sampling will yield unbiased and consistent coefficients for all variables except for the constant term.[11] I therefore use logit estimation in this study.[12]

[11] The constant term can be corrected by subtracting from it the value −4.1710, derived by: ln(proportion of State 1 observations included in sample/proportion of State 2 observations included in sample).

[12] One concern with this identification of a nonentry sample is that the nonentry sample will include observations where entry is extremely unlikely for reasons not captured by the included variables (this is also true if one uses all 169,698 nonentry observations). Such observations could bias upward my technological resource coefficients. Following Gulati (1995) and Baum and Korn (1996), I addressed this by running a sensitivity analysis in which I reestimated the models in this paper after eliminating from my sample any entry or nonentry that would constitute a "pioneering" entry, as follows. For each observation I identified all SICs in which firm i participated in 1981. I then identified all other firms in my sample that participated in any of those SICs in 1981. I then checked whether any of these firms also participated in industry j in 1981. If not, then firm i's entry (or nonentry) into industry j was classified as a pioneering entry and excluded from the sample. This led to the exclusion of 75 entries and 314 nonentries. Results were essentially identical to those reported in the paper, and are available on request.

Effect of Technological Resource Applicability Measures

The first set of logit estimations is presented in Table 4, Models 1–3 (elasticities appear in Table 5). The results for the regression using only traditional measures of entry barriers and firms' resources (model 1) are generally consistent with those of previous studies. All variables are signed as expected. All variables except IGrowth_j are significant at $p < 0.05$. The only surprise of this regression is the lack of significance for industry growth, which is commonly considered to be one of the primary influences on entry. Nevertheless, there is empirical precedent for this result (Montgomery and Hariharan 1991, Lemelin 1982).

Model 2 introduces AbsTech_{ij}, the absolute level of firm i's technological resource base that is applicable to industry j. AbsTech_{ij} is significant and positive, as predicted by Hypothesis 1. Further, the likelihood ratio test indicates that inclusion of AbsTech_{ij} significantly improves the fit of the model ($\chi^2(1) = 134.24$; $p < 0.01$). At the same time, the coefficients for the

Table 4 **Logit Estimation of Entry** (** = $p < 0.01$, * = $p < 0.05$, + = $p < 0.10$)

	Test of Technical Resource Measures (N = 2514)			Test of Appropriability Effects (N = 1380)		
	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	−0.221+	−0.228+	−0.362**	−0.152	−0.304	−1.059*
	(0.130)	(0.134)	(0.137)	(0.178)	(0.187)	(0.494)
IGrowth	0.014+	0.009	0.009	0.001	0.002	−0.004
	(0.008)	(0.008)	(0.008)	(0.009)	(0.010)	(0.010)
IConc	−0.024**	−0.022**	−0.021**	−0.021**	−0.019**	−0.019**
	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)
IR&DS	0.563**	0.464**	0.449**	0.572**	0.474**	0.464**
	(0.038)	(0.039)	(0.039)	(0.049)	(0.050)	(0.050)
IAdvS	0.069*	0.061+	0.062*	0.115*	0.113*	0.103*
	(0.032)	(0.032)	(0.033)	(0.046)	(0.047)	(0.047)
FSales	0.033**	0.016**	0.020**	0.058**	0.035**	0.037**
	(0.006)	(0.006)	(0.006)	(0.013)	(0.012)	(0.012)
FGrowth	0.016**	0.017**	0.016**	0.019**	0.017**	0.017**
	(0.004)	(0.004)	(0.004)	(0.006)	(0.006)	(0.006)
FR&DS	0.144**	0.051	0.079*	0.135**	0.081+	0.087+
	(0.036)	(0.037)	(0.037)	(0.047)	(0.049)	(0.049)
FAdvS	0.110**	0.121**	0.115**	0.105*	0.126**	0.125**
	(0.029)	(0.030)	(0.030)	(0.044)	(0.045)	(0.046)
DiffR&D	−0.451**	−0.369**	−0.371**	−0.444**	−0.371**	−0.375**
	(0.043)	(0.044)	(0.044)	(0.055)	(0.056)	(0.057)
DiffAdv	−0.177**	−0.168**	−0.165**	−0.210**	−0.214**	−0.211**
	(0.035)	(0.036)	(0.036)	(0.053)	(0.054)	(0.054)
AbsTech		0.191**	0.135**		0.131**	0.126**
		(0.026)	(0.024)		(0.030)	(0.030)
RelTech			3.950**		3.209**	3.232**
			(0.776)		(0.859)	(0.862)
Royalty						−0.056*
						(0.028)
Secrecy						0.033
						(0.033)
Learning						0.088*
						(0.043)
Log-lklhd	−1453.54	−1386.42	−1368.67	−796.06	−747.68	−743.24
Lklhd ratio test		$\chi^2(1)$ vs. model 1 = 134.2**	$\chi^2(1)$ vs. model 2 = 35.5**		$\chi^2(2)$ vs. model 4 = 96.7**	$\chi^2(3)$ vs. model 5 = 8.88*

other variables largely retain their magnitudes and levels of significance. I interpret the significance of AbsTech as support for Hypothesis 1—firms are likely to diversify into those industries in which their existing technological resources are highly applicable.

Model 3 introduces RelTech_{ij}, the relative level of firm i's technological resource base that is applicable to industry j. RelTech_{ij} is positive and significant, as predicted by Hypothesis 2, and the likelihood ratio test indicates that inclusion of RelTech_{ij} significantly improves the fit of the model ($\chi^2(1) = 35.50$; $p < 0.01$ compared to model 2). At the same time, the coefficient for AbsTech_{ij} retains its magnitude and significance. The model is thus able to discern the separate effects of absolute and relative technological resource applicability despite the moderate correlation between these variables. Controlling for absolute levels of technological resource applicability, a firm is more likely to diversify into an industry the more applicable its technological resources are to that industry, *relative* to their applicability to other industries. I interpret this result as support for Hypothesis 2.

The inclusion of detailed measures of corporate technological resources and the industries in which they are useful significantly improves the explanatory power of the resource-based model as compared to versions that rely on traditional proxies for resources. In addition to the likelihood ratio test result cited above, inclusion of AbsTech_{ij} and RelTech_{ij} reduces the number of prediction errors by 10%, from 762 in Model 1 to 680 in Model 3. By way of comparison, addition of all variables except for these two technological resource measures to a model that consists only of a constant term reduces prediction errors by 26%.

Effect of Contractual Hazard Measures

The second set of logit estimations are presented in Table 4, Models 4–6. As described above, measures of appropriability—the importance of licensing royalties, secrecy, and exploiting the learning curve—are derived from the Yale survey on R&D. This survey covers approximately half of the manufacturing SICs. Empirical tests involving these measures were consequently restricted to the 621 entries and 759 nonentries in the sample for which data was available. Models 4 and 5 recreate for this reduced sample the conventional resource-based model and the model incorporating AbsTech_{ij} and RelTech_{ij}. Comparison with Models 1 and 3 indicates that results for the reduced sample are substantially similar to those for the complete sample. The primary difference is the insignificance of $\text{FR\&DInt}_i$ in the reduced sample results, due to the higher standard error associated with the decreased number of observations.

Model 6 introduces the three contractual hazard measures, Royalty_j, Secrecy_j, and Learning_j. As predicted by Hypothesis 3a, Royalty_j's coefficient is negative and significant, indicating that a firm is less likely to diversify into an industry when viable contractual alternatives exist to exploit its technological resources. The coefficient for Learning_j is positive and significant, as predicted by Hypothesis 3c, which suggests that a firm is more likely to exploit its technological resources through diversification when those resources are characterized by cumulative, tacit knowledge, which makes their market transfer difficult and hazardous. The coefficient for Secrecy_j is positive but not significant. The hypothesis that a firm is more likely to exploit its technological resources through diversification when those resources are subject to contracting hazards due to expropriation risks associated with information revelation (H3b) is thus not supported. Inclusion of all three variables significantly improves the fit of the model ($\chi^2(3) = 8.88$; $p < 0.05$).

Effect on Estimated Probability of Diversification

Logit estimation does not yield coefficients whose effects on the dependent variable can be directly interpreted. Since logit estimation is not a linear form, the effect of a change in an independent variable depends on the initial level of that variable and on the value of the other variables in the model. Formally, the change in probability of diversification associated with a change in an independent variable from x to x' is calculated by:

$$\frac{\exp\{\beta X'\}}{[1 + \exp\{\beta X'\}]} - \frac{\exp\{\beta X\}}{[1 + \exp\{\beta X\}]}$$

where X and X' are vectors of all independent variables in the model and X' differs from X only in that the variable of concern equals x' rather than x.

The left half of Table 5 shows the effect on the estimated probability of diversifying entry for an increase in each independent variable from its mean to one standard deviation above the mean, conditional on all other variables being at their mean values. By way of illustration, consider a firm whose characteristics all happen to be equal to the sample's mean values (e.g., $\text{FSales}_i = 3.737$). Suppose this firm may potentially enter two industries, $j1$ and $j2$, whose industry characteristics also happen to be equal to the sample's mean values (e.g., $\text{IGrowth}_j = 10.011$). Suppose that AbsTech_{ij1} happens to be equal to the mean value for AbsTech_{ij} (3.020), but that AbsTech_{ij2} is equal to one standard deviation above this (22.279). Then the probability that firm i diversifies into industry $j1$ is 0.466, while the probability that firm i diversifies into industry $j2$ is 0.917.[13]

[13] These estimated probabilities are for the sample, not the population. The constant term has not been adjusted to account for

Table 5 Changes in Estimated Probabilities of Entry

	Effect of Changing Independent Variable From Mean Value to 1 Standard Deviation Above the Mean				Effect of Changing Independent Variable From Median Value to 3rd Quartile			
Variable (units)	Mean	1 Std Dev above mean.	P(Entry|Var. at 1 Std Dev above mean)[a]	Change from P(Entry|Var. at mean)[a]	Median	3rd Quartile	P(Entry|Var. at Third Quartile)[a]	Change from P(Entry|Var. at Median)[a]
IGrowth (%)	10.011	16.095	0.467	+0.011	9.640	12.845	0.461	+0.005
IConc (%)	37.465	58.180	0.352	−0.104	35.000	50.000	0.394	−0.062
IR&DS (%)	1.662	3.610	0.667	+0.214	1.060	2.090	0.569	+0.113
IAdvS (%)	1.555	3.868	0.493	+0.037	0.700	1.590	0.468	+0.012
FSales ($B)	3.737	14.447	0.501	+0.045	1.000	3.450	0.466	+0.010
FGrowth (%)	4.191	15.307	0.500	+0.044	2.806	9.717	0.480	+0.024
FR&DS (%)	1.762	3.518	0.492	+0.036	1.184	2.376	0.477	+0.021
FAdvS (%)	1.227	3.637	0.526	+0.070	0.175	1.309	0.485	+0.029
DiffR&D (%)	1.665	3.500	0.295	−0.161	1.020	2.145	0.375	−0.081
DiffAdv (%)	1.860	4.515	0.350	−0.106	0.810	2.050	0.414	−0.042
AbsTech (patents)	3.020	22.279	0.917	+0.461	0.051	0.630	0.473	+0.017
RelTech (patents)	0.038	0.145	0.555	+0.099	0.003	0.022	0.472	+0.016

[a] Assuming all other variables are held constant at their mean values.

As was discussed earlier, the technological resource measures are highly skewed. Since the changes in probability described above use the mean and standard deviation of each independent variable, such skewness is likely to exaggerate the effect of these variables on probability of entry. The right half of Table 5 presents the change in probability of diversification associated with changing each independent variable from its median value to its third quartile value. The technological resource variables have smaller effects when these values are used. This marked difference in effect on probability of entry between mean-standard deviation and median-third quartile measures exists because the vast majority of firm-industry pairs have extremely low levels of AbsTech_{ij}. Such a difference is consistent with the resource-based view, which is predicated on the notion that rent-generating resources, while few and far between, are significant to firm decision-making when they exist.

state-based sampling. For the population, the probability of entry when all variables are set to their means is less than 0.01, rising to slightly more than 0.09 when AbsTech_{ij} is increased by one standard deviation.

Further Exploration of Diversification Direction: Industry of Manufacture vs. Industry of Use

A patent can be assigned to both the industry in which it is used (SIC of Use) and, if it is a product patent, to the industry in which it is manufactured (SIC of Manufacture). AbsTech_{ij} and RelTech_{ij} are calculated based on equal weightings of both assignments. This implicitly assumes that a firm is as likely to exploit its technological resources by entering an industry in which it can manufacture its patented technology as it is by entering an industry in which it can use its technology. I tested this assumption by constructing alternate measures of AbsTech and RelTech, based solely on SIC of Use or on SIC of Manufacture (AbsTechU/RelTechU and AbsTechM/RelTechM, respectively). These tests, available from the author, indicate that the assumption is correct: For the entire sample, no alternate specification of technological resource applicability significantly improves on the measure used above.

Nevertheless, it is possible that for certain subsets of industries or technologies one of these technology exploitation routes dominates corporate diversification behavior—that firms tend to enter the business in which their technology can be used rather than where

Table 6 SIC of Use and SIC of Manufacture Variables (as function of source of innovation)

Type of Industry	N	Technological measures offering best fit[a]	Statistically significant improvement over next-best model?[b]
User-dominated	373 entries; 399 nonentries	AbsTechMfre; RelTechMfre	Yes ($p < 0.01$)
Supplier-dominated (equipment suppliers)	300 entries; 422 nonentries	AbsTechUse; RelTechUse	Yes ($p < 0.05$)
Supplier-dominated (materials suppliers)	356 entries; 404 nonentries	AbsTech; RelTech	No
Non-dominated	181 entries; 224 nonentries	AbsTech; RelTech	No

[a] As measured by log-likelihood.
[b] As measured by likelihood ratio test.

it can be manufactured, or vice versa. Pavitt (1984) and Pavitt et al. (1989) typologize industries by their primary source(s) of technological innovation. "Supplier-dominated" industries are those that derive most of their innovations from upstream suppliers. A second category of industries is characterized by the need for user input to the innovation process. (For somewhat obscure reasons, Pavitt et al. categorize this category as "specialized supplier" industries. I prefer to term them "user-dominated" industries for clarity.) Pavitt and his colleagues postulate that supplier-dominated industries are vulnerable to technology-based forward integration by upstream firms. Similarly, user-dominated industries are vulnerable to technology-driven backward integration.

If supplier-dominated industries are indeed prey to forward integration by innovative suppliers, then for such industries one would expect entry to be more strongly explained by SIC of Use than by SIC of Manufacture. If user-dominated industries are subject to backward integration by innovative users, then for such industries entry should be more strongly explained by SIC of Manufacture than by SIC of Use. Using these two categories from the Pavitt et al. typology, I test this below.

The Yale survey asked respondents to rate the importance of several sources of innovation in their respective industries, including material suppliers, equipment suppliers, and users. I categorized those industries for which the importance of material suppliers or equipment suppliers as sources of innovation was rated above the mean as supplier-dominated industries.[14] Those industries for which the importance of users as sources of innovation was rated above the mean were categorized as user-dominated industries. Industries with below-average ratings for the importance of suppliers and users were categorized as non-dominated. For each of these industry categories, I reestimated model 3 using three different measures of technological resource applicability: 1) AbsTech and RelTech; 2) AbsTechU and RelTechU; and 3) AbsTechM and RelTechM.

Rather than present the entire estimation results, which remain substantially the same across all runs, Table 6 identifies which specification of technological resource applicability offers the best fit for each industry category, as measured by the chi-square statistic. As the Table shows, and consistent with Pavitt et al. (1989), SIC of Manufacture provides the best fit for user-dominated industries. The SIC of Use measure provides the best fit for equipment supplier-dominated industries, although not for material supplier-dominated industries. The combined Use and Manufacture measure provides the best fit for industries that are neither user- nor supplier-dominated.

These results provide at least crude empirical support for the contention by Pavitt and his colleagues that the direction of technology-based entry varies across indus-

[14] Alternate cutoffs such as the third quartile generated similar results, although significance was reduced due to the lower number of observations.

tries as the primary source of innovation varies. They also provide a cautionary counterbalance to studies emphasizing the benefits of relying on users or suppliers as sources for new innovations. Von Hippel (1988) has detailed a number of industries in which users develop and prototype new innovations that manufacturers then commercialize. Teece (1992) has suggested that such symbiotic relationships with users or suppliers can underpin vertical collaborative ventures. The above results suggest, however, that managers should not be too sanguine about the potential competitive implications of user or supplier technological capabilities.

5. Conclusion

This study is the first attempt of which I am aware to examine the effects of firms' heterogeneous technological resources as measured by patent data on diversification behavior. It is also the first study to examine empirically the frequently voiced, but previously untested, hypothesis that firms prioritize their diversification options according to the *relative* applicability of their resources across these options. Finally, it is the first study to explicitly examine empirically the role of transaction costs on diversification in the context of the resource-based view of the firm. The results suggest that a firm's technological resource base, as manifested in its corporate patent portfolio, significantly influences its diversification decisions. In particular, a firm elects to enter markets in which it can exploit its existing technological resources and in which its existing resource base is strongest. In addition, a firm's diversification decision is influenced by the severity of hazards surrounding contractual alternatives to diversification. Finally, the results suggest that, as Pavitt and colleagues have conjectured, the source of innovation in an industry indicates the direction of likely diversifying entry into that industry.

In addition to using the resource-based view to shed light onto diversification, this study has used the phenomenon of diversification to shed light on the resource-based view. First, resource-based empirical research has lagged its theoretical counterpart in the operationalization of sufficiently detailed, application-specific measures of firms' resources. This has restricted the scope of the framework's empirical research agenda, and perhaps has biased downward the apparent empirical significance of resources to firm behavior and performance. The powerful effect of technological resources on diversification identified in this study suggests that similar operationalization of other resources may further reveal the power of the resource-based view.

Second, the resource-based view remains at odds with transaction cost economics over perceived differences in the feasibility of using markets to exploit rent-generating assets (Montgomery and Hariharan 1991) and, more recently, over the role of opportunism and motivation of hazard mitigation as determinants of organization form (Chi 1994, Argyres 1996, Conner and Prahalad 1996). This study's integration of transaction cost reasoning into the resource-based view suggests that while conflicts between the two theories do exist, the strong complementarities between them should not be ignored.

Finally, this study has developed and used a new measure of a firm's technological resource base. Although similar in spirit to prior patent-based measures of "technological position" (e.g., Jaffe 1986), the measure developed herein is able to link a firm's position to product markets where its technological strength is likely to offer commercial advantage. Future research could entail elaboration of this measure to inform a wide range of research questions, including stock market valuation of patented technology (e.g., Cockburn and Griliches 1988) and broader issues of corporate governance and scope (e.g., Lang and Stulz 1992).[15]

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