

## RESEARCH NOTES AND COMMENTARIES

### CONCEPTUALIZING AND MEASURING CAPABILITIES: METHODOLOGY AND EMPIRICAL APPLICATION

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*This paper attempts to operationalize and measure firm-specific capabilities using an extant conceptualization in the resource-based view (RBV) literature. Capabilities are conceived as the efficiency with which a firm employs a given set of resources (inputs) at its disposal to achieve certain objectives (outputs). We expand on extant theoretical literature on relative capabilities, by delineating the conditions that have to be met for relative capabilities to be measured non-tautologically. We then proceed to suggest an estimation methodology, stochastic frontier estimation (SFE), that allows us to infer firm capabilities. We illustrate this technique with a sample of firms in the semiconductor industry. Our findings underscore the heterogeneity in R&D capability across firms in this industry, as well as the persistence in these capabilities over time. We also find that the market rewards high R&D capability firms, in that they show the highest average values of Tobin's q. Copyright © 2004 John Wiley & Sons, Ltd.*

## INTRODUCTION

The resource-based view (RBV) looks inside the firm for sources of superior performance with respect to competition. In particular, it attempts to link superior firm performance to the resources and capabilities possessed by firms (Teece, 1980; Wernerfelt, 1984; Barney, 1991; Peteraf, 1993). While extremely successful in explaining a number of phenomena, such as diversification, leading

researchers in the field have stressed a number of problems within the theory.

Perhaps the most significant criticism of the RBV has to do with the conceptualization and measurement of capabilities. For instance, Porter (1994), and Williamson (1999) criticize extant operationalizations of capabilities as being tautological. These authors point out that most extant studies identify critical resources/capabilities by comparing successful firms with unsuccessful ones, and then test if the resources/capabilities thus identified are indeed critical. Not surprisingly, the answer to this question is always a yes, making the theory unfalsifiable.

As these researchers suggest, what is needed is a conceptualization and measurement of capabilities

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that are *independent* of their rent generation ability. This paper attempts to delineate a way to accomplish this task. We start by clarifying notions of resources and capabilities. Then we focus on existing conceptualizations of capabilities, concentrating in particular on the notion of relative capabilities. We then suggest an econometric technique, stochastic frontier estimation (SFE), that is ideally suited to accompany this conceptualization.

We illustrate our technique with an empirical application to a sample of firms in the semiconductor industry. Our results suggest that there is significant heterogeneity between firms in their R&D capability. Further, we find evidence for significant persistence in R&D capabilities over time, in tune with what theory would predict. Finally, we find that the market rewards high R&D capability firms, in that they show the highest average values of Tobin's  $q$ .

## THEORETICAL BASE

The literature on capabilities shares one important point in common. As McGrath, MacMillan, and Venkataraman (1995) suggest, 'virtually every definition of competence in the literature refers to some purpose the firm is able to achieve . . . , preferably in a manner superior to that employed by other firms . . . ' Thus, capabilities represent the ability of the firm to *combine efficiently* a number of resources to engage in productive activity and attain a certain objective (Amit and Schoemaker, 1993). A firm's resources are 'assets that it owns, and that are externally available and transferable' (Grant, 1991; Amit and Schoemaker, 1997). While resources like innovative patents *per se* confer great advantages upon a firm, of more interest is the firm's *ability to come up* with such patents consistently.

### Capabilities: theory development

One can think of capabilities as the *efficiency* with which a firm uses the *inputs* available to it (i.e., its resources, such as R&D expenditure), and converts them into whatever *output(s)* it desires (i.e., its objectives, such as developing innovative technologies). This reasoning suggests that capabilities are clearly an 'intermediate transformation ability' between resources (i.e., inputs) and objectives. (We use the terms resources and inputs synonymously

hereon.) Since capabilities are an intermediate step between resources and outputs, one can hope to *see* the inputs that a firm uses and the outputs it achieves, but one can only *infer* its abilities in converting one to the other. This point is crucial—if capabilities are indeed hard to observe, they would be hard to imitate or buy, as the theory suggests.

We start by first considering reasonable objectives that the firm may wish to achieve—among the many one could think of are: producing innovative technologies, introducing new products speedily, and reducing manufacturing cost. Having done this, one then needs to figure out what inputs a firm could use to achieve these objectives.

Further, since our interest is in assessing capabilities in a relative sense, we need some benchmark against which a firm's performance is compared. One obvious method, of course, is to benchmark against the competition (Collis and Montgomery, 1995). This requires that we carefully specify the resources that firms use to achieve their objectives, and ensure that these are comparable across firms. Comparable means a number of things here. At the most basic level, both resources and objectives have to be similar across firms (e.g., R&D expenditures as a resource for all firms). But, more subtly, we have to ensure that we not only look at output, but also account for differences in the quantity of resources available to different firms. In addition, one has to ensure that capabilities are compared across similar external conditions. Finally, the literature has emphasized that it is not sufficient to examine resources and capabilities in isolation—complementarities should also be considered (Helfat, 1997).

## MEASURING CAPABILITIES: STOCHASTIC FRONTIER ESTIMATION

In addition to satisfying the requirements on relative capabilities outlined above, our measurement task requires us to do two things:

1. Measure the maximum possible objective (output) the firm could have achieved, given its set of resources (inputs). This tells us the *best* the firm could have done, if it had used the resource level at its disposal efficiently, to achieve its objective.
2. Observe a firm's actual performance, i.e., the level of objective it actually attained. Given the

estimate of the *best*, from step 1 above, it is possible to measure how far its actual performance was from this best. The greater the gap between its maximum achievable objective and its actual performance, the lower its efficiency, and hence, the lower its capability.

We formalize the above intuition by modeling a firm's activities as an *efficient frontier* or *transformation function* (akin to the notion of a 'production frontier/function' in economics), relating the resources used by a firm to the optimal attainment of its objective(s). Thus, focusing on the R&D activity of a firm, one possible objective might be maximizing the production of innovative technologies, and the possible inputs available for fulfilling this objective would include current and past R&D expenditure. More formally, we would suggest a relationship of the form:

$$\text{Firm's production of innovative technologies} = f(\text{R\&D expenditure, environmental conditions}) \quad (1)$$

where the 'environmental conditions' serve to ensure that external conditions are controlled for across firms. We can write this out in the following econometric specification:

$$\begin{aligned} \ln(\text{TECH\_INNV}_{it}) = & \alpha_0 + \alpha_1 \\ & \times \ln(\text{CUM\_R\&DEXPENSE}_{it}) + \alpha_2 \\ & \times \text{ENV\_CONDNS} + \varepsilon_{it} - \eta_{it} \end{aligned} \quad (1a)$$

Note that the variable names in Equation 1a refer to the respective variables in Equation 1, i.e., TECH\_INNV refers to innovative technologies and CUM\_R&DEXPENSE to R&D expenditure. First, note that the resources available to a firm are *not* the same as its capabilities. Second, the objective, or output of the firm, in this case innovative technologies, is also not a measure of its R&D capability. It is the error term  $\eta_{it}$  that enables us to capture the theory of capability we discussed above. This error term captures sub-par performance by the firm in R&D activity, which could be due to various reasons: e.g., an inefficient division of R&D resources between projects, or poor R&D leadership leading to morale problems. By definition, capability is the inverse of inefficiency—the greater the inefficiency, the lower is the capability. A capability thus represents the transformation ability between inputs and the output of innovative

technologies and is *inferred* from the observation of the inputs and output.

Since  $\eta$  represents inefficiency, we assume that it takes only positive values. More formally, it is assumed to be an independent and identically distributed non-negative random variable, defined by the truncation (at zero) of the  $N(\mu_{it}, \sigma_{\eta}^2)$  distribution with mode  $\mu > 0$  (Greene, 2001). Note that the parameter  $\mu$  captures the mode of R&D inefficiency of firms in the sample. This is, in effect, a random parameters specification.

The parameter  $\alpha_1$  represents the marginal impact on innovative output of deploying an additional unit of the resource. Thus,  $\alpha_1$  represents the percentage change in TECH\_INNV as a result of a percentage change in CUM\_R&DEXPENSE; i.e., it is the marginal product of TECH\_INNV with respect to CUM\_R&DEXPENSE. Notice that by measuring the same resources across firms we can actually compare the R&D capability of one firm with another. Further, the SFE technique calculates capabilities *conditional* on the level of resources firms have. Finally,  $\alpha_3$  represents the impact of external environmental conditions in affecting output.

Note that in the formulation above, R&D expenditure is treated as an exogenous variable for the firm. It is reasonable to suppose, however, that the amount of resources a firm devotes to the production of technological output might well be a choice determined by the output the firm expects to produce. This leads to the well-known problem of endogeneity of the regressors, which has dogged research on productivity analysis for a long time (Griliches and Mairesse, 1995). Not controlling for endogeneity could make parameter estimates both biased and inconsistent. Theoretically, the best solution to this problem is the use of instrumental variables, but in practice it is extremely hard to find 'appropriate instruments that have genuine information about factors which affect firms differentially as they choose their input levels' (Griliches and Mairesse, 1995). A fruitful alternative approach is to model the innovation process 'structurally.' We acknowledge these limitations of our work, but defer the search for effective instruments, or more structural modeling approaches, to future research.

The error term  $\varepsilon_{it}$  represents the purely stochastic error component affecting innovative output. Conceptually, this error term controls for random events, both external and internal to the

firm. An appropriate measurement of capabilities should not erroneously ascribe the effects of positive or adverse random shocks to a firm's high or low capabilities. The existence of two error terms,  $\eta$  and  $\varepsilon$ , ensures that we do not commit this error. Mathematically, the random error component in our case is similar to the standard OLS random error component, and following the usual OLS assumptions is assumed to be distributed as  $N(0, \sigma_\varepsilon^2)$ .

We further enrich our specification by taking into account the role of complementarities between R&D and marketing inputs. This would be parsimoniously incorporated in our SFE framework as follows. Referring to Equation 1a above, we would add another layer to the equation, i.e.:

$$\alpha_1 = \alpha_{10} + \beta_1 \times \ln(\text{MKT\_EXP}_{it}) + u \quad (1b)$$

where  $u$  is a random error term. The coefficient  $\beta_1$  measures the extent of complementarity between CUM\_R&DEXPENSE and MKT\_EXP. A positive and significant value of  $\beta_1$  would suggest that a firm with high marketing expenditure sees better returns on every R&D dollar that it spends.

To sum, the actual estimation of R&D capability proceeds as follows:

- Based on the difference between the maximum innovative output achievable, and the observed output, obtain an estimate of the composite error,  $(\varepsilon_{it} - \eta_{it})$ .
- Based on the composite above, obtain a consistent estimate of firm specific R&D inefficiency,  $\hat{\eta}_{it}$ .
- Now, our focus is on relative capabilities, particularly benchmarking with respect to the competition (Collis and Montgomery, 1995). We incorporate this notion by measuring the capabilities of any firm relative to the highest capability in the sample. To achieve this, we normalize the highest capability in the sample to a value of 100 percent, i.e., that firm would have inefficiency,  $\hat{\eta}_{it} = 0$ . With this calibration of firm-specific capabilities, we can write the R&D capability of a firm as:

$$R\&D\_CAP_{it} = (1 - \hat{\eta}_{it}) \times 100\%$$

Before we go on to the actual empirical application, it is important to compare this method with a

standard linear regression estimated using ordinary least squares (OLS). First, unlike OLS, SFE helps us separate out the influence of luck from that of firm-specific inefficiency. Second, since the OLS approach, by definition, assumes that firms are operating on their efficient frontier, it is not really meaningful to speak of deviations from the sample mean as inefficiency. Such deviations could represent anything, especially luck. At best, the OLS approach can give us a relative ranking of firms—it is not clear, however, that this ranking would be based on the inefficiency of firms. Finally, if there is indeed inefficiency in the sample, the OLS estimator would be statistically inefficient, i.e., would give larger standard errors than the frontier estimator (Habib and Ljungqvist, 2000). In our empirical application we conduct a likelihood ratio test for the appropriateness of the stochastic frontier specification.

## EMPIRICAL APPLICATION

In this section we illustrate the theory and measurement of capabilities discussed above, to estimate the R&D capabilities of firms in the semiconductor and computer equipment industries. From both a theory and managerial perspective, these markets are of interest for their intensive use of science and technology, and constant innovation. The fact that technology has been changing so rapidly in this market gives added urgency and interest to the task of measuring R&D capabilities, and investigating heterogeneity in R&D capabilities across firms.

To estimate firms' R&D capabilities, we need data on both the firm's R&D resources and its R&D outputs, over a time period. Our sample consists of 64 publicly traded firms. The primary SICs for most of these firms are in semiconductors and computers (i.e., SIC codes 357 and 367). Most of these firms fall in SIC code 3674, which is semiconductors. For each firm in our sample, we collected information pertaining to the resources available to R&D domain of activity, and the output from the Compustat database for the years 1980–98.

The Compustat database, however, did not give us information pertaining to the firm's innovative output. For this we conducted an exhaustive content analysis of patent data gathered from the U.S. patent office (USPTO). This involved a citation

analysis of over 10,000 patents issued to various firms over the sample time period.

## SPECIFYING THE R&D EQUATION AND MEASURES USED

### Objective (output)

The goal of R&D is to develop high-quality technological innovations—both product innovations (which form the basis of new product introductions) and process innovations. We thus use maximization of quality-adjusted technological output (TECH\_INNV) as the objective of a firm's R&D function.

### TECH\_INNV

Consistent with the empirical R&D literature (Trajtenberg, 1990; Dutta *et al.*, 1999), we measure technological output using patent counts weighted with citations, to adjust for quality. We construct the citation-weighted patent count as follows. We first calculate the average number of citations received by all the patents belonging to the firms in our sample. The weight assigned to a firm's patent, then, is the number of citations the patent has received divided by the sample average. The sum of these citation-weighted patents, for a particular year, for a particular firm, is the value of TECH\_INNV for that firm for that year.

### Resources (inputs)

Past literature has emphasized the importance of learning-by-doing in high-technology markets (Irwin and Klenow, 1994). This immediately suggests that a firm's past R&D expenditures (CUM\_R&DEXPENSE) are an important resource available to it. Our arguments on complementarity suggest that a firm's marketing expenditure (MKT\_EXP) would have a significant impact on the efficacy of its R&D expenditure.

#### (a) Cumulative R&D expenditure (CUM\_R&DEXPENSE)

We estimate the cumulative R&D expenditure using a Koyck lag structure, with declining weights on annual R&D expenditure into the past. Following past literature (Griliches, 1984), we used a

weight of 0.4. The results were robust to different weights.

#### (b) Cumulative marketing expenditure (MKT\_EXP)

We estimate the cumulative marketing expenditure intensity using a Koyck lag structure, with declining weights on each year's marketing expenditure intensity. We calculate each year's marketing expenditure intensity by dividing the annual sales, general and administrative (SGA) expenditures of the firm by its sales for that year. A weight of 0.5 was used; the results were robust to different weights.

### Control variables

In order to control for the impact of external macroeconomic conditions we introduce year dummies, which are defined as follows.

$$\text{YEAR}_{ik} = 1 \text{ if the observation (year } t) \text{ pertains to year } k; \text{ zero otherwise}$$

### Capabilities

We now specify the *R&D frontier/transformation function*, which allows us to estimate the firm specific capability  $\hat{\eta}_{it}$ .

$$\begin{aligned} \ln(\text{TECH\_INNV}_{it}) &= \alpha_0 + \alpha_1 \\ &\times \ln(\text{CUM\_R\&DEXPENSE}_{it}) + \alpha_2 \\ &\times \text{ENV\_CONDNS} + \varepsilon_{it} - \eta_{it} \end{aligned} \quad (2)$$

In Equation 2, subscript  $i$  represents firms and  $t$  represents years. Note that this equation is identical to Equation 1a discussed in the previous section. The parameter  $\alpha_1$  represents the marginal product of CUM\_R&DEXPENSE, i.e., the percentage change in TECH\_INNV as a result of a percentage change in CUM\_R&DEXPENSE.

## ESTIMATION METHODOLOGY

We estimate the parameters using the method of simulated maximum likelihood. Briefly, the likelihood function is given as

$$L = \prod_{i=1}^N \prod_{t=1}^T \frac{1}{\sqrt{\sigma_\eta^2 + \sigma_\varepsilon^2}} \times \left[ 1 - \Phi \left( \frac{\sigma_\eta [Y_{it} - f(X_{it}, \alpha)]}{\sigma_\varepsilon \sqrt{\sigma_\eta^2 + \sigma_\varepsilon^2}} - \frac{\sigma_\varepsilon \mu}{\sigma_\eta \sqrt{\sigma_\eta^2 + \sigma_\varepsilon^2}} \right) \right] \times \phi \left( \frac{Y_{it} - f(X_{it}, \alpha) + \mu}{\sqrt{\sigma_\eta^2 + \sigma_\varepsilon^2}} \right) \times \left[ 1 - \Phi \left( -\frac{\mu}{\sigma_\varepsilon} \right) \right]^{-1}$$

In order to account for unobserved heterogeneity, we let  $\alpha_1$  be randomly distributed over the population, as  $N(\bar{\alpha}, \sigma_\alpha^2)$ . Further, since the mean of CUM\_R&D is a function of firm-specific variables, such as marketing expenditure, we have (Greene, 2001)

$$E[\alpha_i | z_i] = \alpha + \Delta_{z_i}$$

where  $z_i$  denotes marketing expenditure for firm  $i$ .

To sum, we have a random parameters formulation of the frontier equation, with heterogeneity in both the inefficiency term and in the coefficients of the variables affecting the frontier.

## RESULTS AND DISCUSSION

Parameter estimates and specification test results are reported in Table 1. We now turn to a detailed discussion of our results.

### Innovative frontier (R&D capability, Equation 2)

As a first check of our specification, the likelihood ratio test rejects the null of no skewness

for the residuals at the 99 percent level of confidence. This is important, since the logic of using stochastic frontier estimation is predicated on the skewness of the residuals. The test results thus support the appropriateness of our specification.

### Parameter estimates

First, the coefficient for CUM\_R&DEXPENSE ( $\alpha_1 = 0.8055$ ,  $p < 0.01$ ) is significant and positive. This is not surprising, and supports the conventional wisdom on the subject (Griliches, 1984).

Second, the coefficient  $\beta_1$ , which measures complementarity between marketing expenditures and the cumulative R&D expenditures of a firm, is positive and significant ( $\beta_1 = 0.0232$ ,  $p < 0.01$ ). This suggests the presence of complementarity between R&D and marketing.

Third, there is significant unobserved heterogeneity in CUM\_R&DEXPENSE ( $\gamma_1 = 0.0680$ ,  $p < 0.01$ ). While our notion of capabilities, as represented by the inefficiency error terms, is capturing a lot of the variation in transformative processes across firms, these results suggest there is still heterogeneity that is not being captured explicitly.

### Distribution of R&D capabilities

The first thing we note is the significant heterogeneity in capability between firms in our sample, with an average R&D capability of 76.24 percent and a standard deviation of 18.94 percent. Since a prerequisite for capabilities to serve as sources of competitive advantage is that there be heterogeneity in their distribution, this result is important. Temporally, the patterns suggest one of increasing

Table 1. Parameter estimates for R&D capability: stochastic frontier estimation

Variables	Parameter estimates	Unobserved heterogeneity
<i>Impact of inputs:</i>		
$\ln(\text{CUM\_R\&D})$ : Estimate	$\alpha_1 = 0.8055$ (0.0121)**	$\gamma_1 = 0.0680$ (0.0016)**
$\ln(\text{MKT\_EXP})$ (Complementarity)	$\beta_1 = 0.0232$ (0.0032)**	
Composite error variance ( $\sigma_e^2 = \sigma_\varepsilon^2 + \sigma_\eta^2$ )	$\sigma_e = 1.5645$ (0.0234)**	
Inefficiency error variance ( $\sigma_\eta^2$ )	$\sigma_\eta = 2.2590$ (0.1031)**	

\*\* Significant at 1% level.

Note:

1. Standard errors are in parentheses above.
2. The log-likelihood value is -1222.611. The LR test statistic for the significance of the one-sided error is 237.79, which is a mixed chi-square distribution with three restrictions. This is significant at the 1% significance level.
3. We restricted the variance-covariance matrix for the unobserved heterogeneity components to be diagonal.

average R&D capability, and decreasing heterogeneity over the entire sample. Thus, the mean R&D capabilities for the years 1985, 1990, and 1995 are 68.37 percent, 76.08 percent, and 79.14 percent respectively (the differences are significant at the 5% level). The standard deviations for these years were 21.22 percent, 21.05 percent, and 16.97 percent (significantly different at the 10% level). Taken together, these results suggest an interesting comparison between the years 1985 and 1995—while firms have, on average, improved their R&D capabilities considerably, the gap between the higher and lower capability firms has narrowed. This also seems intuitively reasonable, in that one would expect firms to be adjusting their inefficiencies, albeit slowly.

To get an alternative look we split our sample over the entire time period into three categories, on the basis of R&D capability: low, medium, and high. We then examine the heterogeneity of R&D capability *within* each group. Interestingly, we find significant differences, with standard deviations ranging from 2.36 percent for the high group to 16.23 percent for the low group, with the medium capability group at 4.40 percent (these differences are significant at the 1% level). While this result combines both time-series and cross-sectional variation, and should therefore be treated with caution, it does suggest that firms above a certain R&D capability level tend to be much more tightly bunched together; intuitively, it is much harder to gain incremental competitive advantage at higher levels of capability.

### Differences in R&D capabilities: Further exploration

While the above results are useful and interesting, they suggest a number of avenues for further empirical exploration. To facilitate the analysis that follows, we again split up our sample into three categories based on the distribution of R&D capabilities: low, medium, and high R&D capability. Note that this categorization is different from the one used earlier; to clarify, we assigned firms to categories in each year, based on their R&D capability in that year relative to the rest of the industry. Firms can thus move between groups, an issue we will explore at greater length shortly.

First, we wished to explore whether there was any correlation between market performance measures, such as Tobin's  $q$ , and the R&D capabilities

of firms. The average values of Tobin's  $q$  for the three groups (low, medium, and high) are 0.84, 1.28, and 1.81 respectively, which are significantly different at the 1 percent level. This provides supporting evidence for another cornerstone of the resource-based view on capabilities, namely that they serve as sources of competitive advantage.

Second, we examined whether there were significant differences between the R&D intensities (i.e., R&D expenditure divided by sales) of the three groups of firms (i.e., low, medium, and high R&D capability firms). We do not find any significant differences (the means are 9.29 percent, 10.18 percent, and 11.33 percent for the three groups respectively). Since our measurement of R&D capability explicitly accounts for differences in the R&D resources of firms, one need not, *a priori*, expect a positive relation between capabilities and R&D intensity, which seems to be the case here.

Third, we examined whether there were significant differences between the marketing intensities (i.e., marketing expenditure divided by sales) of the three groups of firms. There were no significant differences between the marketing intensities of the three groups (26.08%, 28.07%, and 29.58% respectively for the low, medium, and high groups). One reason could be that the high-capability firms feel they have the most to gain from marketing expenditure, while the low-capability firms need to spend on marketing to gain competitive advantage that their innovativeness does not give them directly.

### Persistence in R&D capabilities

Theory suggests that part of what makes capabilities so valuable is the fact that they are 'sticky,' i.e., there should be persistence in capabilities over time. To examine this, we considered an identical set of firms in the years 1985, 1990, and 1995 (approximately 30 firms). We rank ordered the firms for each of the years on the basis of their R&D capability, and correlated these ranks across these years. The correlogram is shown in Table 2 (Habib and Ljungqvist, 2000). The correlations are significant at the 1 percent level, thus rejecting the null of no persistence. To put these numbers in perspective, observe that with a sample of 30 firms, with no persistence, the probability of any firm getting the same rank that it had last time is about 0.03, which is a lot less than our correlations (of

Table 2. Correlogram for R&amp;D capability (Spearman's rank order correlation)

	1985	1990	1995
1985	1	0.701**	0.316
1990	0.701**	1	0.607**
1995	0.316	0.607**	1

\*\* Significant at 1% level.

about 0.6). We can examine persistence in a different way, by assessing the probability that a firm will find itself in the same *category* of R&D capability (i.e., high, medium, or low, with the category sizes being equal) over different time periods. Without any persistence, this would be about 0.33 (because the likelihood of being in any group is equal). On redoing the analysis with our numbers, for 5-year intervals (1985, 1990, 1995) the correlation comes out to be close to 0.98; in other words, there is a very high probability of firms remaining in the relative category (high, medium, or low R&D capability) that they started off with. Given these are observations over 5-year intervals, the stickiness in a firm's relative position is remarkable.

## FUTURE RESEARCH DIRECTIONS

In this section we discuss some limitations of our approach, as well as its applicability, and suggest future research directions. At the outset, it is important to emphasize the generality of our method. Thus, all this approach requires is (a) measurable objectives (outputs), and (b) measurable resources (inputs) that go to achieving those objectives. In addition, it is not confined to any single level of analysis. Other than the level of functional domains of activity (R&D) that we have used, one could also think of capabilities as being at the project level (e.g., Henderson and Cockburn, 1994). As far as limitations go, the most obvious one is the use of a parametric approach to estimating capabilities.

Given the data requirements of our approach (secondary data, preferably in a panel setting), we feel that our method would be an ideal complement to more detailed firm-level studies (e.g., McGrath *et al.*, 1995) that focus on particular capabilities and attempt to uncover the underlying reasons for

differences in those capabilities. Further, by tracking these capabilities over time one can examine the impact of any managerial actions taken in the interim.

There are a number of ways one could fruitfully apply and extend our approach. First, and most importantly, one can explicitly incorporate the notion of dynamic capabilities (Teece, Pisano, and Shuen, 1997). We have taken a first step in this direction by examining the persistence of capabilities, but have not modeled the time paths of capabilities explicitly.

Second, modeling dynamic capabilities would help one focus on how a firm's superior capabilities might help it in resource creation for the future. For instance, the firm's ability to regenerate its technological know-how base could be linked to the concept of absorptive capacity (Cohen and Levinthal, 1990).

## CONCLUSIONS

We attempted to accomplish three main tasks in this paper. First, we amplified on an extant conceptualization of capabilities in the literature, suggesting how the notion of relative capabilities could be thought of theoretically. Second, we proposed an econometric technique, SFE, that is well suited to the measurement firm-specific capabilities. Finally, we applied our operationalization and econometric technique to a sample of firms in the semiconductor and computer industries, and estimated firm-specific R&D capabilities. The results provide evidence for the presence of heterogeneity in R&D capabilities in our sample, the persistence of these capabilities over time, and a recognition by the market of the importance of these capabilities.

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