Success in High-Technology Markets: Is Marketing Capability Critical?

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Abstract

We propose a conceptual framework—with the resource-based view (RBV) of the firm as its theoretical underpinning—to explain interfirm differences in firms' profitability in high-technology markets in terms of differences in their functional capabilities. Specifically, we suggest that marketing, R&D, and operations capabilities, along with interactions among these capabilities, are important determinants of relative financial performance within the industry. This paper contributes to the RBV literature by proposing the input-output perspective to conceptualize the notion of capabilities. Specifically, this approach entails modeling a firm's functional activities—viz., marketing, R&D and operations—as transformation functions that relate the productive factors/resources to its functional objectives, if the firm were to deploy these resources most efficiently. Any underattainment of the functional objective, then, is attributable to functional inefficiency, or equivalently, to a lower functional capability of the firm. The input-output conceptualization of a firm's capabilities is then estimated using the stochastic frontier estimation (SFE) methodology. SFE provides the appropriate econometric technique to empirically estimate the efficient frontier and hence the level of efficiency achieved by the various firms.

Our study contributes to a number of literatures, both methodologically and substantively. First, it contributes both conceptually and methodologically to the RBV literature. Conceptually, our study suggests that firm capabilities can be viewed in an input–output framework. Methodologically, the study suggests the use of stochastic frontier estimation to operationalize and estimate firm capabilities. This methodology is, to the best of our knowledge, the first to allow the researcher/manager to *infer* capabilities from archival data. Substantively, our study contributes to the literature on market orientation by suggesting that a stronger market orientation of a firm should be reflected in a higher marketing capability. It also adds to the literature on "design for manufacturability" by explicating the complementarity among the various functional capabilities and offering empirical evidence on their relative importance in influencing a firm's performance. Finally, our study builds on prior literature that has highlighted the importance of marketing–R&D coordination as important determinants of new product development and success. We highlight below some of our main findings.

• A strong base of innovative technologies enhances a firm's sales by favorably influencing consumers' expectations about the externality benefits associated with its product. This suggests that a past track record of consistent innovation is a credible signal to current and potential customers of the firm's continued excellence in a technologically evolving market. Given the importance of influencing customers, managers need to tailor their marketing activities around the need to inform customers of the technological excellence of their firm. Thus, customers need to be informed of the innovative technologies that the firm possesses and of the future R&D initiatives undertaken by it. Similarly, any potential applications of innovative technology developed by the firm, and of technologies under development, should be emphasized.

• Marketing capability has its greatest impact on the (quality-adjusted) innovative output for firms that have a strong technological base. In other words, firms with a strong R&D base are the ones with the most to gain from a strong marketing capability.

• Marketing capability strongly influences the width of applicability of innovations, i.e., a firm's marketing capability enhances its ability to generate innovative technologies that have applications across a range of industries. This result carries a strong message for managers: A strong market orientation is one of the most fertile sources of ideas for innovation. Thus, marketing needs to be involved from the beginning of the innovation process—namely, right at the stage when technological ideas are being generated.

• The most important determinant of a firm's performance is the interaction of marketing and R&D capabilities. This supports the assertion that firms in high-technology markets need to excel at two things: the ability to come up with innovations constantly, and the ability to commercialize these innovations into the kinds of products that capture consumer needs and preferences. This finding offers further evidence on the importance of coordination between R&D and marketing, as suggested in the extant marketing literature.

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Finally, using archival data, our methodology can be used to benchmark a firm's capabilities, with other firms in the industry, along various functional dimensions. This would be an important step in making more informed resource-allocation decisions. Thus, the firm can spend more money on those capabilities where it most lags the competition, or on those capabilities that are shown to have the maximum impact on firm performance.

(*High-Technology Markets; Resource-Based View; Firm-Specific Capabilities; Stochastic Frontier; R&D and Innovation; Patents and Patent Citations; Cross-Functional Coordination; Marketing-Manufacturing Interface; Market Orientation*)

1. Introduction

Firms in high-technology markets are growing at twice the rate of the economy as a whole and have generated significant returns for their shareholders in recent years. However, despite the rapid growth and profitability for these markets, there exists significant variation in the performance of the firms, often within the same industry (*Business Week* 1998).[1] Interestingly, most of the extant literature has attributed variation in interfirm performance to external market factors, where a major component influencing the firm's performance is its ability to curtail competitive rivalry (Porter 1980, Montgomery and Wernerfelt 1988). Other studies have attempted to explain interindustry differences in R&D investment and innovative performance by identifying different appropriability and opportunity conditions across industries (Griliches 1984, Boulding and Staelin 1995). Virtually no role is ascribed to firm-specific factors in these studies.[2]

The few existing detailed case studies of individual firms in high-technology markets emphasize the role of R&D and manufacturing in enhancing firms' performance (e.g., Iansiti and West 1997). The role of marketing is, however, rarely acknowledged. We argue that this picture of high-technology industries is seriously incomplete. A firm might have a strong R&D ability but be incapable of converting it into commercially viable products because of a poor marketing ability. For example, Xerox PARC came up with revolutionary concepts such as the graphical user interface and the laser printer but was unable to exploit them because of its poor marketing ability. Similarly, although AMD came up with the fastest chip in the market (the K6), it was unable to pose a serious challenge to Intel because of the latter's superior marketing and operations abilities.

The above discussion highlights the importance of considering marketing, R&D, and operations capabilities together to understand interfirm differences in performance. To this end we propose a conceptual framework—with the resource-based view (RBV) of the firm as its theoretical underpinning—to assess firm-specific determinants of firm's financial performance in high-technology markets. The RBV (Wernerfelt 1984) views a firm as a bundle of resources and capabilities, with firms differing in their endowments of these resources and capabilities. Because capabilities are difficult to imitate or transfer, possessing superior capabilities bestows enduring competitive advantage upon the firm (Peteraf 1993). Hence, the RBV suggests that intra-industry variations in firms' performance (i.e., firms' competitive environment being the same) can be attributed to differences in their capabilities. While the RBV offers an insightful theoretical foundation, prior empirical efforts to use this framework have been plagued with problems, particularly the problem of operationalizing and measuring firms' capabilities (Teece et al. 1997).

This paper contributes conceptually to the RBV literature by proposing the input–output perspective to clarify the notion of a firm's capabilities. Specifically, this approach entails modeling a firm's functional activities—viz., marketing, R&D and operations—as transformation functions that relate the productive factors/resources to its functional objectives, if the firm were to deploy these resources most efficiently. Any underattainment of the functional objective, then, is attributable to the functional inefficiency (equivalently, a lower functional capability) of the firm. The input–output conceptualization of a firm's capabilities is then

[1]The significant intra-industry variation in firms' performance is not limited to firms in high-technology markets alone but has also been empirically observed in other industries. In fact, Rumelt (1991) reports a higher intra-industry than interindustry variation in firms' profitability.

[2]Boulding and Staelin (1995) do control for firm-specific factors via unobserved heterogeneity, but their emphasis is on the role of industry factors as moderating variables.

estimated using the stochastic frontier estimation (SFE) methodology. SFE provides the appropriate econometric technique to empirically estimate the efficient frontier and hence the level of efficiency achieved by the various firms (equivalently, their functional capabilities). This technique contributes methodologically to the RBV literature, in that it permits a measurement of capabilities while explicitly linking resources to capabilities.

Our study contributes to the literature on market orientation (Deshpande et al. 1993, Jaworski and Kohli 1993, Day 1994) by suggesting a way to infer the market orientation of a firm—namely, by measuring its marketing capability. We suggest that a superior market orientation should be reflected in a higher marketing capability. It also adds to the literature on "design for manufacturability" (Hayes et al. 1988, Srinivasan et al. 1997) by explicating the complementarity between the various functional capabilities. Finally, our study builds on prior literature that has highlighted the importance of marketing and R&D and their coordination as important determinants of new product development and success (e.g., Gupta et al. 1987, Griffin and Hauser 1996, Gatignon and Xuereb 1997) in two ways. First, we explicate and measure the impact of marketing on R&D; second, we measure the impact of the interaction of R&D and marketing capabilities on firm financial performance.

We highlight below some of our substantive findings:

• A strong base of innovative technologies enhances a firm's sales by favorably influencing consumers' expectations about the externality benefits associated with its product. This suggests that a past track record of consistent innovation is a credible signal to current and potential customers of the firm's continued excellence in a technologically evolving market.

• Marketing capability has its greatest impact on the (quality-adjusted) innovative output for firms that have a strong technological base. In other words, firms with a strong R&D base are the ones with the most to gain from a strong marketing capability.

• Marketing capability strongly influences the width of applicability of innovations, i.e., a firm's marketing capability enhances its ability to generate innovative technologies that have applications across a range of industries.

• The most important determinant of a firm's performance is the interaction of marketing and R&D capabilities. This supports the assertion that firms in high-technology markets need to excel at two things: the ability to come up with innovations constantly, and the ability to commercialize these innovations into the kinds of products that capture consumer needs and preferences. This finding offers further evidence on the importance of coordination between R&D and marketing, as suggested in the extant marketing literature.

The rest of the paper is organized as follows. The next section discusses the resource-based view of the firm underlying our empirical analysis and develops the input–output conceptualization of a firm's functional capabilities. Section 3 briefly discusses the data, variables operationalization, and empirical model specifications. We also outline the econometric methodology employed in the analysis. Section 4 presents the parameter estimates and discusses the substantive insights from the study. Section 5 highlights limitations and suggests directions for future research.

2. Conceptual Framework

The conceptual framework is organized as follows. Subsection 2.1 gives an overview of the RBV of the firm, defining the key concepts of resources and capabilities and linking them to sustained competitive advantage. Subsection 2.2 applies the RBV to high-technology markets and discusses in detail the capabilities that important in sustaining competitive advantage in these markets. Finally, subsection 2.3 discusses the operationalization of our conceptual framework.

2.1. Overview of the Resource-Based View of the Firm

The literature on the RBV of the firm (Wernerfelt 1984) attempts to identify conditions and firm-specific factors that underlie the competitive advantage enjoyed by a firm. In this perspective, a firm is viewed as a bundle of *resources* and *capabilities,* with firms differing in their endowment of these resources and capabilities.[3] While resources are defined as productive factors that a firm uses to achieve its business objectives, capabilities, refer to a firm's ability to "deploy these resources ... to effect a desired end" (Amit and Shoemaker 1993).[4] Thus, it is argued that for a firm to enjoy a competitive advantage (i.e., a superior financial performance relative to competition), it must possess superior capabilities, i.e., the ability to deploy resources and other productive factors more efficiently.

For a firm to enjoy a sustained competitive advantage, it must be the case that these capabilities cannot be "competed away," i.e., limits to competition are necessary for a firm to sustain any supernormal profits or rents. The RBV identifies two conditions necessary for a capability to be an enduring source of competitive advantage: *imperfect mobility* and *imperfect imitability* (Peteraf 1993). Imperfect mobility refers to the difficulty of trading in certain capabilities. This might be, for instance, because a capability has arisen from the complex interaction of a number of resources, and hence is firm-specific in nature. For example, it would be hard to buy firm-specific knowledge of buyers, sellers, and worker's capabilities (Prescott and Visscher 1980). Imperfect imitability, on the other hand, refers to the inability of competing firms to imitate a firm's distinctive capabilities. Numerous mechanisms could ensure that a firm's capabilities are imperfectly imitable. Apart from such obvious reasons as patent or property rights, the inherent complexity of most capabilities makes it very hard to ascertain the exact cause of efficiency, thereby making imitation difficult (Lippman and Rumelt 1982). In summary, capabilities that exhibit a high degree of tacitness, complexity, and firm-specificity are likely to be both imperfectly imitable and imperfectly mobile.

[3]The literature on the RBV often uses the term *endowments* to refer to what we call *resources*, and *resources* to refer to what we call *capabilities*. In this paper we suggest that capabilities are imperfectly imitable and hence lead to sustained advantaged, while resources (i.e., endowments) may be imitated by others. We use the terms resources and capabilities throughout this paper.

[4]Note that resources could be either tangible (such as physical assets) or intangible (such as goodwill).

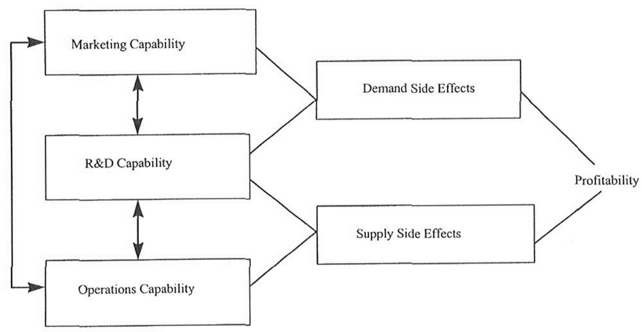
2.2. Firms' Functional Capabilities and Performance in High-Technology Markets

In our conceptual framework, three critical capabilities influence the performance of firms in high-technology markets: R&D, marketing, and operations. In what follows, we show how these capabilities and their interactions bestow either demand-side and/or supply-side advantages on the firm. A demand-side advantage lets a firm charge a higher price, relative to competition, at a given level of demand, or to generate a higher demand (or equivalently, a higher market share) at given price level. On the other hand, a supply-side advantage refers to the fact that a firm enjoys a lower cost structure. We also argue why these three capabilities are imperfectly mobile and imperfectly imitable and thus provide a firm with sustainable competitive advantage. Figure 1 provides a schematic representation of the relationship between a firm's functional capabilities and its financial performance.

Marketing Capability. A firm with a strong marketing capability—exhibiting superiority in identifying customers' needs and in understanding the factors that influence consumer choice behavior—will be able to achieve better targeting and positioning of its brands relative to competing brands. This higher level of product differentiation will enable the firm to enjoy higher margins (Kohli and Jaworski 1993, Day 1994) and hence exhibit better financial performance.

This ability to obtain high-quality customer feedback requires skill at monitoring the environment and building strong relationships with customers, which is a complex undertaking (Deshpande et al. 1993). Such

Figure 1 Firms' Capabilities and Performance



a capability, once built, is not easily imitated or transferable because it is often firm-specific and has a high level of tacitness (Day 1994).

R&D Capability. R&D capability is critical to achieving a superior performance in high-technology markets for two important reasons. First, these markets are characterized by short product life-cycles and a high rate of new product introductions incorporating newer generations of technology. In such markets, a firm with a superior innovative capability will enjoy strong consumer loyalty (Givon et al. 1995), and hence a demand-side advantage, because consumers will be willing to pay a premium for a firm's product if they are assured that the firm will continue to dominate the market over successive generations of the product. Second, a firm's superior R&D capability may also lead to competitive advantage because of supply-side factors. For instance, Japanese firms such as Sony and Hitachi have leveraged their strong capability in process innovation to dominate high-technology markets because of their favorable cost structure.

An important characteristic of R&D in high-technology markets is a significant learning-by-doing effect, which makes it very difficult for competitors to simply buy this know-how in the market and also makes it extremely difficult to imitate (Irwin and Klenow 1994). The difficulties of imitation are further exacerbated by the large tacit component of R&D. These characteristics of R&D capability enable a firm that has a superior competency in R&D to achieve superior sustained performance relative to its competition.

Operations Capability. A strong operations capability in these high-technology markets entails the integration and coordination of a complex set of tasks—combining components and materials from different sources and industries, and with material flows—while enabling the firm to offer its final products at a lower cost (Hayes et al. 1988). The great complexity of the operations function helps to make a superior operations capability imperfectly mobile and imperfectly imitable, thereby conferring competitive advantage upon firms that possess it.

Complementarity Between the Functional Capabilities. In addition to each of the direct effects discussed above, capabilities can serve as important complements to each other. Such interactions can serve to enhance performance over and above the contribution of each of the individual capabilities.

There is a significant literature that has suggested that interaction between marketing and R&D can enhance a firm's performance (Gupta et al. 1987, Griffin and Hauser 1996) beyond their individual effects. For instance, a strong marketing capability is better positioned to give R&D good feedback from customers, which in turn would drive the kinds of innovations needed to improve the product. Similarly, a number of studies on product development have pointed to the importance of interaction between manufacturing and R&D throughout the development process to ensure speedy and successful commercialization of technologies and products at a low cost (Hayes et al. 1988). Finally, prior research (e.g., Srinivasan et al. 1997) has pointed out the high complementarity between marketing and operations capabilities, which can help product development by implementing the "design for manufacturability" concept.

To summarize, in high-technology markets a firm's capabilities in its marketing, R&D, and operations functions, as well as the interactions between them, are critical drivers of competitive advantage. Thus, for firms within the same industry (so that they face a similar competitive structure), we would expect interfirm variations in profitability to be systematically related to interfirm variations in functional capabilities.[5] The proposed conceptual framework (see Figure 1) suggests the following relationship:

$$\begin{aligned} \text{Relative Performance} = f\,(&\text{Relative Marketing Capability},\\ &\text{Relative R\&D Capability, Relative Operations Capability},\\ &\text{Relative Marketing Capability} \times \text{Relative R\&D Capability},\\ &\text{Relative R\&D Capability} \times \text{Relative Operations Capability},\\ &\text{Relative Marketing Capability} \times \text{Relative Operations Capability}). \end{aligned} \tag{1}$$

[5]It is important to note here that the measure of profitability used in such an analysis should be independent of the scale of operation (and hence the amount of resource endowment). For instance, consider two firms, A and B, that differ in their marketing capabilities with firm A having a higher capability. However, firm B has larger financial resources available to it and hence spends more on marketing. In spite of its relative inefficiency, firm B may have higher \$-sales and \$-profits (both measures being scale-dependent) but should have a lower profitability. In our analysis we use Tobin's q, which is scale independent, to measure relative market performance.

2.3. Measuring a Firm's Functional Capabilities—The Input–Output Approach

Recall that a firm's capability is defined as its ability to deploy the resources (inputs) available to it to achieve the desired objective(s) (output). Thus, the higher the functional capability a firm possesses, the more efficiently it is able to deploy its productive inputs to achieve its functional objectives. Any under-attainment of the functional objective, then, is attributable to the functional inefficiency of the firm. Evidently, the lower the functional inefficiency, the higher the functional capability of the firm. Thus, we can use the inverse of a firm's functional inefficiency as the measure of its functional capability.

Specifically, the input–output approach entails modeling a firm's functional activities as an *efficient frontier* or *transformation function* (akin to the notion of a "production frontier/function" in economics; e.g., Silberberg 1990) relating the *productive factors/resources* used by a firm to the optimal attainment of its *functional objective(s)* if the firm were to deploy these resources most *efficiently*. To illustrate, suppose that maximizing the quality-adjusted technological output were the functional objective of the firm's R&D activities. Then, the input–output transformation function approach would relate the *maximum* quality-adjusted technological output the firm could have achieved, given the amount of productive inputs/resources deployed if the firm were to use these resources most efficiently. The SFE methodology (see § 3.3 for details) provides the appropriate econometric technique to empirically estimate the efficient frontier and hence the level of efficiency achieved by the various firms in its R&D activities.

Crucially for our purposes, the input–output approach explicitly recognizes the linkages between resources/inputs and objective/outputs and the moderating role of capability. This is because, given identical resource/input endowments, a firm with a higher functional capability will be able to achieve a higher functional objective/output. Similarly, given identical functional capability, a firm with a larger endowment of resources/inputs will be able to achieve a higher functional objective/output.

Figure 2 gives the schematic representation of the proposed input–output conceptualization of a high-technology firm.

2.3.1. Measuring Marketing Capability. One of the goals of marketing at the firm level is to enhance the value of the firm's products in the minds of its current and potential customers. This goal is partly reflected in enhanced sales, through a better understanding of customer needs and distinctive targeting of appropriate customers. Furthermore, increasing sales is crucial to building market share. We thus use sales revenue as the goal for marketing.

A number of resources available to the firm have been mentioned in past literature. Such resources include the extent of customer awareness and liking about the firm's products built over the years through its advertising effort (the carry-over effect of advertising), the installed base of customers, and the expenditure over the years on marketing activities like distribution and trade promotion efforts to build trade loyalty. Similarly, the literature has suggested the importance of investment on customer relationships (Jackson 1985).

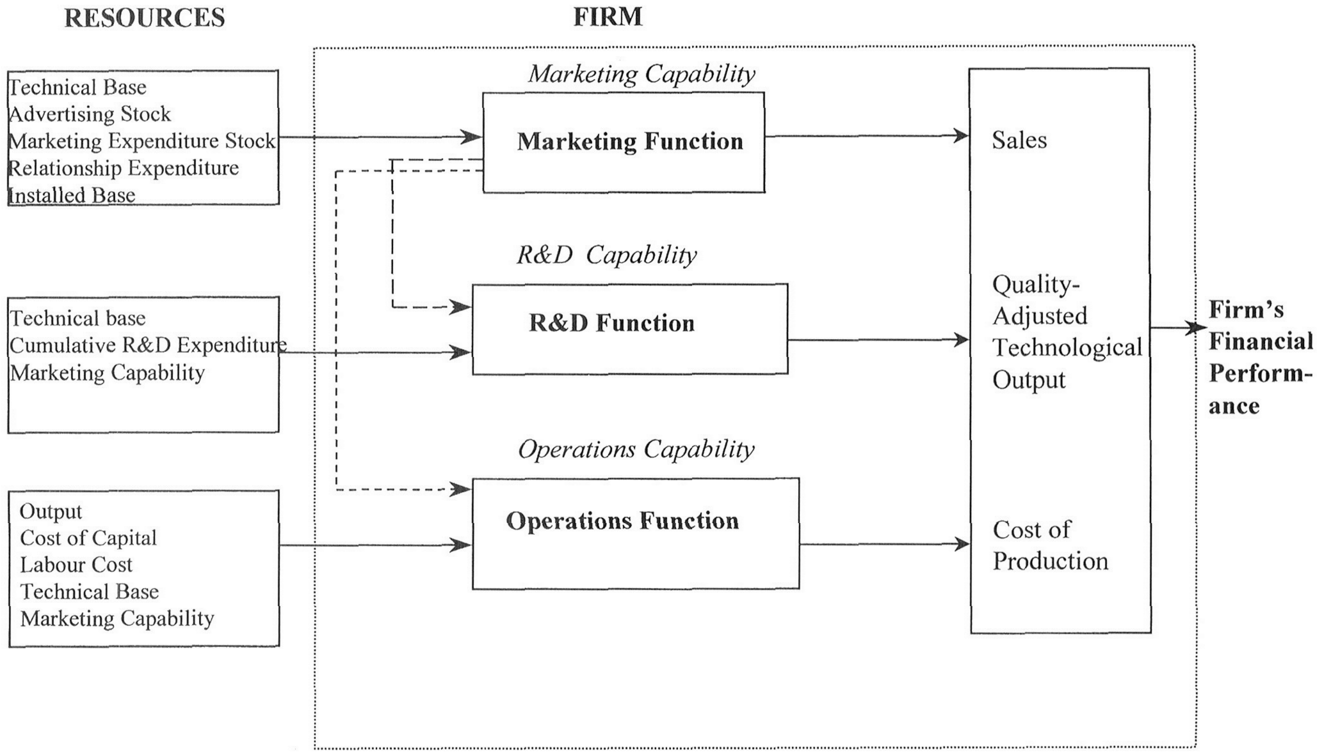
There are two additional resources that are important in high-technology markets: the firm's prior base of technological know-how, and its installed base. The firm's prior level of innovative know-how helps marketing in two ways. First, a large base of technological know-how helps a firm in introducing a steady stream of new products. Second, a large stock of innovative know-how makes it easier for marketing to convince its customers that the firm will be able to keep its technological leadership as technology evolves. Finally, a firm's installed base would be important to the firm in markets where switching costs are high and network externality effects are strong.

The above discussion suggests the following *marketing frontier/transformation function*:

$$\begin{aligned} \text{Sales} = f\,(&\text{Technological Base,} \\ &\text{Advertising Stock, Stock of Marketing Expenditure,} \\ &\text{Investment in Customer Relationships, Installed Base).} \end{aligned} \tag{2}$$

2.3.2. Measuring R&D Capability The goal of R&D is to develop high-quality technological innovations—both product innovations (which form the basis

Figure 2 **Schematic of the Input–Output Framework**



of new product introductions) and process innovations.[6] Prior empirical literature on R&D/innovation has distinguished two dimensions of the quality of technological output: "innovativeness" (Trajtenberg 1990) and width of applicability (Jaffe et al. 1993). We thus use maximization of quality-adjusted technological output as the objective of a firm's R&D function.

The importance of learning-by-doing in high-technology markets immediately suggests that a firm's past R&D expenditures would be an important resource available to it. In a similar vein, Cohen and Levinthal (1990) suggest that a firm's prior stock of innovative technologies can enhance its ability to develop newer generations of innovative technologies. Thus, a firm's technological base would be a crucial resource for R&D.

[6]It is important, therefore, that in considering a firm's innovative output we account explicitly for the quality of such innovations. This point is elaborated on in our discussion of the operationalization of quality-adjusted technological output (see §3.2.1).

Another key driver of a firm's R&D output is its marketing capability. A strong marketing capability provides high-quality consumer feedback to R&D (Griffin and Hauser 1993). Such input can help R&D come up with innovations that are novel in that they represent a substantial change over past technology. Similarly, if marketing does a good job of scanning the environment, it can suggest ideas that are of applicability to a wide variety of markets, within and outside the industry.

The above discussion suggests the following *R&D frontier/transformation function:*

$$\begin{aligned}&\text{Quality-Adjusted Technological Output}\\&\quad = f(\text{Technological Base},\\&\qquad \text{Cumulative R\&D Expenditure, Marketing Capability}). \qquad (3)\end{aligned}$$

2.3.3. Operations Capability The key goal of operations in high-technology markets is to produce at the lowest possible cost without compromising on product quality (Hayes et al. 1988). Thus, we adopt cost minimization as the business objective of a firm's operations/manufacturing function.

Consistent with economic theory (Silberberg 1990), the exogenous variables in the cost function are output volume and factor prices, i.e., cost of capital and unit labor cost.

Similar to the R&D specification, operations can draw on marketing capability to further its goals. Such use of marketing capability is exemplified in the "design for manufacturability" concept (Srinivasan et al. 1997). To start with, operations can use input from marketing, derived from attribute-based models, to come up with product concepts. Furthermore, it can get marketing to give it feedback on various customer-ready prototypes. This enhances the likelihood of the final product being acceptable to consumers while being produced at as low a cost as possible.

In addition to the resources suggested above, operations can take advantage of the firm's stock of innovative technologies. This stock of innovative technologies often provides the basis for process innovations which enhance the efficiency of engineering and/or manufacturing processes (Iansiti and West 1997) and lead to lower cost.

The above discussion suggests the following *cost frontier/operations transformation function:*

$$\begin{aligned}\text{Cost of Production} &= f(\text{Output},\\ &\quad \text{Cost of Capital, Labor Cost},\\ &\quad \text{Technological Base, Marketing Capability}). \qquad (4)\end{aligned}$$

3. Empirical Analysis

3.1. Description of the Data Set

Our conceptual framework offers a resource-based perspective on a firm's capabilities and the impact of these capabilities on its financial performance. To test this, we needed data on a firm's resources, its functional outputs, and its financial performance. Furthermore, because of the importance of stocks of various variables (e.g., sales stock) and the lagged impact of some variables (e.g., R&D expenditure) on performance, we required these data to be over a period of time. This posed a major challenge because no database currently exists that integrates the types of information we needed. To this end, we put together a unique database, integrating data from multiple sources.

Our focal firms are manufacturing firms whose primary business is in semiconductors (i.e., SIC code 3674). We chose to confine our sample to one SIC code to minimize the impact of market structure factors on relative firm performance.[7] Our sample consisted of 92 publicly traded firms in this SIC code. For each firm in our sample, we collected information pertaining to the resources available to each of the three functional areas, the outputs, and firm performance from the Compustat database for the years 1985–1994. We should mention that the Compustat database was incomplete with regard to some variables. In such cases, we consulted original company annual reports to get the information. The Compustat database, however, did not give us information pertaining to the firm's innovative output. For this we conducted a content analysis of patent data gathered from the patent office. Finally, we also collected additional information pertaining to firms' primary product lines from their Web pages.

Our estimation consisted of a random subsample of 72 firms, while we used a hold-out subsample of 20 firms for post-sample prediction tests. Furthermore, we used the observations from the first two years for initializing the stock variables used in the analysis.

3.2. Operationalization of Variables

3.2.1. Dependent Variables (a) *Sales (SALES):* Defined as the dollar amount of actual billings for regular sales completed during the period, reduced by cash and trade discounts.

(b) *Quality-adjusted technological output (TECH_OUTPUT)* The technological output of a firm has been frequently measured using patent counts (see, for example, papers in Griliches 1984), which represent the number of patents assigned to the firm over a time period. Such raw output measures have been subjected to much criticism, because they treat all patents on an

[7] Even within four-digit SIC codes, there may exist variations in market structure. We control for this by introducing dummies that reflect variation in market structure.

[8] Among others, Scherer (1965) has shown that "the distribution of patent values is highly skewed toward the low end, with a long and thin tail toward the high-value side" (Trajtenberg 1990).

equal footing.[8] Thus, we need to adjust raw patent counts for quality. Recall that the literature has highlighted two dimensions of quality of a new technology: "innovativeness" (Trajtenberg 1990) and width of applicability (Jaffe et al. 1993). We discuss below our two operationalizations of the quality-adjusted innovative output construct, *TECH_OUTPUT*, based on these two quality dimensions.

(1) *"Innovativeness"-adjusted technological output (TECH_INNV):* Consistent with the empirical R&D literature (Trajtenberg 1990, Jaffe et al. 1993), we measure the innovativeness of technological output by measuring the number of times the patents of a firm have been cited. The underlying premise here is that the more innovative the technology, the higher would be its citation count. We want to emphasize that prior studies have provided empirical evidence linking patent citations and the innovativeness of technologies (e.g., Albert et al. 1991).[9]

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, would be the value of *TECH_INNV* for that firm for that year. As pointed out in the literature (Trajtenberg 1990), the use of citations to infer quality suffers from a truncation bias. Because our data goes only to 1994, patents issued in or near that year would not have all their citations captured, causing a truncation bias. We explicitly control for this bias while calculating *TECH_INNV*.[10]

(2) *"Width-of-Applicability"-technological output (TECH_WIDTH).* Prior literature (e.g., Jaffe et al. 1993) has suggested that if a patent gets a large number of citations from outside its industry, it reflects a wider applicability of the innovation represented by that patent. We construct the alternative quality-adjusted output measure, *TECH_WIDTH,* as follows. We first calculate the proportion of citations received by a patent from firms belonging outside our focal SIC code (3674). This is equal to the number of citations received by a patent from firms outside the focal SIC code, divided by the total number of citations received by it. The weight assigned to a firm's patent, then, is the proportion of outside citations for the patent, divided by the sample average proportion. The sum of these "proportion-of-outside citation"-weighted patents, for a particular year, for a particular firm, would be the value of *TECH_WIDTH* for that firm for that year. We correct for truncation bias as in the case of *TECH_INNV.*

(c) *Cost of goods sold (COST).* This is defined as all costs directly allocated by the company to production, such as material and overhead, and is a proxy for the average cost of production.

(d) *Relative profitability (REL_PROFIT).* We use Tobin's q as our measure of profitability. This is defined as the capital market value of the firm divided by the replacement value of its assets. Tobin's q has been used widely in the literature, because of its many advantages over accounting measures. It is an inherently dynamic measure in that it maximizes discounted cash flow. Also, as pointed out by Montgomery and Wernerfelt (1988), because Tobin's q is a capital market measure of firm rents, it implicitly uses the correct risk-adjusted discount rate and minimizes distortions resulting from tax laws and accounting conventions. Because our focus is on relative firm performance, we define the index REL_PROFIT_{it} as the ratio of Tobin's q for firm i in year t to the sample average Tobin's q (i.e., $q_{it}/Avg.\ q$).

3.2.2. Explanatory Variables. (a) *Base of technological know-how (TECHBASE).* This construct is based on (quality-adjusted) technological output (*TECH_OUTPUT*, measured either by *TECH_INNV* or *TECH_WIDTH*). The base of technological know-how is computed by estimating a Koyck lag function on *TECH_OUTPUT*, with earlier years of innovative technological output receiving a lower weight than later years. Formally, *TECHBASE* for period t is defined as

[9]Our patent search was exhaustive in that we did not confine it to any particular SIC code. *All* patents that had cited patents of our focal firms were searched for, leading to an examination of approximately 10,000 patents.

[10]Further details on the construction of the citation-weighted index, along with the adjustment for truncation bias, are provided in the technical appendix that is available from the authors on request.

$TECHBASE_t = \Sigma_{k=1}^{k=t} \delta^{t-k} \times TECH\_OUTPUT_k$. Here δ represents the weight attached to past values of innovative output. The higher the value of δ, the greater the spillover from past levels of innovative output.

(b) *Stock of marketing expenditure (MARKETING-STOCK).* To capture the carryover effect of marketing expenditure/effort, we estimate the stock of marketing expenditure available to the firm using a Koyck-lag structure. Formally, *MARKETINGSTOCK* for period t is defined as $MARKETINGSTOCK_t = \Sigma_{k=1}^{k=t} \gamma^{t-k} \times SGAEXPENSE_k$. Here γ represents the weight attached to past values of sales, general, and administrative (SGA) expenses of the firm. While SGA also includes items that are not strictly within the domain of marketing, it is a good proxy for the amount the firm spends on its market research, sales effort, trade expenses, and other related activities. The higher the value of γ, the greater the spillover from past levels of SGA.

(c) *Advertising stock (ADSTOCK).* To capture the carry-over effect of advertising, we estimate the stock of advertising effort available to the firm using a Koyck-lag structure. Formally, *ADSTOCK* for period t is defined as $ADSTOCK_t = \Sigma_{k=1}^{k=t} \omega^{t-k} \times ADEXPENSE_k$. The higher the value of ω, the greater the spillover from past levels of advertising expenditure.

(d) *Installed customer base (INSTALLEDBASE).* To capture the importance of installed base, we estimate the stock of sales available to a firm using a Koyck lag structure. Formally, *INSTALLEDBASE* for period t is defined as $INSTALLEDBASE_t = \Sigma_{k=1}^{k=t} \xi^{t-k} \times SALES_k$. The higher the value of ξ, the greater the spillover from past sales.

(e) *Receivables (RECEIVABLES).* We measure the firm's resources devoted to building customer relationships by the level of its receivables. This is defined as claims against others collectible in cash.

(f) *Accumulated R&D expenditure (CUM R&DEXPENSE).* We estimate the cumulative R&D expenditure using a Koyck lag structure, with declining weights into the past. Formally, *CUM_R&DEXPENSE* for period t is defined as $CUM\_R\&DEXPENSE_t = \Sigma_{k=1}^{k=t} \nu^{t-k} \times R\&DEXPENSE_k$. The higher the value of ν, the greater the spillover from past levels of R&D expenditure.

(g) *Output (OUTPUT).* This is the dollar amount of production for the firm.

(h) *Cost of capital (CAPITALCOST).* This refers to the long-term cost of capital and represents the average interest rate for long-term borrowings for that firm.

(i) *Unit labor cost (LABORCOST).* This is defined as the cost of employees' wages and benefits allocated to continuing operations, divided by the total number of employees.

(j) *Relative R&D capability (REL R&DCAP).* R&D capability (*R&DCAP*) is calculated using the input-output approach and is defined as the inverse of the R&D inefficiency (expressed as a percentage of the maximum achievable innovative output, *TECH_INNV*). We define the index *REL_R&DCAP* by considering the *R&DCAP* of a firm for a certain year relative to the sample average *R&DCAP* (i.e., *R&DCAP/Avg. R&DCAP*).

(k) *Relative marketing capability (REL_MKTCAP).* Marketing capability is calculated using the input-output method. It is defined as the inverse of the SALES inefficiency (expressed as a percentage of the maximum achievable objective, i.e., *SALES*). We define the index *REL_MKTCAP* by considering the *MKTCAP* of a firm for a certain year relative to the sample average *MKTCAP* (i.e., *MKTCAP/Avg. MKTCAP*).

(l) *Relative operations capability (REL OPCAP).* Operations capability (*OPCAP*) is calculated using the input–output method and is defined as the inverse of the operations inefficiency (expressed as a percentage of the minimum achievable cost, *COST*). We define the index *REL_OPCAP* by considering the *OPCAP* of a firm for a certain year relative to the sample average *OPCAP* (i.e., *OPCAP/Avg. OPCAP*).

3.2.3. Control Variables. (a) *Competitive environment ($SUB\_MARKET_{1\text{–}7}$).* Even though we confine our attention to one industry, competitive conditions within the industry might vary, depending on the specific product niches occupied by each firm. Each of these product niches can be thought of as a separate submarket, characterized by unique competitive conditions. To account for such variations and their impact of a firm's sales potential and profitability, we created dummy variables for each of the product lines that exist in our focal industry.[11] The dummy variable SUB_MARKET_{ik} is defined as:

$$SUB\_MARKET_{ik} = 1 \text{ if firm } i \text{ operates in submarket } k\text{, and } 0 \text{ else.}$$

Thus, a firm in three product niches would have three ones and five zeroes for the eight dummies. The fact that firms in our sample are indeed heterogeneous in terms of product markets is demonstrated by the fact that the least populous product category has 4 firms, while the most populous has almost 30.

(b) *Business cycle effects* ($YEAR_{1-9}$). It is likely that macroeconomic conditions would have changed over the 10-year time period that our data cover (e.g., the U.S. economy went through a recession in the late 1980s). We control for such business-cycle effects through dummy variables $YEAR_{1-9}$, which are defined as follows:

$$YEAR_{tk} = 1 \text{ if the observation (year } t\text{) pertains to year } k\text{, and } 0 \text{ else.}$$

3.3. Empirical Model Specifications

In this section we specify the functional forms for the transformation functions associated with marketing, R&D, and operations activities (Equations (5)–(8)) as well as provide the parametric specification of the performance-capability model (Equation (9)).

3.3.1. Modeling Marketing Capability. In subsection 2.3.1 we defined the marketing capability of a firm as its ability to deploy its resources—viz., stocks of technical know-how (*TECHBASE*), marketing expenditure (*MARKETINGSTOCK*), and advertising expenditure (*ADSTOCK*) along with investment in customer relationship (*RECEIVABLES*) and the installed base of customers (*INSTALLEDBASE*)—efficiently to achieve the *maximum* possible sales level (*SALES*). Note that in our input–output conceptualization, a firm's marketing capability is measured by how close the realized sales is to the *sales frontier* given a certain level of resource input. Thus, the further (downward distortion) the realized sales is from the sales frontier, the higher the inefficiency of the firm's marketing function, and consequently the lower is the firm's marketing capability.

We use the Cobb-Douglas (C-D) formulation and specify the sales frontier (equivalently, marketing transformation function) as follows:[12]

$$\begin{aligned}\ln(SALES_{it}) &= \alpha_0^m + \sum_{k=1}^{k=7} \alpha_k^m \times SUB\_MARKET_{itk} \\ &+ \alpha_8^m \times \ln(ADSTOCK_{it}) \\ &+ \alpha_9^m \times \ln(MARKETINGSTOCK_{it}) \\ &+ \alpha_{10}^m \times \ln(TECHBASE_{it}) + \alpha_{11}^m \\ &\times \ln(RECEIVABLES_{it}) + \alpha_{12}^m \\ &\times \ln(INSTALLEDBASE_{it}) + \epsilon_{it}^m - \eta_{it}^m, \end{aligned} \tag{5}$$

where the subscript i represents firms and t represents years. We can rewrite Equation (5) more compactly as $Y_{it}^m = f(X_{it}^m, \alpha^m) + \epsilon_{it}^m - \eta_{it}^m = f(X_{it}^m, \alpha^m) + e_{it}^m$.

In addition to the marketing resources/inputs—viz, *TECHBASE, MARKETINGSTOCK, ADSTOCK, INSTALLEDBASE,* and *RECEIVABLES*—we also included the control variables SUB_MARKET_{1-7} for the following reasons. As mentioned in the previous section, even within the four-digit SIC industry classification, there could be variations in the competitive environment facing a firm. Thus, a firm facing a higher competitive intensity would be able to achieve a lower level of sales revenue (relative to an equally efficient firm in a less competitive submarket) for a given level of deployed resources. We include the dummy variables SUB_MARKET_{1-7} to control for the effect of market factors on a firm's sales frontier. Note that, given

[11]This categorization was done by consulting trade press reports and two independent experts. These experts were given an exhaustive list of all the products carried by the firms in our sample and asked to categorize these products independently. The categorization arrived at was consistent across the experts and consisted of eight categories.

[12]Note that the Cobb-Douglas is a parsimonious specification and provides a first-order Taylor-series approximation to an arbitrary transformation function. We also used the more flexible indirect translog (ITL) specification—a second-order Taylor-series approximation—as an alternative specification. However, the Eichenbaum-Hansen-Singleton (E-H-S) specification test (1983) failed to reject the C-D model in favor of the ITL model. Hence for parsimony, we report only the C-D specification. For similar reasons we selected the C-D specification for the R&D and operations frontiers. Technical details of the E-H-S specification test are given in the technical appendix.

the panel nature of our dataset, explicitly accounting for such cross-sectional (submarket differences) is important because, in the absence of such control variables, a lower sales revenue (relative to the sample), for a given level of resources would be incorrectly attributed to marketing inefficiency, even though it is a result of exogenous factors outside the firm's control.

The interpretation of the parameters is as follows. The parameter α_8^m represents the marginal product of *ADSTOCK*, i.e., the % change in *SALES* as a result of a % change in *ADSTOCK*. A similar interpretation holds for the parameters α_9^m through α_{12}^m. Based on our discussion in §2.3.1, we would expect these parameters to be positive, i.e., α_8^m through $\alpha_{12}^m > 0$. If there is a certain parameter, say $\alpha_8^m < 1$, we infer that the sales revenue exhibits diminishing marginal product with respect to advertising. We do not have any priors on the relationship between the marketing resources and sales (i.e., nature of the marginal productivity of resources) but rather view it as an empirical issue.

In Equation (5), ϵ_{it}^m captures the intrinsic randomness in a firm's sales level. The error component $\eta_{it}^m > 0$ captures the inefficiency in marketing operations resulting in subpar performance by the firm on its sales objective. Such inefficiency (downward deviation from the sales frontier) could arise because of either (a) "allocative inefficiency," i.e., suboptimal allocation of marketing resources (e.g., inappropriate targeting and segmentation), or (b) "technical inefficiency," i.e., suboptimal utilization of resources, possibly because of agency problems. Also, e_{it}^m denotes the composite error term, including the random shock and inefficiency error, and denotes the difference between the observed sales, Y_{it}^m, and the predicted sales, $f(X_{it}^m, \alpha^m)$.

We make the following distributional assumptions regarding the stochastic components ϵ_{it}^m and η_{it}^m. The random shock ϵ_{it}^m is assumed to be distributed normal with mean 0 and variance $\sigma_{\epsilon_m}^2$, i.e., $\epsilon_{it}^m \sim N(0, \sigma_{\epsilon_m}^2)$.[13] The marketing inefficiency error component η_{it}^m is assumed to be distributed truncated normal (i.e., $\eta_{it}^m > 0$) with mean $\mu_m > 0$ and variance $\sigma_{\eta_m}^2$, i.e., $\eta_{it}^m \sim N^+(\mu_m, \sigma_{\eta_m}^2)$. Thus, the parameter μ_m captures the average level of marketing inefficiency (synonymously, average marketing capability) of firms in the sample. Note that in this baseline set-up, all the sample firms have the same (expected) level of capability (although the realized values of capability may vary across firms). However, it can be argued that firms could vary in their marketing capabilities because of unobserved heterogeneity (Boulding and Staelin 1995). We discuss our treatment of such unobserved (intrinsic) variations across firms in their marketing capabilities in §3.4.1.

[13]We later extend the SFE formulation to allow for heteroskedasticity by allowing the variance of the random shock to vary across firms, with the variance assumed to be proportional to the mean sales, i.e., $\sigma_{\epsilon,i}^2 = \sigma_\epsilon^2 \times SALES_i^{\theta}$. See §3.4.2. for additional details. Similar extensions are made for the R&D and operations capabilities models.

3.3.2. Modeling R&D Capability. R&D capability of a firm is viewed as its ability to deploy its resources—viz., stocks of technical know-how (*TECHBASE*), R&D expenditure (*CUM_R&DEXPENSE*), along with its marketing capability (*MKTCAP*)—efficiently to achieve the *maximum* possible quality-adjusted technological output (as measured by either *TECH_INNV* or *TECH_WIDTH*), given the level of the deployed resources. Thus, a firm's R&D capability is measured by how close the realized technological output is to the *innovation frontier*.

For parsimony (see footnote 12), we use the C-D formulation and specify the innovative frontier or R&D transformation function as follows:

$$\begin{aligned}\ln(TECH\_INNV_{it}) &= \alpha_0^r + \alpha_1^r \times \ln(TECH\ BASE_{it}) \\ &+ \alpha_2^r \times \ln(CUM\_R\ \&\ DEXPENSE_{it}) \\ &+ \alpha_3^r \times \ln(MKTCAP_{it}) + \alpha_4^r \times \ln(MKTCAP_{it}) \\ &\times \ln(TECHBASE_{it}) + \epsilon_{it}^r - \eta_{it}^r, \end{aligned} \tag{6}$$

where the subscript i represents firms and t represents years. We can rewrite Equation (6) more compactly as: $Y_{it}^r = f(X_{it}^r, \alpha^r) + \epsilon_{it}^r - \eta_{it}^r = f(X_{it}^r, \alpha^r) + e_{it}^r$.

The interpretation of the parameters is as follows. The parameter α_1^r represents the marginal product of *TECHBASE*, i.e., the % change in *TECH_INNV* as a result of a % change in *TECHBASE*. A similar interpretation holds for the parameters α_2^r through α_4^r. Conceptually, the parameter α_1^r captures the learning-by-doing effect while the parameter α_3^r captures the "voice-of-the-customer" impact of marketing (Griffin and Hauser 1993) on the quality of technological output across both dimensions. Similarly, parameter α_4^r

captures the role of marketing–R&D interaction in enhancing a firm's quality-adjusted technological output. Based on our discussion in §2.3.2, we would expect α_1^r through $\alpha_4^r > 0$.

Similar to marketing capability, the error term ϵ_{it}^r captures the intrinsic randomness in a firm's innovative output with,[14] while $\eta_{it}^m > 0$ captures the inefficiency in R&D operations.

We also estimated the innovative frontier, Equation (6), with *TECH_WIDTH* instead of *TECH_INNV* as the measure for (quality-adjusted) technological output. Recall from §3.2.1 that these two operationalizations correspond to the two quality dimensions of technology, viz. innovativeness and width of applicability. Essentially, both measures represent the (weighted) total number of patents filed by a firm in a year, with the weighting schemes reflecting the two quality dimensions. As with *TECH_INNV*, we would expect the parameters α_1^r through $\alpha_4^r > 0$ in the case of *TECH_WIDTH*.

3.3.3. Modeling Operations Capability. Operations capability of a firm is viewed as its ability to deploy its resources—viz., labor (*LABCOST*) and capital (*CAPCOST*) along with its stocks of technical know-how (*TECHBASE*)—efficiently to achieve the *minimum* possible level of cost of production (*COST*). Thus, a firm's operations capability is measured by how close the realized cost of production is to the *cost frontier/function*.[15]

As before, we use the C-D formulation and specify the cost frontier/operations transformation function as follows:

$$\ln(COST_{it}) = \alpha_0^o + \alpha_1^o \times \ln(OUTPUT_{it}) + \alpha_2^o \times \ln(LABCOST_{it}) + \alpha_3^o \times \ln(CAPCOST_{it}) + \alpha_4^o \times \ln(TECH\ BASE_{it}) + \alpha_5^o \times \ln(MKTCAP_{it}) + \eta_{it}^o + \epsilon_{it}^o \qquad (7)$$

where the subscript i represents firms and t represents years. We can rewrite Equation (7) more compactly as: $Y_{it}^o = f(X_{it}^o, \alpha^o) + \eta_{it}^o + \epsilon_{it}^o = f(X_{it}^o, \alpha^o) + e_{it}^o$.

The interpretation of the parameters is as follows. $\alpha_1^o > 0$ represents the economies of size, so that the production technology exhibits increasing, constant or decreasing returns to scale according as $1/\alpha_1^o$ is greater than, equal to, or less than 1. The parameters α_2^o and α_3^o, being cost elasticities, represent the marginal impact of *LABCOST* and *CAPCOST* on COST and are expected to be > 0. The parameters α_4^o and α_5^o capture the impact of technical know-how (pool of process innovation) and marketing capability on a firm's operational capability and are expected to be <0 (i.e., reducing cost of production).

Similar to marketing and R&D capabilities, ϵ_{it}^o captures the intrinsic randomness in the production process, and $\eta_{it}^o > 0$ captures the inefficiency in the production process resulting in higher-than-optimal cost.

3.3.4. Modeling the Relationship Between Functional Capabilities and Profitability. The relationship between a firm's functional (R&D, marketing, and operations) capabilities and financial performance is specified as follows:

$$\ln(REL\_PROFIT_{it}) = \zeta_0 + \sum_{k=1}^{k=7} \zeta_k \times SUB\_MARKET_k + \sum_{k=8}^{k=16} \zeta_k \times YEAR_{it,k-7} + \zeta_{17} \times \ln(REL\_MKTCAP_{it}) + \zeta_{18} \times \ln(REL\_R\&DCAP_{it}) + \zeta_{19} \times \ln(REL\_OPCAP_{it}) + \zeta_{20} \times \ln(REL\_MKTCAP_{it}) \times \ln(REL\_R\&DCAP_{it}) + \zeta_{21} \times \ln(REL\_OPCAP_{it}) \times \ln(REL\_R\&DCAP_{it}) + \vartheta_{it}, \qquad (8)$$

where the subscript $i = 1, \ldots, 92$ represents firms and $t = 1, \ldots, 10$ represents years 1985–1994.

We control for cross-sectional variations in firms' competitive environment and longitudinal variations resulting from macroeconomic fluctuations through the use of dummy variables, *SUB_MARKET* and *YEAR*.

[14]These random shocks could arise for many reasons. Innovative activity is inherently stochastic in nature, with serendipitous discoveries punctuated by long periods of low output. Furthermore, a host of macroeconomic variables could affect innovative output. Apart from obvious policy variables, external market conditions could play a big role (e.g., the recent crisis in Southeast Asia has forced Intel to put off a manufacturing plant in Malaysia, in turn affecting its incentive to come up with cost-reducing innovations particular to those conditions).

[15]Note that cost function is the dual counterpart of *production frontier/function* that measures the *maximum* level of production that a firm can achieve, given the level of the deployed resources.

The interpretation of the parameters is as follows. The parameters ζ_{17} through ζ_{19} capture the marginal impact of a firm's functional capabilities on its profitability. For instance, ζ_{17} denotes the % change in a firm's profitability (relative to the sample average) as a result of a % improvement in its marketing capability (again, relative to the sample average). Because the parameters ζ_{17} through ζ_{19} (being elasticities) are scale-independent, a comparison of their magnitude yields insights into the relative role of the three functional capabilities in bestowing competitive advantage. The parameter ζ_{20} captures the interaction between R&D and marketing capabilities, so that $\zeta_{20} > 0$ would suggest that a firm with a higher R&D capability can leverage its high marketing capability more than a firm with a lower marketing capability. Similarly, ζ_{21} captures R&D–operations interaction, with $\zeta_{21} > 0$ implying that a firm's profitability is enhanced by better R&D–operations coordination.

3.4. Econometric Methodology—Stochastic Frontier Estimation

Consistent with economic theory, our conceptual framework assumes an optimization behavior for the firm in its R&D, marketing, and operations functions. Thus, the objectives of R&D and marketing functions were postulated as attainment of maximum quality-adjusted technological output and sales, respectively, while the objective of the operations function was postulated as attainment of minimum cost of production for a given level of deployed resources. In reality, a firm may fail to attain optimal results because of inefficient deployment of resources (allocative inefficiency) and/or inefficient utilization of resources (technical inefficiency). In fact, the proposed conceptual framework—viz., the input-output approach—explicitly recognizes the existence of these inefficiencies and links it to the notion of a firm's capability postulated in the RBV literature (e.g., Amit and Shoemaker 1993).

As detailed in §§ 3.1 and 3.2, our data set contains observations on the realized output levels and the levels of deployed resources relating to R&D, marketing, and operations functions for a sample of 92 firms (in SIC 3674) for the period 1985–1994. The econometric task is threefold:

- To calibrate the marketing, R&D, and operations transformation functions (Equations (5)–(7)) linking the functional resources/inputs and outputs
- To estimate the functional capabilities (equivalently, inefficiencies) displayed by these firms
- To measure the relative impact of these capabilities on the firm's financial performance (Equation (8)).

Given the importance of estimating functional inefficiency, it is crucial that we use the appropriate methodology for the task. In the literature, there are two approaches to estimating economic efficiency:[16] (1) data envelopment analysis (DEA) and (2) Stochastic Frontier Estimation (SFE). DEA uses linear programming techniques to construct economic frontier and estimate technical and allocative inefficiencies. The main advantage of DEA is that, being a nonparametric method, no explicit functional form needs to be imposed on the data. However, the main drawback of DEA is that the economic frontier is assumed to be *deterministic or nonstochastic*, so the estimated frontier may be warped if the data are contaminated by statistical noise (Bauer 1990). In contrast, the SFE approach explicitly allows for the existence of inherent randomness in sales, innovation, and production processes (resulting from events outside the firm's control) besides allowing certain types of specification error and omitted variables uncorrelated with the regressors (Aigner et al. 1977; see Ferrier and Lovell 1990 for additional discussion on the relative advantages of the two approaches).

In this paper, we use the SFE methodology to implement the proposed input-output framework. Below, we provide the specifics of the SFE formulation when the optimal behavior entails *maximization* of an objective function (as in the case of marketing and R&D functions, where the objectives are to attain maximum sales and quality-adjusted technological output, respectively).[17] This basic SFE formulation is due to

[16]Note that using a linear model formulation for the transformation function (estimated through OLS) would recover only the "average" linkage between the resources and output rather than the frontier/optimal relationship because the linear model implicitly assumes that firms are operating on the efficient frontier. Furthermore, because the data are assumed to correspond to the efficient frontier, no inefficiency is allowed for, and as such, OLS cannot be used to estimate a firm's functional capabilities.

[17]Analytical details of the SFE formulation corresponding to the *min-*

Stevenson (1980). Sections 3.4.1 and 3.4.2 extend the basic formulation to allow for unobserved heterogeneity and heteroskedasticity.

SFE Formulation for the Maximization Problem. Consider the frontier transformation function

$$Y_{it} = f(X_{it}, \alpha) + \epsilon_{it} - \eta_{it} = f(X_{it}, \alpha) + e_{it}, \quad (9)$$

where Y_{it} denotes the appropriate function of the output (e.g., ln($TECH\_INNV_{it}$), in the case of R&D frontier) for the ith sample firm, $i = 1, 2, \ldots, N$, in the tth time period, $t = 1, 2, \ldots, T$; X_{it} is the vector of appropriate functions of inputs/resources associated with the ith sample firm in the tth time period; and α is the vector of the coefficients for the associated independent variables in the transformation function impacting innovative output. Thus, in Equation (9), $f(X_{it}, \alpha)$ represents the deterministic component of the efficient frontier and represents the maximum expected output given that firm i employs X_{it} level of resources efficiently.

Let ϵ_{it} represent the purely stochastic error component (random shocks) impacting output, assumed to be independent and identically distributed as $N(0, \sigma_\epsilon^2)$. Further, let η_{it} represent the inefficiency error component in the transformation process adversely affecting the output, assumed to be an independent and identically distributed nonnegative random variable, defined by the truncation (at zero) of the $N(\mu, \sigma_\eta^2)$ distribution with mode $\mu > 0$.[18] We further assume that the random shock, ϵ_{it}, and the inefficiency error, η_{it}, are independent, i.e., $E[\epsilon_{it}\eta_{it}] = 0$, and that these error components are distributed independently of the independent variables in the model, i.e., $E[X_{it}'\epsilon_{it}] = E[X_{it}'\eta_{it}] = 0$.

Given a sample of N firms with T observations for each firm, it can be shown (Battese and Coelli 1988) that the sample likelihood function for the SFE formulation corresponding to Equation (9) is given by

$$L = \prod_{i=1}^{N}\prod_{t=1}^{T} \frac{1}{\sqrt{\sigma_\eta^2 + \sigma_\epsilon^2}} \times \left[1 - \Phi\left(\frac{\sigma_\eta[Y_{it} - f(X_{it}, \alpha)]}{\sigma_\epsilon\sqrt{\sigma_\eta^2 + \sigma_\epsilon^2}} - \frac{\sigma_\epsilon \mu}{\sigma_\eta\sqrt{\sigma_\eta^2 + \sigma_\epsilon^2}}\right)\right] \times \phi\left(\frac{Y_{it} - f(X_{it}, \alpha) + \mu}{\sqrt{\sigma_\eta^2 + \sigma_\epsilon^2}}\right) \times \left[1 - \Phi\left(-\frac{\mu}{\sigma_\epsilon}\right)\right]^{-1}, \quad (10)$$

where $\phi(.)$ and $\Phi(.)$ denote the standard normal density and distribution functions, respectively.

Consistent maximum likelihood (ML) estimates of the model parameters α can be obtained by maximizing the sample likelihood function (equation 10). Using the parameter estimates, $\hat{\alpha}$, we can compute the relative functional capabilities of firm i for year t, $\forall i\ \forall t$, as given in the Appendix.

3.4.1. Controlling for Heterogeneity in Firms' Capabilities and Technology—MSM Estimation.

Recall that for the output frontier (Equation 9), μ denotes the expected level of the inefficiency error component, which is assumed the same across all the firms in the sample. In effect, this corresponds to the assumption that the firms are identical in terms of their expected functional capabilities, although they may differ in terms of the realized values of their capabilities. This is a restrictive assumption. Unobserved heterogeneity in firms' capabilities may exist, for instance, because of differences in their managerial capabilities (Boulding and Staelin 1995).

Another implicit assumption in the above formulation is that the model parameters α are assumed to be the same across the firms. Again, this is a potentially restrictive assumption. For instance, consider the marketing capability model, Equation (5). The impact of marketing inputs/resources such as advertising and installed base is likely to vary across firms, depending on the nature of their product lines. One can similarly argue for potential unobserved heterogeneity across firms with respect to Equations (6) to (8).

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imization problem (as in the case of operations where the objective is to attain minimum cost of production) are omitted for brevity. Details are given in the technical appendix, which is available from the authors upon request.

[18] Note that while the random shock ϵ_{it} can take any positive or negative value, the inefficiency error component η_{it} can take only positive values. It is this difference in their supports of distribution that allows for identification. Furthermore, it is the fact that η_{it} is defined only on the positive orthant that allows us to interpret it as the inefficiency component.

It has been pointed out in the literature (Chintagunta et al. 1993) that failure to control for unobserved heterogeneity may lead to inconsistent parameter estimates. To allow for variations in firms' functional capabilities and elasticities, we use a parametric random effects specification (Gonul and Srinivasan 1995). Specifically, we capture unobserved heterogeneity across firms in their marketing/R&D capabilities (Equation (9)) by positing that the parameter μ follows a gamma distribution $\mu \sim \Gamma(\tau,\psi)$, which is a reasonably flexible distribution. To control for unobserved heterogeneity on elasticities, we assume that $\alpha \sim N(\bar{\alpha}, \Sigma_\alpha)$.

Allowing for unobserved heterogeneity, however, makes ML estimation computationally infeasible because of the high order of integrals involved. Therefore, to obtain consistent parameter estimates, we use the method of simulated moments (MSM). The intuition behind the MSM procedure (McFadden 1989) is that if, for instance, the proposed empirical R&D capability specification is a "true" characterization of the linkage between innovative output and R&D resources, then the conditional moments implied by the model (Equation (6)) must match the observed sample counterparts asymptotically. To set up the orthogonality conditions, we use the first moment, $E[Y_{it} \mid X_{it},\alpha]$ and $E[Y_{it}^2 \mid X_{it},\alpha]$, respectively.[19]

3.4.2. Controlling for Heteroskedasticity. Another implicit assumption of the SFE specifications discussed previously is homoskedasticity of the composite error component, e_{it}, so that its variance, $\sigma_e^2 = \sigma_\eta^2 + \sigma_\epsilon^2$, is assumed to be the same across all the firms in the sample. Given the differences in the scale of operations (in terms of sales, number of patents, volume of production) of these firms, it seems reasonable to allow for heterogeneity in the variance of the composite error component and then test for homoskedasticity, instead of imposing it a priori (Kumbhakar 1997). To account for heteroskedasticity parsimoniously, we allow for firm-specific variance for the random shock with variance proportional to the mean output (Baltagi and Griffin 1988). Specifically, we let $\sigma_{\epsilon_i}^2 = \sigma_\epsilon^2 \bar{Y}_i^\theta$, where $\bar{Y}_i = T^{-1} \sum_{t=1}^T Y_{it}$ is the average output level (sales and quality-adjusted technological outputs for the marketing and R&D frontiers, respectively) for firm i. Note that $\theta = 0$ would correspond to the homoskedastic case.

[19]Analytical details are given in the technical appendix, available from the authors upon request.

4. Results and Discussion

4.1. Specification Tests, Comparison with Nested Models and Parameter Estimates

For each of the functional capability models (Equations (5)–(7)) the first test entailed comparing the Cobb-Douglas (C-D) specification with the indirect translog (ITL).[20] In each case, the Eichenbaum-Hansen-Singleton (E-H-S) specification tests (1983) failed to reject the nested C-D specification in favor of the more general ITL specification. Having selected the C-D specification, we then compared the full model with several nested models. The full model had: (1) unobserved heterogeneity in capabilities, (2) unobserved heterogeneity in the marginal products of inputs, and (3) heteroskedasticity of the random shock term. This was compared with models with one or more of these features absent to see which specification fit best. Using the E-H-S test results, we selected the model with the simplest structure consistent with data. Furthermore, using Hansen's *J* test (1982) for over-identifying restrictions, we tested for the fit of the data with the selected model.

Sales Frontier: Based on the E-H-S tests, the selected model entailed a C-D specification with: (1) unobserved heterogeneity in mean inefficiency, (2) unobserved heterogeneity in marginal products/elasticities, and (3) heteroskedasticity of the random shock. MSM estimates of the sales frontier are given in Table 1.

All the parameters are significant, except for *ADSTOCK*, and of the expected sign. The most significant resource is *MARKETINGSTOCK*, followed by *TECHBASE* and *RECEIVABLES*. The elasticities of the inputs are positive and less than one, indicating a diminishing marginal productivity.

[20]For both the C-D and the ITL models, we assumed homoskedasticity and no unobserved heterogeneity. Details of the E-H-S and Hansen's *J* tests (along with the test statistics) are provided in the technical appendix.

Innovative Frontier: Based on the E-H-S tests, the selected model entailed a C-D specification with: (1) unobserved heterogeneity in mean inefficiency, (2) no unobserved heterogeneity in marginal products, and (3) no heteroskedasticity of the random shock. MSM estimates of the innovative frontier are given in Table 2.

The results are consistent with our expectations. Based on the magnitude of the coefficients, we find that *TECHBASE* seems to be the most important input, followed by *CUM_R&DEXPENSE* and *MKTCAP*. Interaction effects between *MKTCAP* and *TECHBASE* are positive and significant.

Cost Frontier: Based on the E-H-S tests, the selected model entailed a C-D specification with: (1) unobserved heterogeneity in mean inefficiency, (2) no unobserved heterogeneity in marginal products, and (3) no heteroskedasticity of the random shock. MSM estimates of the model parameters are given in Table 3.

The effect of *MKTCAP* on cost is significant, suggesting the positive impact of operations-marketing coordination ("design for manufacturability").

Capabilities-Profitability Model: The E-H-S test indicated the presence of significant unobserved heterogeneity in the model parameters ζ across the firms.[21] We conducted the Breusch-Pagan test (Green 1997, p. 552) to test for heteroskedasticity. The χ^2 test statistic of 0.08 with 3 d.f. is less than the critical value of 0.12, so the homoskedasticity assumption is not rejected at 1% significance level. Similarly, Breusch-Godfrey tests (Greene 1997, p. 595) for autocorrelation (AR(P) and MA(P) processes) failed to reject the hypothesis of no autocorrelation at 1% level of significance.

Table 4 reports the MSM parameter estimates. All the parameter estimates are positive and significant. The interaction effect between *REL_R&DCAP* and *REL_MKTCAP* is found to be the most important determinant of inter-firm variations in profitability, followed by *REL_R&DCAP* and *REL_MKTCAP*.

Furthermore, to test the predictive validity of the proposed specification (Equation (8)), we conducted the Hoffman-Pagan post-sample prediction test (1989) on a holdout sample of 20 firms (we used 72 firms for the estimation sample). The χ^2 test statistic of 8.72 with 40 d.f. is less than the critical value of 19.92 at 1% significance level, indicating that the model fits the holdout sample well. An additional measure of goodness-of-fit is provided by the pseudo-R^2 value.[22] The pseudo-R^2 value of 0.92 suggests a good predictive validity for the proposed model.

Table 1 Parameter Estimates (MSM) of Marketing Capability Model

	Parameter Estimates (Standard Error)	
Variables	Population Average Effect	Variance of Unobserved Heterogeneity Component
Impact of Inputs:		
ln(*ADSTOCK*)	$\bar{\alpha}_8^m = 0.2157\ (0.1392)$	$\mathrm{Var}(\alpha_8^m) = 0.0915\ (0.0711)$
ln(*MARKETINGSTOCK*)	$\bar{\alpha}_9^m = 0.6815\ (0.2016)^{**}$	$\mathrm{Var}(\alpha_9^m) = 0.3351\ (0.1025)^{**}$
ln(*TECHBASE*)	$\bar{\alpha}_{10}^m = 0.4118\ (0.1852)^{**}$	$\mathrm{Var}(\alpha_{10}^m) = 0.2704\ (0.1536)^{++}$
ln(*RECEIVABLES*)	$\bar{\alpha}_{11}^m = 0.3752\ (0.1097)^{**}$	$\mathrm{Var}(\alpha_{11}^m) = 0.0512\ (0.0462)$
ln(*INSTALLEDBASE*)	$\bar{\alpha}_{12}^m = 0.2747\ (0.0915)^{**}$	$\mathrm{Var}(\alpha_{12}^m) = 0.0749\ (0.0283)^{**}$
Inefficiency Error:		
Mode of Inefficiency Error Term	$\bar{\mu}_m = 45.0492\ (9.7216)^{**}$	$\mathrm{Var}(\mu_m) = 7.0492\ (3.2815)^{**}$
Variance of Inefficiency Error Term	$\sigma_{\eta_m}^2 = 10.9214\ (4.0358)^{**}$	
Random shock:		
Variance of Random Shock	$\sigma_{\epsilon_m}^2 = 57.7103\ (15.2293)^{**}$	
Heteroskedasticity Parameter	$\theta = 1.6294\ (0.3894)^{**}$	
Minimized Criterion Function	0.00214	
χ^2 Statistic for Hansen's *J* Test (d.f.)	1.1772 (40)	

**: significant at 1% significance level
++: significant at 5% significance level

4.2. Discussion of Substantive Insights and Managerial Implications

Our findings offer a number of substantive insights and managerial implications.

Sales Frontier: Our first substantive insight pertains to the importance of *MARKETINGSTOCK* and *RECEIVABLES* in the sales frontier (Table 1: $\bar{\alpha}_9^m = 0.6815$ and $\bar{\alpha}_{11}^m = 0.3752$). Recall that the stock of marketing

[21] As with the capability models (Equations (5)–(7)) where we allow the parameters α to be randomly distributed across firms, we allow the parameters ζ to be randomly distributed as $\zeta \sim N(\zeta, \Sigma_\zeta)$. This necessitates the use of MSM estimation methodology.

[22] The pseudo-R^2 is computed exactly like the R^2 measure for the linear model. However, because the model is nonlinear, the pseudo-R^2 is not constrained to lie between 0 and 1 (Greene 1997). We thank an anonymous reviewer for suggesting this measure to us.

Table 2 Parameter Estimates (MSM) of R&D Capability Model

	Parameter Estimates (Standard Error)	
Variables	TECH_INNV	TECH_WIDTH
Impact of Inputs:		
α_1^r [ln(*TECHBASE*)]	0.8713 (0.2738)**	0.8258 (0.2910)**
α_2^r [ln(*CUM_R&DEXPENSE*)]	0.7512 (0.1725)**	0.6829 (0.3004)**
α_3^r [ln(*MKTCAP*)]	0.2594 (0.1326)++	0.3217 (0.1783)++
α_4^r [ln(*MKTCAP*) × ln(*TECHBASE*)]	0.5681 (0.1972)**	0.5902 (0.2141)**
Inefficiency Error:		
μ_r [Mode of Inefficiency Error Term]	3.5271 (0.0862)**	3.6483 (0.0715)**
$\sigma^2_{\eta_r}$ [Variance of Inefficiency Error Term]	1.0527 (0.0227)**	1.0391 (0.0385)**
Random Shock:		
$\sigma^2_{\epsilon_r}$ [Variance of Random Shock]	1.2518 (0.0489)**	1.0463 (0.3258)**
Minimized Criterion Function	0.00153	0.00117
χ^2 Statistic for Hansen's *J* Test (d.f.)	0.8415 (35)	0.6435 (35)

**: significant at 1% significance level
++: significant at 5% significance level

Table 3 Parameter Estimates (MSM) of Operations Capability Model

	Parameter Estimates (Standard Error)	
Variables	Population Average Effect	Variance of Unobserved Heterogeneity Component
Cost Elasticities:		
ln(*OUTPUT*)	$\bar{\alpha}_1^o$ = 0.9138 (0.3825)**	Var(α_1^o) = 0.0915 (0.0711)
ln(*LABCOST*)	$\bar{\alpha}_2^o$ = 0.2429 (0.1382)++	Var(α_2^o) = 0.1326 (0.1025)
ln(*CAPCOST*)	$\bar{\alpha}_3^o$ = 0.3183 (0.0947)**	Var(α_3^o) = 0.2274 (0.0826)**
ln(*TECHBASE*)	$\bar{\alpha}_4^o$ = −0.1380 (0.1173)	Var(α_4^o) = 0.0883 (0.0562)++
ln(*MKTCAP*)	$\bar{\alpha}_5^o$ = −0.2705 (0.0728)**	Var(α_5^o) = 0.1662 (0.0473)**
Inefficiency Error:		
Mode of Inefficiency Error Term	$\bar{\mu}_o$ = 18.2315 (6.6821)**	Var(μ_o) = 6.1542 (4.2815)++
Variance of Inefficiency Error Term	$\sigma^2_{\eta_o}$ = 3.5118 (1.0027)**	
Random shock:		
Variance of Random Shock	$\sigma^2_{\epsilon_o}$ = 14.0451 (3.3472)**	
Heteroskedasticity Parameter	θ = 1.8512 (0.2931)**	
Minimized Criterion Function	0.00182	
χ^2 Statistic for Hansen's *J* Test (d.f.)	1.0016 (16)	

**: significant at 1% significance level
++: significant at 5% significance level

expense includes incentives to salespersons, trade incentives, and customer incentives over the years, while receivables proxy a firm's ability to offer longer credit terms to its customers. In many high-technology markets, and especially in semiconductors, a firm sells its product to an OEM, who in turn combines this product with a number of other products and sells the system to the end consumer. In such an industrial market setting, trade incentives and incentives to salespersons are of great importance. Also, the importance of loose credit terms and other such expenditure can now be readily understood as a device to satisfy OEMs as much as possible. The significance of the OEM as an intermediary also explains why advertising is not of great significance in this industry. OEMs are generally more knowledgeable than the average end consumer and are much less likely to be influenced by advertising than by an excellent salesforce.[23]

[23]The result on the nonsignificance of advertising needs to be

Table 4 Parameter Estimates (MSM) of Capabilities-Performance Model

	Parameter Estimates (Standard Error)	
Variables	Population Average Effect	Variance of Unobserved Heterogeneity
Main Effects:		
ln(*REL_MKTCAP*)	ζ_{17} = *0.4791 (0.0992)***	*Var*(ζ_{17}) = 0.1527 (0.0981)
ln(*REL_R&DCAP*)	ζ_{18} = 0.5104 (0.1609)**	Var(ζ_{18}) = 0.2718 (0.0825)**
ln(*REL_OPCAP*)	ζ_{19} = 0.3206 (0.1837)++	Var(ζ_{19}) = 0.1004 (0.0751)
Interaction Effects:		
ln(*REL_MKTCAP*) × *ln*(*REL_R&DCAP*)	ζ_{20} = 0.7382 (0.2811)**	Var(ζ_{20}) = 0.4132 (0.2215)++
ln(*REL_OPCAP*) × ln(*REL_R&DCAP*)	ζ_{21} = 0.1217 (0.0315)**	Var(ζ_{21}) = 0.0217 (0.0179)**
Minimized Criterion Function	0.00136	
χ^2 Statistic for Hansen's *J* Test (d.f.)	0.7425 (50)	

**: significant at 1% significance level
++: significant at 5% significance level

The importance of *MARKETINGSTOCK* and *RECEIVABLES* leads to the following managerial implication for the semiconductor industry and related markets. The focus in such markets should be on building long-term relationships with customers (OEMs). To this end, it is important to have salespeople who are technically competent because the aim is to convince OEMs. Similarly, great care needs to be taken in the selection and training of distributors, who influence the purchase decisions in such markets crucially. Such distributors have to be wooed with appropriate trade incentives to ensure that they push the product enthusiastically. The importance of such "relationship marketing" has already been pointed out for a host of markets (Jackson 1985), but its significance in high-technology markets has rarely been recognized.

Our second substantive insight relates to the importance of prior stock of know-how (*TECHBASE*) in influencing sales (Table 1: $\bar{\alpha}_{10}^{m} = 0.4118$). Consider the case of a customer (i.e., OEM) in a high-technology market. High switching costs in such markets mean that OEMs would wish to go with a firm that is likely to be a technology leader in the future. In such a situation, the focal firm needs to signal the likelihood of it being a technology leader to influence customer expectations appropriately.

Given the importance of influencing customers, managers need to tailor their marketing activities around the need to inform customers of the technological excellence of their firm. A consistent theme needs to be pursued in all interactions with the customer, whether through salespersons or through promotions. Thus, customers need to be informed of the innovative technologies that the firm possesses and of the future R&D initiatives undertaken by it. Similarly, any potential applications of innovative technology developed by the firm, and of technologies under development, should be emphasized to customers. The hiring of star scientists or engineers should be widely publicized—an excellent case in point is the publicity given by AMD to the recent move of Vinod Dham, the engineer chiefly responsible for the Pentium design, from Intel to AMD. Salespersons also need to be trained to highlight a firm's technological excellence in their dealings with customers. In short, managers need to give a lot of thought to configuring their marketing activities around the common goal of communicating to customers the technological excellence of their firm. Customers need to be informed of the innovative technologies that the firm possesses and of the future R&D initiatives undertaken by it.

R&D Frontier: Our results on the R&D frontier lead to a couple of substantive insights. Our first insight relates to the impact of marketing on a firm's innovativeness. We find that marketing capability has its greatest impact on the quality-adjusted output of firms which have a strong technological base (Table 2: α_4^r = 0.5681 & 0.5902). Thus, in addition to the importance of interfunctional coordination suggested in prior literature (Gupta et al. 1987), we also suggest that marketing capability has a disproportionate interactive effect: The higher a firm's technological base, the stronger is the impact of a higher marketing capability on the R&D productivity. This insight translates to a very important managerial implication: It is precisely firms that *are* good technologically that would get the most bang from buck if they improved their marketing capability.

The second substantive insight relates to the impact of marketing capability impact on the extent to which the innovative technology is applicable across a wide range of industries (Table 2: $\alpha_5^r = 0.3217$). Recall that one of marketing's tasks is to listen to the consumer and come up with a pool of ideas. A strong marketing capability would imply that this pool of ideas is wider, spanning a number of applications. Consequently, innovations from R&D that rely on this pool will have applications across a wider range of industries. This result carries a strong message for managers: One of the most fecund sources of ideas for innovation is the results of marketing activity. Thus, marketing needs to be involved from the beginning of the innovation process.

Relative Profitability: Our results relating to relative firm performance suggest one important insight. The most important determinant of firm performance is the

qualified. The industry itself seems to be changing, as suggested by the success of the "Intel Inside" campaign, followed by a high-profile TV campaign by Cisco Systems. Thus, advertising might well be growing in importance, even in the semiconductor industry.

interaction of marketing and R&D capabilities (Table 4: $\zeta_{20} = 0.7382$). This supports the assertion that firms in high-technology markets need to excel at two things: the ability to come up with innovations constantly, and the ability to commercialize these innovations into the kinds of products that capture consumer needs and preferences. This finding offers further evidence on the importance of R&D–marketing coordination, as suggested in the marketing literature (e.g., Griffin and Hauser 1996) and is applicable across a wide range of markets.

5. Conclusions

This paper proposes a conceptual framework with the resource-based view (RBV) of the firm as its theoretical underpinning, to explain interfirm differences in firms' profitability in high-technology markets in terms of differences in their functional capabilities. Specifically, we suggest that marketing, R&D, and operations capabilities, along with interactions among these capabilities, are important determinants of relative financial performance within the industry. The paper contributes to a number of different literatures. First, it contributes to the RBV literature by proposing an input-output conceptualization of a firm's capabilities which is then operationalized using the SFE methodology. Methodologically, the use of the SFE is an important step that permits measurement of a firm's capabilities, using archival data, while explicitly linking the firm's productive resources to the attainment of its objectives.

Our study contributes to the literature on market orientation by suggesting that a stronger market orientation of a firm should get reflected in a higher marketing capability. It also adds to the literature on "design for manufacturability" by explicating the complementarity among the various functional capabilities and offering empirical evidence on their relative importance in influencing a firm's performance.

This paper represents a "first cut" at assessing the role of firm-specific capabilities in intra-industry variation in firms' performance in high-technology markets and has a number of limitations, which suggest avenues for further research. Thus, one could consider a host of different objectives for the three capabilities. For example, operations could be concerned with on-time delivery or with a low defect rate. Marketing could be concerned with service quality or with customer satisfaction. Similarly, for the R&D frontier we could have used objectives such as time to commercialization of a new product (Griffin and Hauser 1996) or the number of new products introduced. It would be interesting to see what new insights result from the changing of objectives or the combining of a number of them.[24]

Appendix

Estimating *REL_MKTCAP$_{it}$* and *REL_R&DCAP$_{it}$*

Note that in Equation (9), $e_{it} = \epsilon_{it} - \eta_{it}$ is the composite error term, including the random shock and the inefficiency error component, and represents the difference between the observed output Y_{it} and the predicted output $\hat{Y}_{it} = f(X_{it}, \hat{\alpha})$, where α denotes the parameter estimate. A consistent estimate of the inefficiency for firm i in period t is given by (Battese and Coelli 1988):

$$\hat{\eta}_{it} = E[\eta_{it} \mid e_{it} = \hat{e}_{it}] = \mu_{it}^* + \sigma_*^2 \left\{ \phi\left(-\frac{\mu_{it}^*}{\sigma_*^2}\right)\left[1 - \Phi\left(-\frac{\mu_{it}^*}{\sigma_*^2}\right)\right]^{-1} \right\}, \quad \text{(A.1)}$$

where

$$\mu_{it}^* = \frac{\mu\sigma_\epsilon^2 - \sigma_\eta^2[Y_{it} - f(X_{it}, \hat{\ })]}{\sigma_\eta^2 + \sigma_\epsilon^2} \text{ and } \sigma_*^2 = \frac{\sigma_\eta^2\sigma_\epsilon^2}{\sigma_\eta^2 + \sigma_\epsilon^2}. \quad \text{(A.2)}$$

A consistent estimate of firm i's inefficiency (as a % of maximum achievable output, given the level of resources) in period t is given by $\hat{\eta}_{it}/\hat{Y}_{it}$. As mentioned earlier, we take the inverse of inefficiency as the measure of the firm's capability. Thus, the consistent estimate of capability of firm i in period t, is given by $CAP_{it} = \hat{Y}_{it}/\hat{\eta}_{it}$, which is scale-independent.

We estimate the sample average capability as follows. Let $\hat{e} = (\hat{e}_{11}, \hat{e}_{12}, \ldots, \hat{e}_{1T}, \ldots, \hat{e}_{N1}, \hat{e}_{N1}, \ldots, \hat{e}_{NT},)$ be the vector of sample values of the composite error components for $i = 1, 2, \ldots, N$ firms for time periods $t = 1, 2, \ldots, T$. Then the consistent estimate of the sample average inefficiency is given by

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$$\bar{\bar{\eta}} = E[\eta \mid e = \hat{e}] = \mu^{**} + \sigma_{**}^2 \left\{ \phi\left(-\frac{\mu^{**}}{\sigma_{**}^2}\right)\left[1 - \Phi\left(-\frac{\mu^{**}}{\sigma_{**}^2}\right)\right]^{-1} \right\}, \quad \text{(A.3)}$$

where

$$\mu^{**} = \left[-\sigma_\eta^2\, \bar{\bar{e}} + \frac{\mu\sigma_\epsilon^2}{NT}\right]\left[\sigma_\eta^2 + \frac{\sigma_\epsilon^2}{NT}\right]^{-1};$$

$$\sigma_{**}^2 = \frac{\sigma_\eta^2\sigma_\epsilon^2}{\sigma_\epsilon^2 + NT\,\sigma_\eta^2}; \text{ and, } \bar{\bar{e}} = N^{-1}\,T^{-1} \sum_{i=1}^{N}\sum_{t=1}^{T} \hat{e}_{it}. \quad \text{(A.4)}$$

Thus, a consistent estimate of the sample average capability is given by CAP $= \bar{\bar{Y}} / \bar{\bar{\eta}}$ where $\bar{\bar{Y}}$ refers to the sample average of output, and is given by $\bar{\bar{Y}} = N^{-1}T^{-1} \Sigma_{i=1}^{N} \Sigma_{t=1}^{T} Y_{it}$. The relative capability of firm i in period t is thus given by $REL\_CAP_{it} = [\hat{Y}_{it}/\bar{\bar{Y}}] \times [\hat{\eta}_{it}/\bar{\bar{\eta}}]$.

Analytical details are given in the technical appendix.

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