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Absorptive Capacity in High-Technology Markets: The Competitive Advantage of the Haves

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The rapid rate of knowledge obsolescence in many high-technology markets makes it imperative for firms to renew their technological bases constantly. Given its critical importance, excellence in renewal of technological base would serve as a *dynamic capability*. Drawing on past literature, we identify this dynamic capability associated with acquiring and utilizing external technological know-how with the notion of *absorptive capacity* (AC).

We ask the following questions: (a) What would cause some firms to have a higher AC than others? and, (b) What is the impact of AC on a firm's profitability?

We build a conceptual framework suggesting that marketing, R&D, and operations capabilities have a significant positive impact on a firm's AC. We test our framework on a data set of firms in high-technology markets. Using an econometric technique called stochastic frontier estimation, we *infer* the AC of firms from an observation of the know-how they actually absorb. We find that firm-specific capabilities significantly impact AC. Also, we find that AC has a significant impact on profitability and that this impact is moderated by the pace of technological change: the greater the pace of change, the greater the impact.

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1. Introduction

An important element of a firm's innovation management strategy is the acquisition of know-how that forms the basis of future innovations (Drucker 1985). As Jelinek and Schoonhoven (1990) highlight, in industries such as semiconductors, computers, and biotechnology, "success lies in not pulling it off once ... but replicate technological innovations repeatedly over the long run." Innovation in such industries relies on cutting edge developments in a number of basic scientific and engineering fields such as materials science, electrical engineering, and electrophysics, e.g., IBM's development of a copper (instead of the aluminum usually used) interconnect for use on chips, which relied on breakthroughs in photolithography, electrical engineering, and design testing (Spooner 2000). While the renewal of its technological knowledge base is crucial to a firm, this is by no means an easy task. Given the sheer number and breadth of technological fields to draw from, no one firm can possibly hope to come up with all the required research on its own. This immediately suggests that every firm needs to look *outside* its boundaries and acquire knowledge from other firms, research labs, and universities to keep pace with the changing technological landscape.[1]

Our work builds on the literature suggesting the importance of marketing in technologically turbulent and "information intensive" markets (Glazer 1991, Glazer and Weiss 1993) by looking at know-how as an *information asset* to be acquired and utilized by a firm in its innovation activities. This lets us discuss theoretically how marketing can affect the ability of a firm to value technological options as well as its ability to utilize them effectively. Given the central importance of

[1] In the discussion that follows, we shall be focusing exclusively on technological know-how or knowledge. However, for brevity, we shall often refer to this as just know-how or knowledge. It should be emphasized that our focus is only on technological know-how.

such renewal, it is obvious that firms that do better at this task would gain competitive advantage over their rivals. In the language of the resource-based view (RBV) of the firm, this ability to acquire and utilize external know-how could serve as a *dynamic capability* of a firm, leading to a sustained competitive advantage. Drawing on past literature (Cohen and Levinthal 1990), we refer to this particular dynamic capability as *absorptive capacity* (AC).

The identification of AC with a dynamic capability suggests a number of research questions. First, because a capability can be a source of competitive advantage only if there is heterogeneity among firms in the possession of that capability we ask, What causes some firms to have a higher AC than other firms? Second, by definition, a useful capability has to have a significant impact on profits if it is to be a source of competitive advantage. This leads to the question, What is the impact of AC on a firm's profitability?

1.1. Related Literature

The theoretical base that our paper relies on is the RBV. This theory has emphasized the role of firm-specific resources and capabilities in helping a firm enjoy a sustained competitive advantage (Wernerfelt 1984, Barney 1991). We build on this notion by conceptualizing dynamic capabilities in terms of regeneration of critical resources. In addition, we draw on the stream of work on AC pioneered by Cohen and Levinthal (1990). Theoretically, we build on the notion of AC as a dynamic capability by conceptualizing the process of know-how absorption as essentially one of properly valuing and utilizing a number of uncertain knowledge assets. Empirically, we advance the literature by using objective and precise measures for constructs such as technological know-how absorption and suggesting an econometric methodology to infer AC. We view one of our major contributions as the merging of the AC and the RBV literatures in a meaningful manner.

From a substantive perspective, our paper is related to a rich stream of work in marketing that has looked at the link between marketing and innovation. This work has pointed to the important role played by marketing in the new product development process (Gupta et al. 1987, Griffin and Hauser 1993, Wind and Mahajan 1997, Srinivasan et al. 1997). Our work is also closely related to prior literature examining the process of information acquisition and formal planning in technologically turbulent and "information intensive" markets (Glazer 1991, Glazer and Weiss 1993). It is also in accord with literature in marketing (Sinkula 1994, Moorman and Miner 1997, Miner et al. 2001) that has examined the role of information processing and organizational learning and suggested that the efficiency with which a firm uses knowledge is a function of its prior learning. Our work complements a growing literature in marketing that examines the role of information and know-how acquisition by firms (e.g., Rindfleisch and Moorman 2001, Prabhu et al. 2005). Finally, our work is related to current research in marketing that has used the notions of resources and capabilities to study issues such as the impact of customer satisfaction (Mittal et al. 2005) and the option value of marketing capabilities, which lets them be deployed against future opportunities (Moorman et al. 2005).

The rest of the paper is organized as follows. The next section develops our conceptual framework. Section 3 discusses our empirical model specification and outlines the econometric methodology we use. Section 4 discusses the empirical application in more detail—we describe the data set, operationalize the variables, and report our empirical findings. Section 5 concludes with suggestions for further research.

2. Conceptual Framework

The RBV suggests that firm-specific resources and capabilities are crucial to explaining differences in profitability across firms (Wernerfelt 1984, Peteraf 1993). While both resources and capabilities are sources of competitive advantage, RBV draws important distinctions between them. Thus, Amit and Shoemaker (1993) suggest that "*capabilities*... refer to a firm's capacity to deploy *resources*, usually in combination, using organizational processes, to effect a desired end. They are information-based, tangible or intangible processes that are firm-specific and are developed over time through complex interactions among the firm's *resources*." For example, a firm's R&D capability could be its skill at converting R&D expenditure (a resource) into innovations. Similarly, its marketing capability could be the excellence with which the firm converts marketing expenditure (a resource) into such metrics as sales or customer satisfaction. We should emphasize that we are not suggesting that resources can not be sources of competitive advantage themselves; capabilities, by virtue of being complex transformational processes, are more firm specific and, hence, harder to imitate or buy, which potentially confers a sustainable competitive advantage on the firm.

The notion of resources and capabilities was further enhanced in an important contribution by Hogarth et al. (1991) and other authors (Teece et al. 1997, Eisenhardt 2000). These authors suggested a multistage framework of competitive advantage, with stages steadily increasing in order of complexity. Earlier stages are "static" in that they deal with existing resources and capabilities, while later stages are "dynamic" in that they deal with the ability of firms to *renew* their resources and processes of transformation.

We follow past literature by conceptualizing dynamic capabilities in terms of regeneration of critical resources. Our focus is on high-technology markets, marked by rapid change in technological know-how both in terms of the depth of know-how required as well as the broad array of technical fields used. The need to look out and acquire knowledge, then utilize it meaningfully, is crucial to the task of know-how regeneration. Past researchers have referred to this ability to acquire and utilize know-how from outside the firm itself as the firm's *absorptive capacity* (Cohen and Levinthal 1990, Henderson and Cockburn 1994). Given its central importance in technological renewal, clearly AC would be an important dynamic capability for firms in technological markets.

2.1. Conceptualizing Absorptive Capacity

In the RBV/input-output framework (Dutta et al. 1999), one could think of firms using a set of resources at their disposal (such as R&D and marketing expenditures) and combining these in a complex manner to absorb the maximal amount of know-how from outside. Clearly, firms that have more resources should be able to absorb more; therefore, while measuring AC we need to condition on the level of resources deployed. Thus, our conceptualization defines absorptive capacity (AC) as the efficiency with which a firm absorbs, relative to what it could have absorbed given the resources it has deployed. Our measurement of AC is consistent with this conceptualization. In what follows, we explain each of the components of our conceptualization: first, the resources that a firm has at its disposal to achieve its goal of absorbing know-how (which explain how much it could absorb), and second, the reasons for a firm's differential abilities to absorb technological know-how from outside, which is our conceptualization of AC.

2.1.1. Resources Influencing the Level of Knowledge Absorption (Know-How Frontier). The amount of know-how a firm can possibly absorb will depend on the level of its resources. We suggest three resources that we think would be important in influencing know-how absorption.

R&D Expenditure. R&D expenditure is the most fundamental resource available to firms to produce technological know-how. All else being equal, firms with higher R&D expenditure should manage to absorb more know-how (Cohen and Levinthal 1990). Following past literature (Griliches 1984), we normalize R&D expenditure with the firm's sales.

Prior Stock of Innovation. A large literature has pointed out the important role played by a firm's technological achievements in shaping its ability to utilize new knowledge (Stiglitz 1987). This literature has suggested that both the quantity and the quality of one's prior technological experience enable a firm to recognize and assimilate more know-how from outside (Cohen and Levinthal 1990).

The existing literature, however, has not explicated the exact relationship between a firm's prior technology base and the nature of technological know-how that it wishes to absorb from outside its boundaries and outside its domain of expertise. One argument—the learning-to-learn hypothesis (Stiglitz 1987)—is that of positive spillovers from past technological base to absorption of know-how even from hitherto new areas. Alternatively, a larger stock of prior innovations may actually hinder the firm from actively pursuing technological know-how from outside (possibly because of something similar to the "not invented here" syndrome). We treat this as a purely empirical question.

Marketing Expenditure. Firms that spend more resources interacting with customers will have a richer sense of the issues customers face with existing technologies and any technological breakthroughs by competitors. For instance, Iansiti and West (1997) speak of the marketing resources spent by firms that enhance the "market sensing" abilities of a lot of the high technology firms. These resources enable firms to increase their boundary spanning activity beyond the status quo (Han et al. 1998). This enables them to scan the market for new technological options and offer them a larger base of technologies to draw from based on customer and competitor interactions. As in the case of R&D, we normalize our marketing expenditure with the firm's sales.

Summarizing, the maximum amount of know-how a firm could possibly absorb will depend on its R&D expenditure, its marketing expenditure, and its prior stock of innovation. We can write the expression for the maximum know-how absorbable as:

$$\begin{aligned}&\text{Maximum Know-How Absorbable}\\&\quad = f(\text{R\&D Expenditure}, \text{Marketing Expenditure},\\&\qquad \text{Innovation Stock}). \qquad (1)\end{aligned}$$

We reiterate that the dependent variable in Equation (1) is *not* a firm's AC but only represents the best-case scenario for know-how absorption. In reality, there will be a "gap" between the actual and the maximal levels of know-how absorbed. It is the firm's ability to get as close as possible to this maximal that represents its AC.

2.1.2. Factors Causing Heterogeneity in Absorptive Capacity Across Firms. Given the criticality of technological know-how, all firms in the industry are likely to be aware of the importance of know-how regeneration and would try to renew their knowledge resource bases as best as they can. One can conceive of this process as that of "looking" outside the boundaries of the firm and making judgments on what knowledge to acquire and what price to pay for it. The key here is that if all firms are aware of the exact value of the asset they wish to acquire and if this value is common knowledge, they will end up bidding such that there are no ex post rents to be had from the asset (Barney 1991, Peteraf 1993). At this point it is natural to ask, What would help some firms to erect ex ante/ex post barriers to competition in the process of know-how absorption?

To clarify the discussion and make it more precise, suppose that there are a number of knowledge assets out there with a distribution of valuations.[2] For a number of reasons, however, there is uncertainty surrounding this valuation (such uncertainty would be natural in turbulent markets). Now, firms use some criterion to decide which asset(s) to acquire—the criterion essentially tells them how much to pay for the assets they do wish to acquire. (One could think of a number of criteria—firms could try maximizing expected value, or they could try minimizing the mean squared error; the exact criterion is not of primary importance here.) In this scenario, firms are differentiated from each other in two ways. First, they differ in their ability to pick the "winning" technologies. In essence, this amounts to making superior guesses on the correct valuation of knowledge assets in the face of uncertainty.

Second, having acquired these knowledge assets, a firm needs to transform them into innovative output. We suggest that some firms are better at transforming these knowledge assets into innovative output because they possess superior combinatorial ability and/or complementary capabilities that help them achieve superior outcomes (Helfat 1997).[3]

Previous scholars have suggested a multistage framework of competitive advantage (Hogarth et al. 1991), with stages steadily increasing in order of complexity. Thus, they suggest that dynamic capabilities that deal with the ability of firms to *renew* their resources and processes of transformation tend to rely on other complementary capabilities (Teece et al. 1997, Eisenhardt 2000), that are firm-specific and developed over time through complex interactions among the firm's *resources*. We build on this literature and suggest that a firm's functional capabilities in the domain of marketing, operations, and R&D play a key role in enhancing the firm's efficiency in absorbing and utilizing technological know-how from outside, through enhancing the firm's ability to value knowledge assets, and enhancing the firms ability to transform these assets into superior outputs. We now discuss how each of the three functional capabilities enhance the efficiency of knowledge absorption (AC).

Rationale I—Superiority in Valuing Technological Assets. We argue that both R&D and marketing are important capabilities that enhance a firm's AC by impacting its ability to value technological assets.

R&D Capability. A firm which is good at technological innovation has evidently demonstrated a proven expertise in picking important technologies to work on. In addition, the firm's R&D excellence in various fields means that it would be in a strong position to judge the relative merits of various technologies. For example, Intel faced a plethora of technological possibilities in designing its new manufacturing plant—a number of these technologies were new approaches to lithography and planarization (Iansiti and West 1997). Intel's genius in this case was to *choose* correctly from among these options to come up with a setup that would work best. We thus suggest that superior R&D capabilities will significantly enhance a firm's ability to value technological assets.

Marketing Capability. Marketing capability would be an important factor affecting a firms ability to pick properly from a variety of technological assets. First, for a firm to keep abreast of various technological developments, it has to have excellent abilities to scan the environment. Kodama (1992), Von Hippel (1989), and others point out how firms with superior market scanning abilities seem to be much better at sifting through technological options; i.e., the cost of sifting through various options seems to be much lower for such firms, since much of the infrastructure in terms of firm-specific routines (e.g., for getting customer feedback) is already in place. Sharp, for example, is a firm that lets "demand articulation" drive a number of its R&D efforts. Its investments in a number of nascent technologies that later paid off, such as opto-electronics, were a direct result of its expectations of what the market was going to be like in the future. In summary, we suggest that firms with higher market-scanning ability would be more efficient at sifting through various technological options and, hence, have superior absorptive capacity.

Rationale II—Superiority in Utilizing Technological Assets. We suggest that the following functional capabilities would enhance a firm's AC by enhancing the efficiency with which it utilizes technological assets.

[2] This and what follows is clearly a simplification of the process of knowledge regeneration. However, the simplification comes with a major payoff—while abstracting away from a number of issues that are not our focus, it helps us narrow down issues such as the "true value" of the asset, the "uncertainty" surrounding this true value, and the ability of firms to bid correctly for this asset.

[3] We wish to emphasize that the two cases discussed are to facilitate exposition of the knowledge-absorption process. Clearly, firms will not be engaging in just one or the other—and, equally clearly, both of the cases will impact knowledge absorption in tandem. A recent paper (Makadok 2001) discusses similar dimensions in a slightly different context and refers to them as resource picking and capability building, respectively.

Marketing Capability. Prior literature (Day 1994, Srinivasan et al. 1997) suggests that a firm's marketing capability is one of the most important complementary assets a firm can possess, helping it to utilize innovations better. A superior marketing capability confers both demand and supply-side advantages to a firm; i.e., it helps reduce the cost of marketing innovations and increase the demand for the innovation among consumers. An excellent example of the role of marketing capability in a high-technology firm is Intel, which has successfully executed a branding strategy in the face of stiff competition from AMD that had developed faster chips multiple times. The advantages of picking the right technology and bringing it to market are particularly salient in high-technology industries, since they are marked by short life cycles and a huge first-mover advantage.

R&D Capability. A firm's R&D capability is the skill with which the firm transforms resources such as R&D expenditure into high-quality innovations. Clearly, a firm with high R&D capability will be able to derive much greater benefit from a given set of technological know-how acquired from outside, since its transformation skills are higher. We thus suggest that higher R&D capability would lead to higher AC.

Operations Capability. Operations capability in technology intensive markets entails the integration and coordination of a complex set of tasks. These activities consist of combining components and materials from different sources and industries and managing material flows to enhance output in an efficient manner (Hayes et al. 1988). Thus, the more efficient a firm is in this domain, the higher its efficiency in integrating know-how from outside. The complexity of this process makes it less imitable and confers an advantage to the firm in utilizing know-how from outside. Iansiti and West (1997) suggest the crucial role played by operations in ensuring the successful conversion of innovations into usable products. These authors and others such as Srinivasan et al. (1997) have suggested how R&D and operations capabilities rely on each other to help a firm come up with high-quality innovations.

In summary, we suggest how the three functional capabilities of a firm—marketing, operations, and R&D—enhance the absorptive capacity of a firm along two dimensions. First, superior abilities in recognizing the true value for the asset, which means the firm (on average) chooses and pays correctly. This is a very important advantage to possess when so much uncertainty surrounds every possible know-how asset. Second, superior abilities to utilize technological know-how which results in higher marginal returns and, hence, competitive advantage over other firms that might have paid identically for the asset.

Formally, our conceptual framework so far suggests the following relationship, explaining interfirm differences in AC:

$$\begin{aligned}&\text{Absorptive Capacity}\\&\quad= f(\text{R\&D Capability}, \text{Marketing Capability},\\&\qquad\qquad\text{Operations Capability}).\end{aligned} \tag{2}$$

We would expect each of the factors above to have a positive impact on a firm's AC.

Finally, if AC is to be a meaningful capability, its impact on various outcomes (such as profits) should be firm specific. The second part of our framework below discusses this issue.

2.2. Why Absorptive Capacity Matters: The Impact of Absorptive Capacity on Profitability

A high absorptive capacity has to do with regenerating a firm's know-how base and keeping abreast of cutting-edge scientific developments taking place outside. When is this ability likely to be of most use? The answer is, precisely when markets are changing so rapidly and the environment is so turbulent that today's knowledge becomes obsolete tomorrow. Past literature points to significant differences brought about in firm strategy because of the rate of change of the environment (Glazer and Weiss 1993, Balakrishnan and Wernerfelt 1986, Pasa and Shugan 1996). What this suggests is that the pace of technological change is likely to moderate the impact of absorptive capacity on profitability and, further, that the *higher* this pace, the *greater* the impact of absorptive capacity on profitability.

Yet another reason for the greater importance of AC in more turbulent markets relies explicitly on RBV theory. Recall that one of the factors that make firm-specific capabilities such as AC so valuable is that they cannot be imitated or bought easily. Now, faster change in markets essentially makes comprehending AC even harder for competitor firms—in the language of RBV, it increases causal ambiguity (Lippman and Rumelt 1982). Thus, as before, we should expect that AC should be even more valuable in times of rapid change.

In the next section, we discuss the econometric methodology that we use to estimate AC, highlighting the close links between our estimation strategy and RBV theory.

3. Measuring Absorptive Capacity: Estimation Issues

The econometric challenge is to measure a firm's AC (which is unobservable and, hence, cannot be measured directly) and to estimate the impact of firm-specific factors responsible for interfirm differences in

AC. Recall that in our conceptualization, AC refers to the efficiency with which a firm absorbs know-how from outside. This is estimated by measuring the shortfall between the actual and the maximal levels of know-how absorbable (again, an unobservable variable) given the firm's resources. Thus, to estimate AC, we first need to estimate the *know-how frontier* that gives the know-how absorbable under the most efficient deployment of the firm's resources. The technique we use, called stochastic frontier estimation (SFE), is perfectly suited to this purpose. It helps us *infer* capabilities (AC, in this case) from an observation of the *outcomes* of superior or inferior AC, i.e., an observation that firms have absorbed more or less technological know-how from outside. The SFE technique thus helps us stay close to the basic notion of capabilities in the RBV in that it treats capabilities as unobservable complex transformational processes.

3.1. Estimating the Optimal Level of Know-How Absorbed: The Know-How Frontier

The know-how frontier represents, in the input-output terminology (Dutta et al. 1999), the maximum "output" a firm could produce given a set of inputs. Based on the earlier discussion (§2.1.1), the task is to estimate the unknown parameters (α's) of the following equation:

$$\begin{aligned}\ln(\text{Know-How Absorbed}_{it}) &= \alpha_0 + \alpha_1 \times \ln(\text{R\&D Expenditure}_{it}) \\ &\quad + \alpha_2 \times \ln(\text{Marketing Expenditure}_{it}) \\ &\quad + \alpha_3 \times \ln(\text{Innovation Stock}_{it}) \\ &\quad + \alpha_4 \times (\text{Market Conditions}_i) + \varepsilon_{it} - \eta_{it} \qquad \text{(3a)}\end{aligned}$$

or, more compactly,

$$Y_{it} = f(X_{it}, \alpha) + \varepsilon_{it} - \eta_{it} = f(X_{it}, \alpha) + e_{it}. \qquad \text{(3b)}$$

A few comments on this specification are in order. First, note that the know-how frontier is given by $f(x_{it}, \alpha) + \varepsilon_{it}$, where the first term (the deterministic component) represents the impact of deployed resources, while the stochastic term ε_{it} represents "luck," or the impact of factors beyond the firm's control (e.g., macroeconomic conditions). We assume that ε_{it} is distributed normal with mean zero and variance σ_ε^2, i.e., $\varepsilon_{it} \sim N(0, \sigma_\varepsilon^2)$, so that both good and bad luck are equally likely. The term η_{it} captures the "gap"/shortfall between the maximal ($f(X_{it}, \alpha) + \varepsilon_{it}$) and the actual ($Y_{it}$) level of know-how absorption. We assume η_{it} to be an independent and identically distributed nonnegative normal random variable, defined by the truncation (at zero) of the $N(\mu, \sigma_\eta^2)$ distribution with mode $\mu > 0$. To facilitate estimation, we make some further assumptions on the error terms, namely, that the random shock ε_{it} and the inefficiency error η_{it} are independent, i.e., $\mathrm{E}[\varepsilon_{it}\eta_{it}] = 0$, and that these error components are independently distributed of the independent variables in the model; i.e., $\mathrm{E}[X'_{it}\varepsilon_{it}] = \mathrm{E}[X'_{it}\eta_{it}] = 0$.

Second, one could argue reasonably that our resources are actually endogenous variables in that the firm would choose appropriate levels of R&D and marketing expenditures with the production of some output in mind. Endogeneity is a potential problem in our framework and subsequent estimation. Unfortunately, this problem has dogged the literature on productivity measurement for well over four decades now. The theoretical solution to endogeneity is well recognized—use instruments for those variables that might be endogenous. It is the implementation of this theoretical suggestion that has proved problematic in that effective instruments are almost impossible to find. To quote Griliches and Mairesse (1995) "...the available instruments are likely to be quite poor and possess little resolving power...." In our case, with factors such as the "innovation stock" of a firm (involving long time lags), the task of finding appropriate instruments becomes even harder.

Given our distributional assumptions, for a sample of N firms with T observations for each firm, it can be shown (Stevenson 1980, Battese and Coelli 1988) that the sample likelihood function for the SFE formulation corresponding to Equation 3(b) is given by:

$$\begin{aligned}L = \prod_{i=1}^{N}\prod_{t=1}^{T} &\frac{1}{\sqrt{\sigma_\eta^2+\sigma_\varepsilon^2}} \\ &\times \left[1-\Phi\left(\frac{\sigma_\eta[Y_{it}-f(X_{it},\alpha)]}{\sigma_\varepsilon\sqrt{\sigma_\eta^2+\sigma_\varepsilon^2}} - \frac{\sigma_\varepsilon\mu}{\sigma_\eta\sqrt{\sigma_\eta^2+\sigma_\varepsilon^2}}\right)\right] \\ &\times \phi\left(\frac{Y_{it}-f(X_{it},\alpha)+\mu}{\sqrt{\sigma_\eta^2+\sigma_\varepsilon^2}}\right) \times \left[1-\Phi\left(-\frac{\mu}{\sigma_\varepsilon}\right)\right]^{-1}, \qquad (4)\end{aligned}$$

where $\phi(\cdot)$ and $\Phi(\cdot)$ denote the standard normal density and distribution functions, respectively. Consistent maximum likelihood (ML) estimates of the model parameters $\langle \alpha\text{'s}, \sigma_\varepsilon^2, \mu, \sigma_\eta^2 \rangle$ can be obtained by maximizing the sample likelihood function, Equation (4).

3.2. Estimating Absorptive Capacity

Having estimated the model parameters ($\hat{\alpha}$'s), the predicted frontier is computed as $f(X_{it}, \hat{\alpha})$ and, hence, the estimated shortfall is $\hat{e}_{it} = f(X_{it}, \hat{\alpha}) - Y_{it}$. Now, the second econometric task is to estimate AC from the shortfall $\hat{e}_{it}$ above. As suggested earlier, the *smaller* this shortfall, the lower the inefficiency in know-how absorption and, hence, the *greater* the AC. However, it would be incorrect to ascribe the shortfall $\hat{e}_{it}$ completely to a firm's lack of absorptive capacity. Thus, a firm may have done badly because of bad "luck," i.e., causes beyond its control such as macroeconomic conditions.

Given our distributional assumptions, it can be shown (Battese and Coelli 1988, 1995) that a consistent estimate of the inefficiency for firm i in period t is given by

$$\hat{\eta}_{it} = \mathrm{E}[[\eta_{it} \mid e_{it} = \hat{e}_{it}] = \mu^*_{it} + \sigma^{*2}\left\{\phi\left(-\frac{\mu^*_{it}}{\sigma^{*2}}\right)\left[1-\Phi\left(-\frac{\mu^*_{it}}{\sigma^{*2}}\right)\right]^{-1}\right\}, \quad (5)$$

where

$$\mu^*_{it} = \frac{\mu\sigma^2_\varepsilon - \sigma^2_\eta[Y_{it} - f(X_{it}, \hat{\alpha})]}{\sigma^2_\eta + \sigma^2_\varepsilon} \quad \text{and}$$

$$\sigma^{*2} = \frac{\sigma^2_\eta \sigma^2_\varepsilon}{\sigma^2_\eta + \sigma^2_\varepsilon}. \quad (6)$$

A consistent estimate of firm i's inefficiency in period t is given by $\hat{\eta}_{it}$. We normalize the highest absorptive capacity in the sample to a value of 100%, i.e., that firm would have inefficiency $\hat{\eta}_{it} = 0$. With this calibration, we can write a consistent estimate of the AC of firm i in period t as:

$$\mathrm{AC}_{it} = (1 - \hat{\eta}_{it}). \quad (7)$$

3.3. Explaining Firm-Specific Differences in Absorptive Capacities

One of the main features of our conceptual framework in §2.1 is the heterogeneity across firms in their AC. To account for heterogeneity in AC, we assume that the mode of the inefficiency error term μ is heterogeneous across firms. In particular, we assume that

$$\begin{aligned}\ln(\mu_{it}) = \mu^* &+ \gamma_1 \times \text{R\&D Capability}_{it} \\ &+ \gamma_2 \times \text{Marketing Capability}_{it} \\ &+ \gamma_3 \times \text{Operations Capability}_{it} + \sigma_\mu \varepsilon, \end{aligned} \quad (8)$$

where ε is a standard normal variable and σ^2_μ measures the variance in the mode of the inefficiency term due to unobservable effects. The maximum likelihood estimation procedure gives us estimates of the γ parameters. From our discussion of the conceptual framework (§2.1) we would expect each of the γ parameters to be negative and significant in its impact. The negative sign implies that the variable has a negative effect on a firm's inefficiency in absorption; i.e., it has a *positive* impact on a firm's AC. For example, we would expect that an increase in the firm's marketing capability would actually lower the mean of inefficiency (equivalently, enhance AC). It should be pointed out that this specification of AC heterogeneity adheres closely to RBV theory in that it attempts to explain some factors that would cause differences among firms in AC but still leaves a portion of the heterogeneity unexplained. This is as it should be—if we could explain all the heterogeneity in AC across firms, the capability would be rendered completely transparent and, hence, easily imitable.

3.4. Estimating the Impact of AC on Profitability

Our conceptual framework suggests that the impact of AC on profitability will be moderated by the pace of technological change in the market. Following Dutta et al. (1999), we examine relative profitability. We thus specify the profitability equation as:[4]

$$\begin{aligned}&\text{Rel\_Profit}_{it} \\ &= \beta_0 + \beta_1 \times \text{Rel\_Profit}_{i,t-1} + \beta_2 \times \text{Rel\_R\&D Capability}_{it} \\ &\quad + \beta_3 \times \text{Rel\_Marketing Capability}_{it} \\ &\quad + \beta_4 \times \text{Rel\_Operations Capability}_{it} + \beta_5 \times \text{Rel\_AC}_{it} \\ &\quad + \beta_6 \times \text{Rel\_AC}_{it} \times \text{Rel\_Tech\_Obsolescence}_{it} + \varepsilon_{it}. \end{aligned} \quad (9)$$

We would expect all the coefficients to be positive and significant, although the parameter we are specially interested in is β_5, i.e., the impact of AC on profitability *after* accounting for the effects of static capabilities (viz., marketing, R&D and operations capabilities).

In order to account for persistence in profitability (Geroski et al. 1993, Erickson and Jacobson 1992), we include a lag of profitability as an explanatory variable.[5] Apart from the fact that including the lagged dependent variable is essential to avoid misspecification, given the known dynamic properties of profitability measures such as ROI, doing so also helps isolate the impact of AC as a dynamic capability and rule out alternative explanations for its significance.[6] The inclusion of the lagged dependent variable implies that the usual fixed effects estimator is biased (Nickell 1981). We use a GMM estimator proposed by Arellano and Bond (1991), which consists of sweeping out firm-specific effects through first differencing and then using lagged values of the endogenous variable as instruments. One has potentially

[4] Our definition of relative profitability differs from some earlier definitions in the literature (e.g., Dutta et al. 1999). Please refer to §4.3 here for additional details. The current definition is better suited to measures such as return on investment (ROI), which could potentially be negative. We thank an anonymous reviewer for pointing this out to us.

[5] We thank an anonymous reviewer for pointing out the importance of accounting for dynamics in the profitability specification as well as suggesting the specification we now use.

[6] We also compare the specification that includes lagged profitability to one that accounts for dynamics through an AR(1) specification on the residuals (following Smith 1992), and find that the specification with lagged profitability is superior. We thank an anonymous reviewer and the associate editor for suggesting this comparison.

a number of instruments available, with the number growing as the length of the panel increases. The fact that the residuals are mean zero conditional on the instruments gives us a set of orthogonality (moment) conditions. Given more moment conditions than the number of parameters to estimate, the model is overidentified and one can check for the validity of the moment conditions using Hansen's J statistic (Hansen 1982). Further, it is important for the consistency of the estimator that there be no second-order autocorrelation in the residuals; again, one can check for this using a Lagrange multiplier test (Arrelano and Bond 1991).

4. Empirical Application

In this section, we illustrate the theory and measurement discussed above to estimate the absorptive capacities of firms in the semiconductor and computer industries. We chose these markets for a number of reasons. From a theory point of view, such markets are characterized by intensive use of science and technology and rapid change, with firms needing to innovate constantly to survive. This is an ideal setting where the regeneration of know-how would be of importance. Further, firms seem to differ greatly in their ability to come up with new generations of technology.

4.1. Description of the Data Set

Our sample consists of 64 publicly traded firms whose primary business is in semiconductors and computers (i.e., SIC codes 35 and 36). More precisely, the SIC codes used are 3571, 3572, 3576, 3577, 3661, 3663, 3669, and 3674. Because our focus is on technological know-how absorption as measured through patents, a firm has to have some history of patenting. We restricted our sample to firms that had at least 15 patents over at least five years. These numbers were chosen to ensure that firms had a "reasonable" history of coming up with innovations as measured through patenting, and that we could get a representative panel data set of firms. We had the further restriction that the firms be publicly traded (as it turns out, there are essentially no private firms that patent extensively, so this restriction does not rule out any more firms than the restriction on patenting above). For each firm in our sample, we collected information pertaining to the resources available to R&D and marketing domains of activity from the Compustat database for the years 1980–1998. Financial measures were also obtained from Compustat.

The Compustat database, however, did not give us information pertaining to firms' innovative output. For this we conducted an exhaustive content analysis of patent data gathered from the U.S. Patent Office. This data yielded a number of measures, notably the construct of "outside technological know-how." While we go into details in the operationalization section below, we would like to point out that in all we performed a content analysis of over 150,000 patents. This effort involved extensive programming both at the data collection stage and at the content analysis stage. Descriptive statistics for key variables are given in Table 1.

Table 1 Descriptive Statistics

Variable	Mean	Std. dev.	Minimum	Maximum
R&D (million $)	186.79	374.81	0.110	2,893
Sales (million $)	24,629.06	5,142.45	1.21	32,751
ROI	0.1522	0.1171	−0.4879	0.5484
Citation weighted patent count (annual)	79.63	193.62	0	1,884.26

4.2. Variable Definition for the AC Equation

Consistent with our conceptual framework, our discussion of variable operationalization is divided into two parts. We first enumerate the dependent and independent variables that are important to the determination of the know-how frontier (Equation 3a). Following this, we discuss the variables that account for firm-specific heterogeneity in AC (Equation 8). Readers who are more interested in the estimation results and discussion can proceed directly to §4.4 without loss of continuity.

4.2.1. Determining the Know-How Frontier (Equation 3a).

1. *Technological Know-How Absorbed* (*TKH_ABS*). Since this variable is central to our empirical focus, we discuss its operationalization in detail. The variable conceptually represents the *amount of technological know-how* (*actually*) *absorbed by the firm from outside*. There are two parts to this definition that need operationalization. First, what is technological know-how? Second, what is "outside?" To operationalize both of these issues, we rely on patents. Each patent is classified under various nine-digit classifications called the U.S. classification. This is an extremely detailed technological classification system devised by the U.S. patent office (USPTO). The classes to which a specific patent belongs are decided by the USPTO examiner who awards the patent. We can determine exactly what technical areas a patent lies in by looking at the classes it is assigned to. The following steps illustrate how our measure is created.

(a) We examine each patent for each firm, for each year (our unit of analysis is a firm/year). Consider firm i, with J $(j=1,\dots,J)$ patents in year t. We refer to each of its patents as the *focal* patents in what follows and denote them as F_{ijt}.

(b) First, we determine what classes each focal patent is in. Thus, suppose there are only two focal patents, with patent F_{i1t} in classes {A1, C1, Z1} and patent F_{i2t} in classes {B1, C1, G1, Z1}. From this, we construct an array of unique patent classes for the firm for that year. In our example, this array denoted D_{it} is given by $D_{it} = \{A1, B1, C1, G1, Z1\}$. Now, D_{it} represents the number of classes firm i has patented in, in year t—we refer to this as the firm's *domain of expertise* (DOE).[7] Note that this takes into account the firm's history of innovation; if a firm has been patenting with fecundity in a specific technological area, know-how in that area is clearly not from "outside," as far as the firm is concerned.

(c) Given the DOE, we now look inside each patent and get a list of those patents it has cited. The USPTO examiner ensures that this list is as complete as possible, since the scope of a patent's monopoly is determined by it. The list represents in an exact sense the "prior art" in the field that this patent is drawing upon. Thus, it represents the technological know-how that the firm is drawing on. We first knock out those backward citations that belong to the focal firm itself (these are *self-citations*). We now examine each of the remaining backward cited patents to get at a list of their U.S. classes. Thus, suppose our two focal patents F_{i1t} and F_{i2t} have backward cited patents B_1, B_2, and B_3. Also suppose that the array of unique classes that B_1 through B_3 lie in, denoted as K_{it} is: $K_{it} = \{A1, C1, R1, L1\}$. Call this array the *know-how drawn on* (KHDO).

(d) Given both the DOE and the KHDO, we now compare the two. More precisely, we count the number of unique classes that are in the KHDO but *not* in the DOE. This represents the number of technological classes that the firm has drawn on from *outside its domain of expertise* and is our measure of know-how absorbed from outside. For the example above, classes {R1, L1} lie outside the domain of expertise of the firm. This count is normalized with the total number of classes that are backward cited, so our measure is continuous.

(e) In summary, the following points are important to clarify. First, the use of patent classes helps us define technological know-how very precisely, using objective classifications developed by the USPTO. Second, the measure defines "outside" in a precise manner—both as outside the firm's areas of expertise and as outside the firm itself. This is a fairly stringent measure—previous research has either used non-self patents (Jaffe et al. 1993) or outside technological areas (Ahuja and Lampert 2001) but not both.

[7] We experimented with various heuristics here, e.g., assigning a class to the DOE only if showed up more than a certain number of times, considering only the first three digits of the class, etc. Also, we considered the domain of expertise over a period of two to three years, i.e., considering all the classes the firm had patented in during the past two to three years. None of this made a significant difference to the results.

2. *R&D Expenditure* (*R&D_EXP*). This is defined as the amount of R&D expenditure for firm i for year t, divided by its sales for that year.

3. *Marketing Expenditure* (*MKT_EXP*). We measure this as the sales and general expenditure (SGA) for firm i for year t, divided by its sales for that year.

4. *Stock of Innovation* (*INNOVSTOCK*). 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 equal footing. For instance, Scherer (1965) has shown that "the distribution of patent values is highly skewed towards the low end, with a long and thin tail towards the high-value side" (Trajtenberg 1990), thereby implying that patents differ in terms of "quality." Thus, we need to adjust for innovativeness (quality) while doing the patent counts.

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 its citation count.

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. Call the sum of these citation-weighted patents, for firm i, for year t, TECH_INNV_{it}. The INNOVSTOCK_{it} is then given as:

$$\text{INNOVSTOCK}_{it} = \sum_{k=1}^{t} \delta^{t-k} \times \text{TECH\_INNV}_{k}. \qquad (10)$$

Consistent with past literature (Griliches 1984), we form a stock with declining weights ($\delta = 0.4$) on past innovative output. Note that our data is necessarily right truncated, since some patents would still be getting citations after the cutoff date of our sample. We correct for the resulting truncation bias. (Please see the Technical Appendix for details at http://mktsci.pubs.informs.org.)

5. *Market Conditions* (*MKT_COND*). To control for market conditions that might differ across various submarkets the firms are in, we divide our sample on the basis of the four-digit SIC code that firms are in. Our sample has eight such codes, with most firms falling in SIC code 3674. For estimation purposes, the variables are coded as dummies—we thus have seven dummy variables.

4.2.2. Factors Causing Heterogeneity in Absorptive Capacity (Equation 8). Our conceptual framework suggests that functional capabilities such as marketing, R&D, and operations enhance a firm's AC. The theory base we rely on suggests that capabilities refer to a firm's capacity to deploy resources, usually in combination, using organizational processes to effect a desired end (e.g., Amit and Shoemaker 1993, McGrath et al. 1995). They are information-based, tangible or intangible processes that are firm specific and are developed over time through complex interactions among the firm's resources. Our operationalization of capabilities attempts to capture each of these aspects. Thus, we explicitly consider the resources available along the three functional dimensions and the desired outputs in each case. We then estimate the functional capabilities by calculating the efficiency of the transformation from resources to desired output. The efficiency of this transformation would vary by firm and would likely be a function of the kinds of complex interactions that are generally unobservable and hard to imitate, satisfying the RBV's basic conditions.

1. *Marketing Capability* (*MKT_CAP*). We proxy the ability of firms to scan markets by their marketing capability. To estimate marketing capability, we use the conceptualization and technique suggested by Dutta et al. (1999), which is consistent with the notion of capability in the RBV literature. Briefly, we suggest that the objective of the marketing function is to use the resources at its disposal to maximize sales. Given a set of resources, we can, using the SFE methodology, estimate the maximum amount of sales the firm could have achieved. The closer the firm's actual sales were to this maximum, the higher its marketing capability. We use as resources available to the firm the level of sales, general, and administrative expenditures (SGA) and the level of its receivables. Estimation is done using SFE (and is similar to the estimation of AC). Since we use observable resources to infer the excellence of the firm's transformative processes, this ties our methodology closely to the notion of capabilities in the RBV tradition. Further details of the estimation of marketing capability are provided in a Technical Appendix at http://mktsci.pubs.informs.org.

2. *R&D Capability* (*RD_CAP*). A firm's R&D capability follows a conceptualization similar to other firm-specific capabilities. Thus, we suggest that a firm uses the resources available to it (R&D expenditure, prior technological stock) to try to maximize its output of quality-weighted innovations. The closer it actually gets to this maximum, the higher its R&D capability. We operationalize quality-weighted innovations through citation-weighted patent counts. As before, we use SFE to estimate capabilities. Further details of our correction for truncation bias in citation weights and our estimation procedure are given in the Technical Appendix at http://mktsci.pubs.informs.org.

3. *Operations Capability* (*OP_CAP*). Similar to a firm's R&D and marketing capabilities, its operation capability is a measure of its ability to take the resources available to it (such as capital and labor stock) and minimize costs. We take the resources available to firms as capital and labor expenditures. Our output variable is the cost of goods sold. Again, SFE is used to estimate operations capability—details are given in the Technical Appendix at http://mktsci.pubs.informs.org.

4.3. Variables for the AC–Profitability Relationship (Equation 9)

1. *Relative Profitability* (*REL_PROFIT*). We use return on investment (ROI) as our measure of profitability. This is defined as operating income divided by assets. It has been widely used in the literature (Erickson and Jacobson 1992, Hult and Ketchen 2001). We obtain the relative profit of firm i for period t by subtracting the sample average ROI for period t from the firm's ROI in period t; i.e.,

$$\text{REL\_PROFIT}_{it} = \text{ROI}_{it} - \frac{1}{N}\sum_{i=1}^{N}\text{ROI}_{it}.$$

2. *Relative R&D Capability* (*REL_RDCAP*). We obtain the relative R&D capability of firm i for period t by subtracting the sample average R&D capability for period t from the firm's R&D capability in period t; i.e.,

$$\text{REL\_RDCAP}_{it} = \text{RDCAP}_{it} - \frac{1}{N}\sum_{i=1}^{N}\text{RDCAP}_{it}.$$

3. *Relative Marketing Capability* (*REL_MCAP*). We obtain the relative marketing capability of firm i for period t by subtracting the sample average marketing capability for period t from the firm's marketing capability in period t; i.e.,

$$\text{REL\_MKTCAP}_{it} = \text{MKTCAP}_{it} - \frac{1}{N}\sum_{i=1}^{N}\text{MKTCAP}_{it}.$$

4. *Relative Operations Capability* (*REL_OPCAP*). We obtain the relative operations capability of firm i for period t by subtracting the sample average operations capability for period t from the firm's operations capability in period t; i.e.,

$$\text{REL\_OPCAP}_{it} = \text{OPCAP}_{it} - \frac{1}{N}\sum_{i=1}^{N}\text{OPCAP}_{it}.$$

5. *Relative Absorptive Capacity* (*REL_AC*). We obtain the relative absorptive capacity of firm i for period t

by subtracting the sample average absorptive capacity for period t from the firm's absorptive capacity in period t; i.e.,

$$\text{REL\_AC}_{it} = \text{AC}_{it} - \frac{1}{N}\sum_{i=1}^{N}\text{AC}_{it}.$$

Our measure of AC_{it} is obtained from SFE estimation using Equation (7).

6. *Relative Technological Obsolescence* (*REL_TECH_OBS*). To operationalize technological obsolescence, we develop a new measure based on objective secondary data. The idea behind our measure is as follows: The more fast-changing a market, the greater its rate of technological turnover. Thus, if market A uses newer technology (on average) than market B, we would say that market A is more fast-changing. In terms of our measure, a more fast-changing market would correspond to a higher rate of technological obsolescence. To operationalize this idea we look at the patents produced by firms in a certain market. Call these the focal patents, and suppose there are P of these patents. Now, each of these patents has a certain issue data associated with it, which is the date the USPTO granted the patent. Denote the issue date associated with focal patent p as T_p. Now, we look at the issue date for each of the backward citations of each patent. Denote these dates by T_{pb}, with $b = 1, \ldots, B$, where B is the number of backward citations. Recall that these backward citations represent the base of know-how that the focal patent draws on. TECH_OBS is then computed as the inverse of the average difference between the issue date of the focal patents and the issue dates of the backward citations. Formally, we compute

$$\text{TECH\_OBS} = \left(\frac{1}{PB}\sum_{p=1}^{P}\left[\sum_{b=1}^{B}(T_i - T_{ib})\right]\right)^{-1}. \tag{11}$$

Clearly, the lesser the average difference, the *newer* the technology firms in the industry draw on, and the higher the rate of technological obsolescence in the industry, i.e., the *higher* the value of TECH_OBS. Similar to the other variables, we obtain the relative technological obsolescence, REL_TECH_OBS of firm i for period t by subtracting the sample average technological obsolescence for period t from the firm's technological obsolescence in period t.

4.4. Results and Discussion

Pattern in AC Over Time. Before we discuss the factors that cause firm-specific differences in AC, it is interesting to look at broad averages for AC estimates over time. Figures 1 and 2 show the distribution of AC for two different time periods, 1985 and 1995 (these represent years near the beginning and end of our sample, respectively). Two things stand out. First, the average AC for our sample has gone up considerably from about 31% to about 54%. Second, the heterogeneity in the distribution of AC has not changed much between 1985 and 1995 (the standard deviations are about 17.8% and 17.3%, respectively). These factors suggest that firms seem to be enhancing their AC over time—to the extent that AC is a source of regeneration and competitive advantage, firms seem to be taking the right steps to ensure they stay in the race.

Estimating the Know-How Frontier. Maximum likelihood estimates of the parameters of the frontier equation are given in the top half of Table 2. Not surprisingly, R&D expenditure has a significant positive impact on the know-how frontier ($\alpha_1 = 0.2649$, $p < 0.01$), suggesting that firms with higher R&D expenditures can absorb more technological know-how. Since our specification is in logs, we can interpret the coefficients as elasticities. Thus, the elasticity of R&D expenditure is approximately 0.26; a 1% increase in R&D expenditure increases the amount of know-how absorbed by 0.26%. Marketing expenditure also has a significant impact on the frontier itself ($\alpha_2 = 0.4185$, $p < 0.01$). Finally, a firm's prior technological stock has a strong impact on the maximum amount of

Figure 1 **Distribution of AC in 1985**

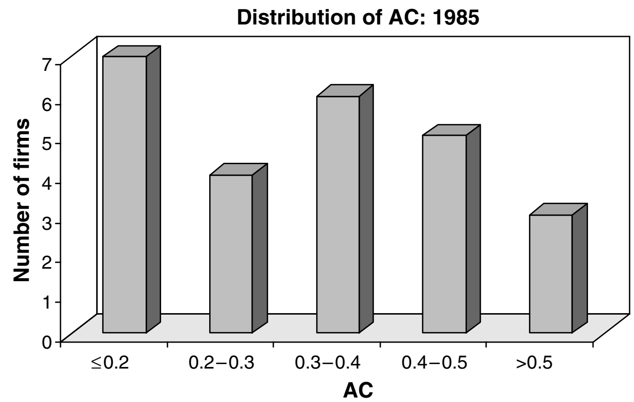

Figure 2 **Distribution of AC in 1995**

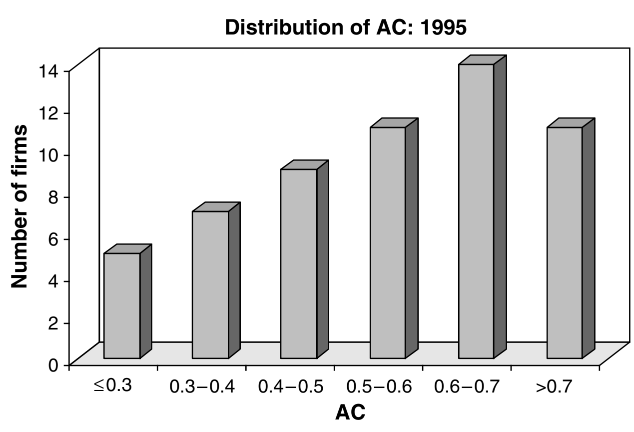

Table 2 Parameter Estimates of Absorptive Capacity Model (Equations 3a and 8)

Variables	Coefficients (std. errors)
Stochastic frontier inputs	
Intercept (α_0)	5.3375 (0.2170)**
ln(RD_EXP) (α_1)	0.2649 (0.0797)**
ln(MKT_EXP) (α_2)	0.4185 (0.1404)**
ln(INNOVSTOCK) (α_3)	0.6377 (0.02409)**
Factors affecting AC	
Intercept (μ^*)	4.4383 (0.4473)**
RD_CAP (γ_1)	−2.4595 (0.9944)*
MKT_CAP (γ_2)	−5.8951 (1.2098)**
OP_CAP (γ_3)	−0.1095 (0.03067)**
Variance parameters	
Random shock (σ_ε^2)	2.1304 (0.3281)**
Inefficiency error (σ_η^2)	0.6736 (0.0515)**
Log likelihood function	−1.1994E+03

*Significant at 5% level, **significant at 1% level.

know-how it can absorb ($\alpha_3 = 0.6377$, $p < 0.01$). Recall that we had suggested earlier that past innovative stock could affect the frontier in two opposite ways—positively through learning-to-learn effects (Stiglitz 1987), and negatively through effects such as the not-invented-here syndrome. We view our findings as evidence that learning-to-learn effects seem to be stronger in our sample—firms that have been engaging consistently in the production of innovations are well positioned to enter new technological areas. Finally, although not reported in Table 2, four of the seven market dummies were significant.

Factors Causing Heterogeneity in AC. Coming to the specification for heterogeneity in AC, we find that each of the firm-specific capabilities has a significant impact. (Note that a negative sign before a coefficient implies that it has a negative effect on a firm's inefficiency in absorption, i.e., it has a *positive* impact on a firm's AC.)

As we had discussed earlier, capabilities refer to a firm's capacity to deploy resources, usually in combination, using organizational processes to attain a desired objective. Thus, capabilities usually refer to tangible or intangible processes that are firm specific and are developed over time through complex interactions among the firm's resources. This makes it harder for other firms to imitate firm capabilities, making them useful sources of competitive advantage. The finding that absorptive capacity is significantly influenced by the three functional capabilities—marketing ($\gamma_1 = -5.89$, $p < 0.01$), R&D ($\gamma_2 = -2.45$, $p < 0.05$), and operations ($\gamma_3 = -0.10$, $p < 0.01$)—suggests why higher-order dynamic capabilities such as AC are likely to be even harder to imitate. This is entirely in keeping with what a resource-based perspective of the firm would suggest and emphasizes the role of dynamic capabilities as sources of competitive advantage. It is also in accord with literature in marketing (Sinkula 1994, Moorman and Miner 1997, Miner et al. 2001) that has examined the role of information processing and organizational learning, and suggested that the efficiency with which a firm uses knowledge is a function of its prior learning. Our paper speaks to this literature by examining how the complex routines and processes developed over time in firms (as represented by capabilities in marketing, R&D, and operations) impact the firm's ability to learn from outside.

The significance of marketing capability to a firm's AC complements a number of research streams in marketing. For instance, prior literature has emphasized the importance of *valuing* information, especially in turbulent environments (Glazer 1991, Glazer and Weiss 1993) and the role of marketing therein. This is directly related to our paper, since a major dimension of AC is the impact it has on correctly picking technologies. Our conceptualization explicitly hypothesizes a role for marketing capability in picking the right technologies and is the first to demonstrate this significant role. Further, our finding also complements earlier research in the market orientation literature that has found a relation between a firm's market orientation and its innovativeness (Deshpande et al. 1993, Han et al. 1998). Specifically, we demonstrate a role for the firm's marketing capability higher up in the value chain of ideas, as well as its role in enhancing the firm's ability to exploit the technology it accesses to develop new generations of technology.

Finally, by examining the factors behind differential absorptive capacity, our paper complements a growing literature in marketing (e.g., Rindfleisch and Moorman 2001, Prabhu et al. 2005) that has examined the role of information acquisition in interfirm arrangements such as acquisitions and strategic alliances. The notion of relative absorptive capacity of the partner firms plays an important role in the ability of the firms to benefit from such an arrangement. By examining the factors behind differential absorptive capacity, our paper suggests a reevaluation of the

Table 3 Parameter Estimates of Profitability Model (Equation 9)

Variables	Estimates (std. error)	Unobserved heterogeneity (std. error)
REL_PROFIT_LAGGED (β_1)	0.382 (0.146)***	0.116 (0.0734)**
REL_RDCAP (β_2)	0.122 (0.038)***	0.142 (0.086)*
REL_MKTCAP (β_3)	0.096 (0.046)**	0.288 (0.113)**
REL_OPCAP (β_4)	0.008 (0.007)	0.047 (0.039)
REL_AC (β_5)	0.264 (0.121)**	0.221 (0.128)*
REL_AC∗TECH_OBS (β_6)	0.187 (0.091)**	0.076 (0.070)

Note. Hansen's test of overidentifying restrictions: $\chi^2_{182} = 86.32$. Arellano-Bond test for first-order autocorrelation: $z = -9.26$***. Arellano-Bond test for second-order autocorrelation: $z = -1.43$.

*Significant at 10%, level, **significant at 5% level, ***significant at 1% level.

relative strengths that each firm brings to the table. For instance, a firm with high marketing capability may be able to benefit from an R&D alliance in terms of enhanced absorption of technological know-how.

Link Between AC and Profitability. We had hypothesized that AC would have a significant impact on profitability, with the impact moderated by how technologically fast paced the environment was. The estimation results are given in Table 3. All the variables except operations capability are significant and of the expected sign. As expected, there is significant persistence in profitability ($\beta_1 = 0.382$, $p < 0.01$). Hansen's test of overidentifying restrictions suggests the appropriateness of the specification ($\chi^2_{182} = 86.32$, $p > 0.1$) in that the overidentifying restrictions are not rejected. Finally, the Arellano-Bond test does not reject the null of no-second-order autocorrelation ($z = -1.43$, $p > 0.1$), which is important for the consistency of the estimator used.

Turning to the role of AC itself, we find that AC has a significant direct effect on firm profitability ($\beta_5 = 0.264$, $p < 0.01$). This is the immediate impact; we can calculate the long-run impact of AC as $\beta_5/(1 - \beta_1) = 0.42$. The interaction effect of AC and obsolescence ($\beta_6 = 0.187$, $p < 0.05$) is significant and positive, suggesting that indeed AC has a greater impact on profitability in markets where technologies become obsolete at a faster rate. These two findings complement and extend prior literature that has emphasized the importance of valuing information especially in turbulent environments (Glazer 1991, Glazer and Weiss 1993).

Although enhancing AC takes consistent efforts over a period of time, our results suggest that these efforts do pay off in terms of their impact on profitability. In fact, the long-run impact is even greater than the immediate impact. On a theoretical note, the positive finding also supports the conceptualization of AC as a dynamic capability. It is interesting that even though industry experts have highlighted that it is very important for firms to renew their technological base by accessing and utilizing know-how from outside their boundaries, there has been little empirical evidence of such an ability having an impact on firm profitability. We believe that our finding is among the first to demonstrate a link between AC and firm profitability.

Finally, the finding that absorptive capacity has a bigger impact on firm profitability in more fast-changing environments suggests that this capability has the potential to play an increasingly important role in the competitive advantage of firms. In particular, as globalization and know-how transfer across firm and national boundaries leads to faster rates of technological innovations across diverse industries, firms that have developed this ability are likely to enhance their competitive position.

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' ability to absorb technological know-how from outside. The paper contributes to a number of different literatures.

First, it contributes to the RBV literature by conceptualizing dynamic capabilities in terms of regeneration of a firm's resources base. The paper identifies the acquisition and utilization of technological know-how as a dynamic capability and develops a framework for examining the dimensions of absorptive capacity (AC). This contributes theoretically to the literature on AC, both by tying it in explicitly to the RBV and by elucidating the factors that would affect know-how absorption. Methodologically, the use of the stochastic frontier estimation (SFE) is an important step that permits us to infer a firm's AC purely by observing how much technological know-how it has managed to absorb and by other firm-specific variables.

From a substantive perspective, it contributes to the marketing literature by emphasizing the role played by marketing capability at the earliest stages of innovation, i.e., at the stage when technological options need to be valued and chosen from. Given the important role played by innovative capacity and innovativeness in general, in theories of market orientation further evidence of marketing's impact on innovative capacity is indeed welcome.

The paper also suffers from a number of limitations that provide opportunities for future research. First, methodologically, one would like to control for the endogeneity of firm choices such as R&D expenditure. Not controlling for endogeneity could potentially lead to biased and inconsistent estimates for our parameters. An ideal way to account for endogeneity would be to model the innovation process structurally, similar to Olley and Pakes (1996). Second, one could conceptualize AC along multiple dimensions, e.g., speed of absorption versus depth of absorption. That is, some firms may be excellent at absorbing know-how quickly but do it over a very narrow area, while other firms may absorb more slowly over a broader area. Such a conceptualization would tie the notion of AC to ideas of exploration and exploitation and potentially permit a more fine-grained analysis of firm innovativeness.

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