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Corporate acquisitions are strategic actions that loom large in the minds of many senior managers. Despite decades of study, little systematic research exists on a central question: Why do the acquisitions of some firms perform better than those of others? The work that has examined this question has mostly focused on deal-specific variables (i.e., how the acquisitions are conducted). In this article, the authors highlight a firm-specific, marketing-driven variable—namely, product capital—that affects acquisition performance and predicts which firms are better positioned to acquire in the first place. The authors also present a mechanism by which product capital affects performance—namely, through acquirers’ superior selection and deployment of targets’ innovation potential. This article shows that firms with high product capital (i.e., those with greater product development and support assets) make smarter acquisition decisions. Such firms are better at selecting targets with innovation potential and then deploying this potential to gain competitive advantage. The performance consequences of this superiority in the selection and deployment of target firms manifest in the long-term financial rewards to the acquiring firm. The results of an analysis of acquisitions in the pharmaceutical industry across seven countries and over 11 years (1992–2002) provide empirical support for the arguments.

Why Some Acquisitions Do Better Than Others: Product Capital as a Driver of Long-Term Stock Returns

Corporate acquisitions are widespread today, and the numbers associated with them are striking. There were more than 30,000 acquisitions worldwide in 2004. The announced value of these acquisitions was $1.95 trillion, down from an all-time high of $3.4 trillion in 2000 (Gallagher 2004). Indeed, it is not rare for there to be acquisitions with price tags that are larger than the gross national products of some small countries. Given the stakes involved, many chief executive officers obsess over potential acquisitions, and policy makers cast a keen eye on their potential impact.

Perhaps not surprisingly, the economics, finance, and management streams of literature are replete with work on acquisitions. The conclusion of decades of scholarship on the subject is that acquisitions “[d]o not create superior post-acquisition performance for acquiring firms” (King et al. 2004, p. 192; see also Agrawal, Jaffe, and Mandelker 1992; Bouwman, Fuller, and Nain 2003; Datta, Pinches, and Narayanan 1992; Dyer, Kale, and Singh 2004; Jensen and Ruback 1983; Mueller 1995). It might seem that acquisitions are “like second marriages, a triumph of hope over experience … with even higher failure rates than the liaisons of Hollywood stars” (The Economist 2000, p. 19). The causes of failure are many. Some managers may...
believe that the odds do not apply to them and thus persist in making ill-fated acquisitions. This is the hubris hypothe-
sis (Roll 1986). Agency theory provides another explana-
tion for failure (see Bergen, Dutta, and Walker 1992).
Acquisitions are a quick way to grow, and managers whose
rewards are linked to short-term measures of growth in the
size of their firm may pursue their own interests at the
expense of the firm’s shareholders (Kroll et al. 1997; Schmid and Fowler 1990).

However, it would be incorrect to conclude that all acqui-
sitions are the result of misplaced managerial confidence or
misaligned managerial incentives. Indeed, anecdotal evi-
dence suggests that some acquisitions prove to be smart
business actions (Hitt, Harrison, and Ireland 2001; Raven-
scraft and Long 2000). Although the average returns to
acquirers may well be poor, these averages may also con-
ceal much variance. What are the differences between win-
ners and losers in the acquisitions game? Despite decades
of scholarship on acquisitions, this is a question for which
the answers are still sketchy. As Kaplan (2000, p. 3) notes,
“Existing work offers little insight into the determinants of
an acquisition’s success or failure.” Similarly, Bouwman,
Fuller, and Nain (2003, p. 10) point out that though “much
of the research to date has focused mainly on measuring
merger gains and losses, there has been little exploration
of how mergers actually create or destroy value.”

The limited research that attempts to explain variance in
acquisition performance has largely focused on how acqui-
sitions are conducted. As such, explanations for the success
or failure of acquisitions have largely been based on deal-
specific variables. For example, the finance and manage-
ment streams of literature have linked financial outcomes to
various deal-specific variables, such as whether an acqui-
sition is friendly or hostile, whether it is a cash or stock offer,
and whether it is vertical or horizontal (see Anand and Singh 1997; Andrade, Mitchell, and Stafford 2001; Bouw-
man, Fuller, and Nain 2003; Mueller 1995). In the manage-
ment literature, early attempts to look beyond variables that
are unique to the deal suggest that some level of product-
market relatedness between the acquirer and the target
(Lubatkin 1987; Singh and Montgomery 1987) and the transfer of acquirer resources to the target (Capron and Hul-
land 1999) can help postmerger performance. Nevertheless,
a recent meta-analysis of 74 years of research on the effect
of acquisitions on firm performance (King et al. 2004, pp.
187, 197) concludes that “unidentified variables may
explain significant variance in post-acquisition perform-
ance, suggesting the need for additional theory development
and changes to mergers and acquisitions (M&A) research
methods.... Researchers simply may not be looking at the
‘right’ set of variables as predictors of post-acquisition
performance.”

In this research, we present a new perspective on the suc-
cess or failure of acquisitions. We make four main contribu-
tions to the extant literature. First, in contrast to prior
research, which has largely focused on how to acquire, we
examine which firms are better positioned to acquire in the
first place. We argue that some firms should probably not
engage in acquisitions at all, no matter how much they
know about deal-specific success factors. Our explanation
for the success or failure of acquisitions is based squarely
on a firm-specific variable: product capital. Product capital
refers to the product development and product support assets that a firm has built over time. After controlling for
deal-specific factors, we show that firms that invest before-
hand in product capital are more likely to succeed at acqui-
sitions than other firms. Growth, we argue, must be built
before it is bought.

Second, we respond to calls from marketing scholars for
greater research in marketing on strategic decisions that
occur at the highest levels of the organization (e.g., Day and
Montgomery 1999; Varadarajan and Clark 1994). Acquisi-
tions provide an important context in which to respond to
these calls, but marketing scholars have rarely examined
them (for exceptions, see Capron and Hulland 1999; Rao,
Mahajan, and Varaiya 1991). Focusing on acquisitions
enables us to capture the impact of marketing-related assets
on the performance outcomes of key strategic actions. As a
consequence, we hope to make marketing’s contributions
more salient to senior managers and analysts.

Third, we link strategic actions to financial metrics of
performance that are so relevant to managers today (Srivas-
tava, Shervani, and Fahey 1998, 1999). An important issue
in this regard is that the performance outcomes of acquisi-
tions may be evident only in the long run (Agrawal, Jaffe,
and Mandelker 1992; Loughran and V Nhi 1997). Neverthe-
less, most acquisitions research has focused on short-term
outcomes (King et al. 2004). The limited research on long-
term outcomes of acquisition tends to rely on self-reported
measures of performance (e.g., Capron 1999). However,
acquisitions are often associated with management turnover
(Krug and Hegarty 1997), making it difficult to locate
knowledgeable informants. Moreover, retrospective,
survey-based accounts are prone to memory and self-
justification biases (Golden 1992). Noting the remarkably
high percentage of acquisitions that were evaluated as “suc-
cessful” by acquiring managers, a recent review by Federal
Trade Commission staff (Pautler 2003, p. 4) points out that
 “[o]ne can readily ask whether these surveys, using execu-
tive opinions as a benchmark for success, provide a valid
test, because one can hardly expect the executives involved
in the deal and responsible for its success to be unbiased
evaluators of the deal.” Furthermore, response rates can be
poor (Kaplan, Mitchell, and Wruck 2000), and responses
can be positively biased (Shimizu and Hitt 2005). By using
newly developed metrics of long-term shareholder value,
we hope to overcome the limitations of previous research
on acquisitions and encourage research in marketing that
uses these metrics to assess the impact of other strategic
actions important to firms.

Fourth, in the acquisitions context, we emphasize the
importance of a variable that is central to marketing and
management strategy: innovation. Innovation is often a cen-
tral motivator of acquisitions, especially in technology-
intensive contexts (e.g., Puranam, Singh, and Zollo 2003).
For example, of the ten studies on acquisition motives that
Chakrabarti, Hauschildt, and Silvèrkrüpp (1994) review, nine
list innovation or product-line expansion as a key acquisi-
tion motive. We show that firms with high product capital
select targets with greater innovation potential and deploy
the innovation potential of targets more extensively than do
firms with low product capital. The outcomes of superior
selection and deployment are reflected in the superior long-term financial performance of firms with high product capital.

We structure the rest of the article as follows: The following section presents our theoretical framework, from which we derive a series of hypotheses on the role of product capital in making successful acquisitions. Next, we describe the method we use to test these hypotheses empirically. We end with a discussion of our results and conclusions.

THEORY

Product Capital and Acquisitions

We define “product capital” as the product development and product support assets that a firm’s current and prior investments create. We integrate under the construct of product capital two key assets that are built over time: product support and product development assets. “Product support assets” are those devoted to the promotion of consumer adoption of new products, “Product development assets” are those devoted to the creation, development, and improvement of new products. Although the resource-based view of the firm typically emphasizes the strategic importance of product development relative to product support assets (see, e.g., Hitt, Harrison, and Ireland 2001; Makadok 2001), work on the marketing–finance interface has done the opposite (Srivastava, Shervani, and Fahey 1998, 1999).

Because product capital depends not only on a firm’s current investments but also on its prior pattern of investments, it is path dependent and difficult to imitate (Peteraf 1993). In addition to internal investments, a critical means by which firms accumulate superior assets is by outsmarting competitors in the selection of superior assets through external acquisitions (Prabhu, Chandy, and Ellis 2005). Firms with superior selection ability apply it before the actual acquisition of the assets by discriminating between winning and losing assets. Crucially, the ability to select better assets implies that such firms are also better able to avoid acquiring bad assets. As Makadok (2001, p. 388) notes, the avoidance of bad assets may have “an even greater impact on a firm’s economic profit” than the selection of good assets. However, good target selection is insufficient in itself. It is also necessary that acquiring firms engage in extensive deployment of the target’s innovation potential and turn it into a source of future cash flows (Makadok 2001).

In the following paragraphs, we argue that the market and research experience that firms gain from building product support and development assets provides them with a superior ability to select and deploy acquisitions. Specifically, we argue that firms with high product capital are better at (1) selecting acquisition targets with greater innovation potential and (2) deploying this innovation potential more extensively than other firms. In turn, better selection and deployment lead to better long-term acquisition performance. Figure 1 provides a graphic overview of our arguments. In presenting our arguments, we note that selection and deployment are broad constructs and can encompass more than the innovation dimension we examine here (see Slotegraaf, Moorman, and Inman 2003; Sorescu, Chandy, and Prabhu 2003). For reasons of parsimony and to ensure fit with our technology-intensive empirical context, we focus only on the selection and deployment of innovation potential and leave the study of other dimensions to further research.

Selecting Better

Why are firms with high product capital better at selecting targets with greater innovation potential than their counterparts with low product capital? First, firms with high product capital are better able to evaluate the innovation potential of target firms. As Cohen and Levinthal (1990) argue, the ability to evaluate outside knowledge is largely a function of the level of prior related knowledge. Indeed, firms with high product development, such as those that conduct their own research and development (R&D) and consistently invest in it, are better able to use externally available scientific and product-related information (Allen 1977). Similarly, high-product-support firms, through long-term, sustained marketing investments in support of their products, achieve a better understanding of the marketplace on both the demand and the supply side. For example, a strong sales force not only promotes a firm’s products but also brings to the firm customer feedback and competitor information that can be used to guide the firm in choosing new investments (Gordon and Schoembachler 1997). Second, firms with high product capital have a greater incentive to select targets better because they stand to lose more (i.e., to dilute a more valuable asset base by choosing badly). The cost of diluting their existing product capital by making bad choices imposes a discipline on such firms and ensures that they apply caution in choosing targets. Managers of high-product-development firms would not want to burden their scientists with a potentially mediocre target.

Figure 1

OVERVIEW: PRODUCT CAPITAL AND THE PERFORMANCE OF ACQUISITIONS
pipeline. Moreover, firms with high-product-support assets, such as a strong sales force base, have a greater need to “feed the marketing machine” with a constant stream of new products. Acquiring targets with high innovation potential would help complement or augment the acquirer’s own stream of innovations in the pipeline.

Finally, even if low-product-capital firms succeed in identifying good targets, they will face greater difficulty in attracting such targets than will high-product-capital firms. Managers and employees at attractive targets may balk at the prospect of being acquired by a firm with a weak record of investing in product development and support. As such, low-product-capital firms may find themselves acquiring targets with low innovation potential because they have fewer choices. Therefore, we hypothesize the following:

\[ H_1: \text{Firms with higher product capital select acquisition targets with greater innovation potential than do other firms.} \]

**Deploying Better**

In addition to the role of high product capital in helping firms select better targets, it confers several advantages on acquirers in terms of their ability to deploy extensively the innovation potential of targets they acquire. First, the successful deployment of the target depends on the quality of the target selected in the first place. You cannot squeeze blood from a stone; nor, for that matter, can innovations be realized from targets that have little innovative potential. Because high-product-capital firms are likely to select targets with higher innovation potential, they are already at an advantage in terms of deployment compared with low-product-capital firms.

Second, high-product-capital firms have a greater ability to assimilate new assets (Cohen and Levinthal 1990) and realize potential synergies with the target (Makadok 2001) by transforming promising ideas into productive outputs. To deploy new assets, such as technological know-how, effectively, the acquiring firm must first be able to analyze and understand these assets (Kim 1997; Szulanski 1996). However, new know-how acquired from outside the firm is likely to be difficult to analyze and understand because it may be from different fields, embody different heuristics, or be embedded in contexts that differ from that of the acquirer (Leonard-Barton 1995; Zahra and George 2002). Firms with high-product-development assets are more likely to possess the breadth and depth of existing know-how that is crucial to analyzing and understanding new technical know-how. Similarly, acquiring firms need to be able to take newly assimilated know-how and combine it with existing know-how, thus transforming both into product outcomes (Zahra and George 2002; Zahra, Ireland, and Hitt 2000).

Finally, expectations of greater professional success will persuade key employees in target firms to remain with high-product-capital firms postacquisition. The labor market for top technical talent is fiercely competitive, and opportunistic rivals often seize on the uncertainty and disruption generated by acquisitions to lure star scientists away from target firms (Chaudhuri and Tabrizi 1999). Acquirers with high product capital are better placed to retain their stars because such employees will perceive the long-term benefits of remaining with the combined firm. As we noted previously, high-product-capital firms are more likely to leverage product ideas generated by these employees and to apply them to productive ends. Therefore, key employees are able to perceive (1) the professional rewards that are likely to accrue to them as a result of the acquisition and (2) the impact that their work will have on the world at large. Moreover, given their understanding of target firms’ assets, high-product-capital firms are also likely to act in a way that minimizes disruption and uncertainty after acquisition. For all these reasons, key employees in the target firm are more likely to remain a source of productive outputs for the combined firm. Thus:

\[ H_2: \text{Firms with higher product capital deploy the innovation potential of targets more extensively than do other firms.} \]

**Performing Better**

Crucial to the performance of an acquisition is the postacquisition integration process (e.g., Hitt, Harrison, and Ireland 2001; Singh and Zollo 1998). No matter how good a target may seem at the time it is acquired, its potential can be realized only if it is successfully integrated into the parent firm, and this takes time to ascertain. Integration can be difficult because for most firms, acquisitions tend to be somewhat infrequent and unique, even in an age of merger frenzy in the overall economy. A firm can take many avenues to integrate a target, from preserving its organizational structure to completely restructuring it. Unanticipated organizational clashes and disruptions may occur during the integration. If the integration process fails, even an acquisition with great potential will turn out badly. Because the deployment journey is often long and full of uncertainty, investors face a daunting task in assessing the financial returns to acquisitions.

What, then, is the best way to evaluate the financial performance of acquisitions? Prior research has evaluated returns to acquisition using stock performance measured both in the short run, immediately surrounding the acquisition announcement (see Datta, Pinches, and Narayanan 1992), and in the long run, after the effects of the integration process have become apparent (Loughran and Vijh 1997). Relying purely on short-term returns to assess acquisition performance would be appropriate if investors (1) fully understand the determinants of a successful acquisition and (2) have sufficient information to forecast accurately how the integration process affects an acquirer’s future cash flows. If these assumptions are met, acquirers that make better acquisitions will be rewarded with increased stock returns immediately, around the day of the acquisition announcement. However, these assumptions are stringent in that they require investors to have “structural knowledge and skills that none of us possess” (Kurz 1994, p. 860). Partly for this reason, at a recent round table organized by the Federal Trade Commission, some of the foremost researchers on mergers and acquisitions concluded that “short-term … studies are not very helpful regarding the sources of gains or the determinants of success” of acquisitions (Kaplan 2002, pp. 52–53).

In light of these arguments, we focus our hypotheses on long-term stock returns to acquisitions. We argue that extensive deployment of the target’s innovation potential can make a unique, positive contribution to the acquirer’s long-term market value for several reasons. First, conversion of product ideas into product outputs provides a validation of the choice of target and points to the possibility of future
synergies from joint technological and marketplace activities in the combined firm (Puranam, Singh, and Zollo 2003). Second, extensive deployment promotes an increased but more efficient usage of a firm’s “lumpy” or multiuse assets (Rubin 1973). For example, a firm that converts a larger number of product ideas from the target into finished products can apply its manufacturing and distribution assets over a wider array of products. Such sharing can yield efficiency and productivity gains (and, thus, greater cash flows) from the greater use of underused capacity. Third, because product introductions are discrete in nature, the cash flows that result from them can be volatile (Caves 1989). A sustained conversion of new product ideas from target firms facilitates smoother cash flows for the combined firm. Finally, by retaining more scientific personnel, acquirers that deploy extensively minimize disruption and uncertainty in the new product process (Chaudhuri and Tabrizi 1999). Such firms retain the tacit knowledge embodied in individuals and teams in the target firm and thus lay the foundation for increased and smoother cash flows over the long run. In summary, given the crucial role of the postacquisition integration process, we hypothesize that extensive deployment is a vital factor driving long-term performance.

H3: Firms that deploy the innovation potential of targets more extensively create higher long-term shareholder value than do other firms.

Taken together, H1–H3 argue that product capital has an indirect impact on the long-term financial value of a firm through its impact on strategic actions, such as the selection and deployment of acquisition targets. Specifically, we propose that (1) product capital drives target selection (H1), (2) product capital and selection together drive deployment (H2), and (3) product capital affects long-term acquisition performance through its impact on deployment (H3). Next, we present an empirical study that tests these hypotheses and, in the process, explores how product capital explains the long-term performance of corporate acquisitions.

METHOD

Empirical Context

We test our hypotheses on data from the pharmaceutical industry, which is an ideal context for our empirical analyses for several reasons. This industry is vitally important from a business and policy point of view. The importance of product innovation assets and the difficulty of developing these through in-house efforts alone mean that firms in the industry are constantly looking for such assets from external sources. As such, acquisitions are frequent in the pharmaceutical industry, but their outcomes and financial consequences are anything but uniformly positive (Koberstein 2000). This article is partly an attempt to respond to multiple calls for the formal study of the outcomes of acquisitions in this socially and commercially important industry (Danzon, Epstein, and Nicholson 2003). Restricting our empirical context to a specific industry also allows for comparability across acquisitions and helps ensure against concerns about internal validity.

Data and Sample

Through archival methods, we collect data on a large number of variables that measure (at the firm level) product development and support assets, the quality of firms’ selection and deployment of targets, and the acquiring firms’ long-term performance following acquisitions. In all, we collect data from ten different sources to test our hypotheses. Table 1 presents an overview of our data and the sources we use.

We obtain our sample of acquisitions from the Security Data Company Thomson Mergers and Acquisitions (SDC M&A) database, a comprehensive database of financial transactions conducted by U.S. and foreign firms. We review all 1414 acquisitions undertaken by pharmaceutical firms (Standard Industrial Classification [SIC] 2843) in the database during 1992–2002. Of these, 798 are acquisitions by publicly traded firms. Marketing and R&D data were available for 56 publicly traded acquirers; this corresponds to a sample of 238 acquisitions.

To assess comparability with the entire population of publicly held pharmaceutical acquirers, we compare the assets, sales, and R&D expenditures of the firms in our sample to that of those in the entire population. As Table 2 indicates, these values are not significantly different from each other, suggesting that the firms in our sample are comparable to those in the population as a whole. In the “Results” section, we also present detailed descriptive statistics on all the performance variables in our model. These statistics indicate that the performance of acquisitions in our sample is similar to those in cross-industry samples studied in previous research (Loughran and Vijh 1997; Mitchell and Stafford 2000). The 56 acquirers in our sample have headquarters in the United States, United Kingdom, France, Belgium, Switzerland, Germany, and Japan. We convert all accounting and financial data for non-U.S. firms into U.S. dollars using daily exchange rates.

Model

Our goal is to show how product capital affects the long-term performance of acquisitions through better selection and deployment of target firms. Our hypotheses suggest that (1) product capital affects the selection of targets, (2) product capital and selection together affect the deployment of targets, and (3) the deployment of targets affects long-term performance. Therefore, our econometric model contains three equations, in which selection, deployment, and long-term performance are the dependent variables:

(1a) \(\text{Selection}_{i,j,t} = \beta_0 + \beta_1 \text{Support}_{i,t} + \beta_2 \text{Development}_{i,t} + \beta_3 \text{Target size}_{j,t} + \beta_4 \text{Acquirer assets}_{i,t} + \Sigma \psi_i \text{Firm dummy}_i + \epsilon_{i,j,t} \)

(1b) \(\text{Deployment}_{i,j,t} + m = \delta_0 + \delta_1 \text{Support}_{i,t} + \delta_2 \text{Development}_{i,t} + \delta_3 \text{Selection}_{i,j,t} + \delta_4 \text{Relative size}_{i,j,t} + \delta_5 \text{Relatedness}_{i,j,t} + \delta_6 \text{Transaction lag}_j + \delta_7 \text{Acquirer assets}_{i,t} + \Sigma \psi_i \text{Firm dummy}_i + \epsilon'_{i,j,t} + m' \) and

(1c) \(\text{Long-term performance}_{i,j,t} + n = \nu_0 + \nu_1 \text{Unanticipated deployment}_{i,j,t} + \nu_2 \text{Unanticipated ROA}_{i,j,t} + \nu_3 \text{Unanticipated ROA}_{i,j,t} + \epsilon''_{i,j,t} + n' \)
Table 1
VARIABLES AND DATA SOURCES

<table>
<thead>
<tr>
<th>Conceptual Variable</th>
<th>Notation</th>
<th>Measured Variable</th>
<th>Data Source</th>
</tr>
</thead>
<tbody>
<tr>
<td>Acquisition announcement dates</td>
<td></td>
<td>Acquisition announcement dates</td>
<td>• SDC M&amp;A database</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>• LexisNexis</td>
</tr>
</tbody>
</table>

**Dependent Variables**

| Long-term performance | Long-term performance_{i,j,t+n} | LCARs and BHARs: Changes in long-term stock prices over a one- or two-year post-announcement horizon measured using industry-adjusted long-term cumulative abnormal returns and buy-and-hold abnormal returns. | • Center for Research on Security Prices |
|                       |                                 |                                                        | • DataStream                     |

**Selection and Deployment Variables**

| Selection               | People                  | Citation-weighted patent output of top scientists      | U.S. Patent and Trademark Office database |
|                        | Product                 | Number of products in the pipeline at the time of the acquisition | • Delphion database |
|                        |                        |                                                        | • Pharmaprojects                 |

| Deployment              | People                 | Retention of top scientists                           | U.S. Patent and Trademark Office database |
|                        | Product                | Progress of target’s product postacquisition          | • Delphion database |
|                        |                        |                                                        | • Pharmaprojects                 |

**Product Capital**

| Product support         | Support_{i,t}          | Sales force counts, calls, and expenditures           | • Verispan Inc.                 |
|                        | Development_{i,t}       | R&D expenditures                                      | • COMPUSTAT                      |
|                        |                        |                                                        | • DataStream                     |

**Control Variables**

| Target size            | Target size_{i,t}      | Target sales                                         | • COMPUSTAT                      |
| Relative size          | Relative size_{i,j,t}  | Target sales/Acquirer assets                          | • DataStream                     |
| Acquirer resources     | Acquirer assets_{i,t}  | Acquirer assets                                       | • Factiva                        |
| Relatedness            | Relatedness_{i,j,t}    | SIC match                                             | • SDC M&A database               |
| Transaction lag        | Transaction lag_{i,j}  | Time from announcement to completion of transaction   | • Pharmaprojects                 |
| Unanticipated accounting financial performance | UROA_{i,j,t+n} | Unanticipated component of a ROA_{i,j,t+n} time series | • LexisNexis |
|                        |                        |                                                        | • DataStream                     |

Table 2
DESCRIPTIVE STATISTICS ON ACQUIRERS (INCLUDED IN THE SAMPLE VERSUS POPULATION)

<table>
<thead>
<tr>
<th></th>
<th>Acquirers Included in Sample (n = 56)</th>
<th>Population of Pharmaceutical Acquirers* (n = 208)</th>
<th>t-Statistics for Differences Between Acquirers Included in Sample and All Acquirers (p Value)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sales</td>
<td>4.16</td>
<td>2.88</td>
<td>1.33 (.18)</td>
</tr>
<tr>
<td>Assets</td>
<td>5.35</td>
<td>3.65</td>
<td>1.38 (.16)</td>
</tr>
<tr>
<td>R&amp;D spending</td>
<td>.48</td>
<td>.35</td>
<td>1.13 (.26)</td>
</tr>
</tbody>
</table>

*Acquirers for which sales, assets, and R&D information is available in either COMPUSTAT or DataStream.

Notes: Values are in billions of dollars.

where i is the acquirer, j is the target, and t is the time of the acquisition. In our empirical analysis, we set m at one year and n at one and two years. We discuss each of the variables in the following section. We also test (and subsequently report) whether the errors are correlated across the three equations to determine whether ordinary least squares (OLS) is an adequate modeling option. The significance of the coefficients $\beta_1, \beta_2, \delta_1, \delta_2, \delta_3,$ and $\nu_1$ implies that product...
capital affects selection and deployment and that deployment affects long-term performance.

To control for firm-specific effects, we include firm dummies in the selection and deployment equations, but in the interest of brevity, we do not report them in the model or the tables. We do not include firm dummies in the performance equation because all fixed effects are already reflected in previous period price, which we incorporate in our measures of long-term performance.

A concern in modeling the long-term abnormal performance following an acquisition is that only new, unanticipated information that follows the acquisition announcement affects these abnormal returns (e.g., Aaker and Jacobson 1994; Mizik and Jacobson 2003). Indeed, only this new information can cause changes in long-term abnormal returns. Information on the targets selected or on acquirers’ product capital leading up to the acquisition is available and evident to investors at the time the acquisition is undertaken. Therefore, the effect of this information on the firm’s stock price has already been incorporated into the stock price at the time of the acquisition and has no role thereafter, except through its effect on deployment. In contrast, how the deployment of the target will unfold post-acquisition is not evident at the time of the acquisition. Even so, investors have some expectations about deployment, and these expectations are incorporated into the stock price at the time of the acquisition. Therefore, only the unanticipated component of deployment is gradually incorporated into the long-term stock market performance measures as information on deployment becomes available post-acquisition. For these reasons, we use a measure of unanticipated deployment (we describe this in greater detail subsequently) rather than deployment per se to predict long-term performance.

Finally, we test whether investors, though fully rational, are subject to structural uncertainty regarding the deployment of the acquisition. Structural uncertainty refers to a lack of knowledge of the “laws of nature” that govern the relationships among economic variables (see Brav and Heaton 2002; Brennan and Xia 2001; Chen, Francis, and Jiang 2005). In the context of postacquisition deployment, structural uncertainty may exist because investors do not a priori understand (1) the determinants of deployment and (2) the functional form of the equation that relates these determinants to deployment. If investors recognize the functional form of the impact of product support, product development, and selection on postacquisition deployment (Equation 1b), they should use Equation 1b as their deployment expectation model at the time the acquisition is announced. Furthermore, if investors indeed form their expectations according to the model that we posit herein (Equation 1b) and if we assume that better deployment increases firm value, investors should immediately (on the announcement day) reward firms that are expected to deploy better. Specifically, the fitted values of deployment from Equation 1b should significantly affect the short-term cumulative abnormal returns (SCARs). However, we find no significant relationship between the SCARs (measured over the five-day event window) and the fitted values from our deployment equation, indicating that investors do not appear to understand immediately the functional form of the deployment equation as we state herein. This suggests that investors form their deployment expectations using some other unknown factors that appear to be orthogonal to product capital and selection. Therefore, in testing our models, we assume that structural uncertainty exists in our context.

**Measures**

**Dependent variables: long-term financial performance.** Consistent with recent developments in the finance literature and with our own research objectives, we use several measures of long-term financial performance based on stock market data. Specifically, we use long-term cumulative abnormal returns (LCARs) and buy-and-hold abnormal returns (BHARs) (e.g., Barber and Lyon 1997) to measure Long-term performance, $e_{i,t+n}$.

We compute LCARs during the $(1, T)$ postevent horizon (monthly returns measured starting with the month following the acquisition announcement, where $T = 12$ for the one-year returns and $T = 24$ for the two-year returns) using the following formula:

$$
LCAR_{PT} = \sum_{t=1}^{T} (R_{i,t} - R_{p,t}).
$$

where $R_{i,t}$ is the rate of return of acquiring stock $i$ in month $t$ and $R_{p,t}$ is the rate of return on the corresponding country pharmaceutical index in month $t$.

We compute BHARs during the $(1, T)$ postevent horizon (monthly returns measured starting with the month following the acquisition announcement, where $T = 12$ for the one-year returns and $T = 24$ for the two-year returns) using the following formula:

$$
BHAR_{PT} = \prod_{t=1}^{T} (1 + R_{i,t}) - \prod_{t=1}^{T} (1 + R_{p,t}).
$$

Are these long-term measures reliable predictors of the returns from acquisitions rather than of the overall performance of the firm per se? In other words, could it be possible that good firms simply continue to do well after acquisitions? By definition, LCARs and BHARs are measures of abnormal returns, and therefore they capture only new, unanticipated information. If, at any point in time, the financial markets expect a firm that has performed well to continue to do so, the markets will immediately incorporate this information in the firm’s stock price, and the firm will now trade at higher price:earnings ratios or market:book ratios. Subsequently, therefore, the firm’s expected abnormal returns will be zero until some new information becomes available. Because we measure abnormal returns following the announcement of an acquisition, our measures pick up the effect of returns from the acquisition itself rather than overall performance of the firm per se.

**Independent variables: selection and deployment of targets, unanticipated deployment, and product capital.** We assess target selection by measuring the innovation potential of targets at the time of acquisition. We use two sets of measures to do so; one is based on products, and the other is based on people (i.e., product development personnel).
We measure the product dimension of selection using the number of products that the target has in the pipeline at the time of the acquisition. This measure captures the target’s current innovation potential.

The innovation potential of the target also depends on the quality of the research output of its scientists. Simply counting the scientists associated with the target’s patents is problematic because doing so would not account for the quality of their output. Therefore, we measure the people dimension of selection using the citation-weighted patent output of the top five scientists of each target at acquisition. We identify the top five scientists for a target on the basis of individual scientists’ patent output in the five years preceding the acquisition. We choose the top five scientists for two reasons. First, this ensures comparability across targets of different sizes. Second, research in economics has focused on the output of “star scientists” (Zucker and Darby 1996) rather than on the overall patent output of the firm as an important indicator of future returns to the acquirer. The importance of intellectual human capital in innovation cannot be overstated; indeed, firms benefiting from the work of star scientists in pharmaceutical research enjoy faster technological progress and higher economic rents (e.g., Zucker and Darby 1996). We collect information on all patents assigned to the target in the five years preceding acquisition. For each target, we identify all scientists associated with patents that were approved five years before the acquisition. As a people-based measure of selection, we use the average citation-weighted output of the top five scientists for each target. Previous research has shown that citation-weighted patents are a better measure of a firm’s ability to appropriate returns from its innovations than are unweighted patents (Hall, Jaffee, and Trajtenberg 2000). However, we also conduct tests on unweighted patents to check for robustness; these results are consistent with those using the citation-weighted patents measure.

For the sake of parsimony and because we do not have a priori reasons to expect differential effects of these variables, we combine the product and people dimensions of selection into a single variable that captures the innovation potential of the target at the time of the acquisition. (Note that an analysis that uses the people and product measures separately yields similar results). Specifically, we use a standardized average of the product and people measures we discussed previously to construct Selectioni,j,t.

We capture the extent of deployment by measuring the extent to which acquirers realize the innovation potential of the target postacquisition. As with selection, we use two sets of measures; one is based on products, and the other is based on people.

We capture the product dimension of deployment by measuring the extent to which the target’s products that were under development at the time of the acquisition made progress postacquisition. Using the Pharmaprojects database, we measure the number of products in the target’s pipeline that (1) advanced to the Phase 3 (large scale) trial stage, (2) advanced to the product launch stage, (3) applied for new indications, or (4) were launched in countries in which they were not previously marketed. We code the products as having progressed if they fulfilled any of these conditions in the period following the acquisition. This operationalization captures the acquirer’s ability to develop the target’s products further.

We measure the people dimension of deployment using the number of the target’s top scientists retained after acquisition. Researchers have emphatically argued for the necessity of retaining the target’s top scientists if the acquisition is to succeed (Bower 2001; Paulter 2003). For example, Bower (2001, p. 99) states, “One huge challenge acquirers must face is holding on to key people. The expertise of these individuals is far more valuable than the technology they’ve developed. Generally, the acquisition won’t succeed if they leave.” For each target, we use the names of the top five scientists identified while measuring the selection variable, and we obtain their patent record from the Delphion database. We collect data on all patent applications under the names of all 776 scientists in our sample. On the basis of the patent application date, we then identify whether the scientists were still working for the acquirer up to two years after the acquisition. As a people-based measure of deployment, we use the percentage of top scientists retained by the acquirer one year after the acquisition. To check for robustness, we also conduct tests using a two-year window for retention. The results are consistent with those from the one-year window.

We combine these product and people components into a single variable that captures how well the acquirer deploys the innovation potential of the target in the postacquisition integration phase. Specifically, as with selection, we use a standardized average of the product and people measures to construct Deploymenti,j,t + m.

In addition to investigating the effect of product capital on deployment, we examine the effect of deployment on long-term postacquisition performance. Unanticipated deploymenti,j,t + m is the component of the deployment measure that investors do not anticipate (i.e., not captured in the short-term stock market reaction at the time of the acquisition). To calculate it, we need to understand the market expectation model for deployment, or the model investors use to estimate future deployment. For variables with a time-series history, such as earnings (Ball and Brown 1968; Bernard and Thomas 1990), it is reasonable to assume that investors form expectations about future values by considering prior values, so an autoregressive model is typically used to specify the functional form of the expectation formation mechanism (see, e.g., Aaker and Jacobson 1994; Mizik and Jacobson 2003).

However, deployment is not available in time series, because in general, acquisition events are rare (for most firms) and do not occur at regular intervals. Intuitively, this makes it less likely that investors understand that deployment follows from the relationship we posit in Equation 1b. Furthermore, in testing our assumption of structural uncertainty, we find that the fitted values of deployment from Equation 1b do not significantly affect the short-term abnormal returns to acquisitions, which suggests that this relationship is indeed unknown to investors at the time of the acquisition announcement.

Given structural uncertainty, we do not assume that investors understand the functional form of the relationship among deployment, product capital, and selection. Thus, we do not specify the market expectation model that investors
use when evaluating the acquisition returns; rather, we assume that its effect is captured in the short-term returns to the acquisition announcement. Therefore, we compute unanticipated deployment as the residual from the following equation:

\[ \text{Deployment}_{i,j,t+m} = u_0 + \rho \text{SCAR}_{i,j,t} + \epsilon''_{i,j,t+m} \]

The short-term returns capture the anticipated component of deployment, and the residual captures the unanticipated component. In the Appendix, we present a proof of why this approach provides a conservative test of our hypothesized impact of unanticipated deployment on long-term abnormal performance.

Recall that we define product capital as the product development and product support assets that a firm’s current and prior levels of product investments create. We measure product support assets using present and prior levels of promotional investments (see Dekimpe and Hanssens 1999; Slotebraaf, Moorman, and Inman 2003). Sales force investments have been highlighted as the most important promotional investment in the pharmaceutical industry (e.g., Sorescu, Chandy, and Prabhu 2002; Yeoh and Roth 1999). We obtain data on three measures of sales force investments: number of salespeople, number of calls made by the salespeople, and dollars spent on the sales force. We combine these variables into one measure of promotional investments using a standardized sum of the three measures.\(^1\) To create Product support\(_i,t\), a measure of product support that captures the accumulation of these promotional investments, we use a Koyck-type distributed lag function with a decay parameter of \(\lambda = .3\) (see Davis and Thomas 1993; Dutta, Narasimhan, and Rajiv 1999).

We measure product development using present and past levels of R&D expenditures (e.g., Boulding and Staelin 1995; Dutta, Narasimhan, and Rajiv 1999). These investments capture the level of technological investments in the firm’s products and are known to be an important input into a firm’s stock of technical knowledge (Hall, Griliches, and Hausman 1986). As with product support, we use a Koyck-type distributed lag function with a decay parameter of \(\lambda = .3\) to create Product development\(_i,t\). We also perform analyses using values of \(\lambda\) for product support and product development that range from .15 to .4. The results remain robust to these changes.

**Control variables.** In predicting the quality of firms’ selection of targets, we control for the size of the target because target size could affect innovation potential (Sorescu, Chandy, and Prabhu 2003). We measure Target size\(_{i,j,t}\) using the target’s annual sales in the year preceding the acquisition. In predicting the extent of firms’ deployment of targets, we control for several other factors that can help or hinder the postacquisition integration process:

- **Relative size\(_{i,j,t}\):** The larger the target acquired relative to the parent firm, the more problematic the integration process is likely to be (e.g., Kusewitt 1985; Seth 1990). We measure relative size using a ratio of the sales of the target firm to those of the parent in the year preceding the acquisition.
- **Relatedness\(_{i,j,t}\):** The greater the relatedness between the acquirer and the target, the smoother the integration process is likely to be and, therefore, the better the deployment of the target’s innovation potential (Singh and Montgomery 1987). We measure relatedness using a dummy variable that takes the value of one if the primary SIC code of the acquirer and target is the same and zero if otherwise.
- **Transaction lag\(_{i,j,t}\):** The shorter the time elapsed from the announcement of the acquisition to the completion of the financial deal, the higher is the likelihood of a smooth transaction between the target and the acquirer and, thus, the better the deployment (see Hapseslagh and Jemison 1999). We use the number of days between the acquisition announcement and the completion of the financial transaction as an indication of the target’s willingness to participate in the acquisition.

We also include the following control variable to estimate both selection and deployment:

- **Acquirer assets\(_i,t\):** We test whether product capital has an effect on selection and deployment beyond the effect of overall firm resources.

Finally, we include the following control variable to estimate long-term performance:

- **Unanticipated accounting performance\(_{i,j,t+m}\):** Consistent with previous research (e.g., Aaker and Jacobson 1994; Mizik and Jacobson 2003, 2004), we compute a measure of unanticipated accounting performance and include it as a determinant of long-term abnormal returns. As such, we control for a possible reversal of causation in performance, in which better performance could lead to better deployment rather than the opposite. Specifically, we compute unanticipated accounting performance as the residual from a first-order autoregressive model for return on assets (ROA):

\[ \text{ROA}_{i,t} = \alpha_0 + \alpha_1 \text{ROA}_{i,t-1} + \epsilon_{i,t}. \]

**RESULTS**

Table 3 presents descriptive statistics for the performance variables: (1) LCARs over a one- and two-year horizon (LCAR\(_{p12}\), LCAR\(_{p24}\)) and (2) BHARs over a one- and two-year horizon (BHAR\(_{p12}\), BHAR\(_{p24}\)). As Table 3 shows, the means of the long-term stock market returns variables are not significantly different from zero over the entire sample. This finding is consistent with previous research conducted using larger acquisitions samples across multiple industries (see, e.g., Loughran and Viji 1997; Mitchell and Stafford 2000). Therefore, these statistics indicate that our sample, though drawn from only one industry, shares a similar profile with larger, multi-industry samples, providing support for the external validity of our results. The descriptive statistics also show significant variation in returns. The last two columns in Table 3 provide evidence for our assertion that the success of acquisitions varies substantially across firms; the performance of the top quartile of acquisitions is dramatically different from that of the bottom quartile. Table 4 presents descriptive statistics for the remaining variables.

**Tests of Hypotheses**

To select the appropriate estimation method for Equations 1a, 1b, and 1c, we first test whether the errors are cor-

\(^1\)We also obtain (with some difficulty) advertising expenditures for a subsample of our data (58 observations). For this subsample, advertising expenditures correlate highly with sales force measures (\([\text{advertising expenditures, sales force counts}] = .82, p < .01\), and \([\text{advertising, sales force expenditures}] = .74, p < .01\). These results suggest that our sales force measures provide a reasonable proxy for overall product support.
related across the three equations. A Breusch-Pagan test of independence indicates that the errors are not correlated. In addition, because the equations are recursive and the errors are independent, the rank-and-order conditions for identification are met with no additional exclusion restrictions (for a formal proof, see Land 1973). Therefore, we use OLS to estimate the three equations. We also check the appropriateness of pooling the observations across countries in a single model. Specifically, we run models with fixed intercepts for each country and find no country-specific intercepts that are significant at the 5% significance level.

Finally, we test for autocorrelation in the selection and deployment equations (Equations 1a and 1b). A Wooldridge test for autocorrelation in panel data suggests that the error terms are not autocorrelated in the deployment model (F = .013, p = .913) or the selection model (F = 2.018, p = .194). We present the full results, including relevant coefficients and their significance levels, in Table 5. Next, we describe the hypotheses tests in detail. The coefficients we show correspond to those in Equations 1a, 1b, and 1c.

Product capital and selection. In support of H1, the results show that product capital has a positive impact on the quality of target selection. Specifically, the greater the product development and support assets of the parent, the greater is the innovation potential of the target selected. The coefficients for product support and product development, respectively, in the selection equation are $\beta_1 = .16 \ (p < .01)$ and $\beta_2 = .90 \ (p < .10)$.

Product capital and deployment. In support of H2, the two components of product capital have a positive effect on deployment. The coefficients for product support and product development, respectively, in the deployment equation are $\delta_1 = .26 \ (p < .01)$ and $\delta_2 = 1.37 \ (p < .05)$. Furthermore, selection is a significant determinant of deployment ($\delta_3 = .18$, $p < .05$). This suggests that the better the innovation potential of the target selected, the more extensive is the deployment of this potential, as we expected.

Deployment and performance. In support of H3, unanticipated deployment has a positive effect on performance. These results are consistent across the various measures of performance: $\text{LCAR}_{p12} (\nu_1 = .16, p < .01)$, $\text{LCAR}_{p24} (\nu_1 = .18, p < .01)$, $\text{BHAR}_{p12} (\nu_1 = .24, p < .01)$, and $\text{BHAR}_{p24} (\nu_1 = .21, p < .01)$. The percentage of variation explained is in line with similar studies that use measures of abnormal stock returns (e.g., Chaney, Devinney, and Winer 1991).

Controls. We find that acquirer assets do not have a significant effect on selection and deployment after we control for product capital. This suggests that better selection and

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**Table 3**

<table>
<thead>
<tr>
<th>Measure of Firm Performance</th>
<th>Number of Observations</th>
<th>M (%) [p Value for the t-Test of Zero Mean]</th>
<th>SD (%)</th>
<th>Average for Bottom Quartile (%)</th>
<th>Average for Top Quartile (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Long-term cumulative abnormal returns during the one year following the event (LCAR\textsubscript{12})</td>
<td>238</td>
<td>5.09 (.06)</td>
<td>40.94</td>
<td>–35.56</td>
<td>50.50</td>
</tr>
<tr>
<td>Long-term cumulative abnormal returns during the two years following the event (LCAR\textsubscript{24})</td>
<td>226</td>
<td>4.70 (.18)</td>
<td>52.88</td>
<td>–53.54</td>
<td>65.32</td>
</tr>
<tr>
<td>Long-term buy-and-hold abnormal returns during the one year following the event (BHAR\textsubscript{12})</td>
<td>238</td>
<td>4.65 (.15)</td>
<td>49.17</td>
<td>–42.07</td>
<td>59.69</td>
</tr>
<tr>
<td>Long-term buy-and-hold abnormal returns during the two years following the event (BHAR\textsubscript{24})</td>
<td>226</td>
<td>–.75 (.85)</td>
<td>63.30</td>
<td>–71.19</td>
<td>75.77</td>
</tr>
</tbody>
</table>

---

**Table 4**

<table>
<thead>
<tr>
<th>Variable</th>
<th>Measure</th>
<th>Minimum</th>
<th>Maximum</th>
<th>M</th>
<th>SD</th>
</tr>
</thead>
<tbody>
<tr>
<td>Product support\textsuperscript{a}</td>
<td>Sales force expenditures ($)</td>
<td>63,000</td>
<td>570,564,554</td>
<td>74,668,676</td>
<td>139,574,132</td>
</tr>
<tr>
<td>Number of salespeople</td>
<td>8</td>
<td>4999</td>
<td>1227</td>
<td>1482</td>
<td></td>
</tr>
<tr>
<td>Number of sales calls</td>
<td>500</td>
<td>4,130,777</td>
<td>534,664</td>
<td>998,654</td>
<td></td>
</tr>
<tr>
<td>Product development\textsuperscript{a}</td>
<td>R&amp;D expenditures ($)</td>
<td>539,000</td>
<td>2,918,000,000</td>
<td>417,157,572</td>
<td>683,074,911</td>
</tr>
<tr>
<td>Selection\textsuperscript{b}</td>
<td>Number of products in the pipeline</td>
<td>0</td>
<td>35</td>
<td>5</td>
<td>8</td>
</tr>
<tr>
<td>Citation-weighted patents of top scientists</td>
<td>1</td>
<td>8667</td>
<td>351</td>
<td>1034</td>
<td></td>
</tr>
<tr>
<td>Deployment\textsuperscript{b}</td>
<td>Number of products deployed</td>
<td>0</td>
<td>11</td>
<td>1</td>
<td>2</td>
</tr>
<tr>
<td>Percentage of top scientists retained</td>
<td>0</td>
<td>100</td>
<td>49</td>
<td>39</td>
<td></td>
</tr>
<tr>
<td>Controls</td>
<td>Target size ($)</td>
<td>900,000</td>
<td>3,615,000,000</td>
<td>198,142,940</td>
<td>554,279,632</td>
</tr>
<tr>
<td>Acquirer assets ($)</td>
<td>4,372,000</td>
<td>37,241,250,000</td>
<td>5,356,433,838</td>
<td>9,120,515,254</td>
<td></td>
</tr>
<tr>
<td>Relative size (acquirer/target)</td>
<td>2.24</td>
<td>2785</td>
<td>251</td>
<td>470</td>
<td></td>
</tr>
<tr>
<td>Relatedness</td>
<td>0</td>
<td>1</td>
<td>56</td>
<td>50</td>
<td></td>
</tr>
<tr>
<td>Transaction lag (days)</td>
<td>0</td>
<td>697</td>
<td>62</td>
<td>84</td>
<td></td>
</tr>
<tr>
<td>Unanticipated ROA\textsuperscript{a} (%)</td>
<td>–159.56</td>
<td>137.95</td>
<td>0</td>
<td>21.57</td>
<td></td>
</tr>
</tbody>
</table>

\textsuperscript{a}Measured for the acquirer.
\textsuperscript{b}Measured for the target.
Additional Analysis

Additional controls. In addition to the control variables we discussed previously, we collect data on three determinants of long-term abnormal returns identified in a recent meta-analysis of postacquisition performance (King et al. 2004): method of payment, relatedness of the acquisition, and prior acquisition experience. Consistent with King and colleagues’ (2004) results, we find that these variables do not significantly affect long-term performance, but unanticipated deployment maintains its significance. Because we attempt to model effects in a manner consistent with rational investor behavior, in which only unanticipated information can affect long-term abnormal returns, we do not include these variables in the estimated model.

Short-term returns. In addition to using the short-term abnormal returns to compute a measure of unanticipated deployment, we compute descriptive statistics on these measures as an additional validation check for our sample. Consistent with previous findings in the acquisition literature (e.g., Andrade, Mitchell, and Stafford 2001), we find that the average cumulative abnormal returns to acquirers for either a three- or a five-day window surrounding the acquisition announcement are approximately −1% (p < .05).

SUMMARY AND DISCUSSION

This article highlights a major contribution of marketing in the context of a strategic decision—corporate acquisition—that looms large in the minds of many top managers. Despite decades of work on acquisitions and their performance, most studies suggest that returns to acquisitions are poor. Indeed, some authors go so far as to argue that firms would be better off not acquiring: “If CEOs had kept their checkbooks under lock and key and simply matched the stock market performance of their industry peers, shareholders would have been far better off” (BusinessWeek 2002, p. 60). Furthermore, little work has tried to explain the variation in performance outcomes.

Why are some acquisitions successful and others not? Few answers exist to this elemental question. The work that has examined this question has mostly focused on the role of deal-specific rather than firm-specific variables in explaining performance differences. In contrast, our findings highlight a firm-specific, marketing-driven variable—product capital—that affects acquisition performance. We also present a mechanism by which product capital affects performance—namely, through acquirers’ superior selection and deployment of targets’ innovation potential. We argue that firms with high product capital (i.e., those with greater product development and support assets) make smarter

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2An examination of the ROA series reveals that one firm (Celgene) experienced an unusually high change (+62.5%) in ROA from period 1 to period 2. Eliminating this observation from Equation 1c causes the size and significance levels of the coefficient of our hypothesized variable—unanticipated deployment—to remain effectively unchanged. Moreover, eliminating this observation renders the coefficient for the control variable (unanticipated ROA) to be positive and significantly different from zero in the performance equation (p < .01). Because we do not have a conceptual basis to drop this observation and because this observation is not otherwise an outlier or an influential point in the selection and deployment equations, we keep it in our sample and report the results on the complete sample.
acquisitions. Such firms are better at selecting targets with innovation potential and then deploying this potential to gain competitive advantage. The performance consequences of this superiority in selection and deployment of externally created assets manifest in long-term financial rewards to the acquiring firm.

This article also has several limitations, some of which may provide the spark for further research in the area. First, this study does not offer a comprehensive model of determinants of acquisition success. Rather, in answering calls for research that explains variance in acquisition returns, it identifies a set of marketing-driven variables that account for a significant portion of variance in postacquisition performance. However, we acknowledge that acquisitions are complex actions, and our research is but an initial attempt to examine them. For example, the potentials for cost reduction and for increased distribution coverage are important reasons for acquisitions; we do not specifically address these factors here. Second, we do not examine the antecedents of the decision to acquire other firms, and we do not examine joint ventures as alternatives to acquisitions. These are both rich areas for further research.

Third, although our theorizing is general in scope, our empirical context is restricted to a single industry: pharmaceuticals. Focusing on a single, economically important industry can reduce concerns about internal validity. However, the pharmaceutical industry is unique in some ways, and findings from this study should be extrapolated to other industries with caution. Additional research using data from other contexts will be valuable in exploring the generalizability of our arguments, especially because the importance of innovation can vary across industries. In particular, research on less technology-intensive contexts could examine other dimensions of deployment than those we examine in this research.

Implications for Practice

Acquisitions worth billions of dollars hardly seem to cause a stir these days, but the stakes remain high and may be getting higher. Botched acquisitions can cause major problems in corporate suites. Failure rates are high, but as we note herein, successes exist. Recently, The Economist (1999, p. 15) raised the following query to would-be acquirers: “How, the prudent boss should ask, can we be one of the minority that succeed, rather than of the majority that fail?”

To this prudent boss, we say, “Build before you buy.” Our results suggest that growth through acquisitions alone is not a good idea. Firms that attempt to buy growth without first building from within are likely to make bad acquisition decisions. They are also likely to be punished in the long run by the stock market for their acquisitions. Firms that invest in product capital acquire better targets, deploy these acquisitions better, and perform better in the long run.

Firms may acquire for many reasons. For example, prior research has suggested that managerial hubris and misaligned incentives can be behind many acquisitions. Ravenscraft and Scherer (1987, pp. 217–18) note that “[i]thousands of would-be managers and middle managers pour from the business administration schools each year imbued with naïve views of merger-making as a quick, easy road to wealth creation…. New merger-making entrepreneurs appear continuously, eager to try their hand at the game and convinced that they will succeed even where others have stumbled.”

We suggest that a reason some succeed and others stumble is that successful firms tend to emphasize innovation potential in their selection of targets, whereas unsuccessful firms do not. Successful firms also leverage this innovation potential by deploying it more extensively. By retaining top scientists after acquisitions and by applying product ideas from targets more widely and effectively, such firms pave the way for future success. For example, before its merger with Wellcome, Glaxo’s most important acquisition was of a U.K. firm, Allen & Hanburys, which brought it “a brilliant scientist, Dr. David Jack” (Ravenscraft and Long 2000, p. 306). Jack directed Glaxo’s scientific efforts for 26 years, developing a leading position in respiratory and gastrointestinal ailments.

The popular image of the scientist is that of a person who is happiest when his or her lab is well supplied. Sales force assets may appear to be unlikely tools for the retention of top scientists. Indeed, our results indicate that the R&D assets owned by the acquiring firm are not the only types of assets that persuade top scientists to remain with the combined entity. Firms that invest substantially in product support assets, which promote consumer adoption of new products, retain significantly more of their top scientists than other firms. Perhaps the prospect of greater market impact for the outputs of their labs and the potential to play on a larger stage persuade top scientists to remain with acquirers that possess high-product-support assets.

Implications for Research

A central implication of this study is that marketing-related assets, such as product support and development assets, play a more substantial role in long-term firm performance than is assumed by much research on corporate actions. By focusing on acquisitions—strategic decisions that are often viewed as being outside the realm of marketing research and practice—we show that marketing affects important constituencies, as well as metrics, that have not traditionally been studied in the field.

Our results suggest that acquirers’ product-related assets affect constituencies that range from insiders in the top echelons of management to outsiders who hold shares in firms. Indeed, because firms with greater product capital are better at holding on to star scientists postacquisition, this study also suggests that marketing’s role extends outside marketing departments per se to include those, such as R&D, that are traditionally viewed as having little to do with, or even being at odds with, marketing.

Our findings—as well as our theoretical and empirical frameworks, which link variables of interest to marketers to metrics from the strategy and finance literature—also argue for the importance of interdisciplinary research in the study of acquisitions. After all, the outcomes of acquisitions are far reaching for firms. From innovation to brand equity and from corporate governance to organizational knowledge to financial returns, the consequences of acquisitions reverberate across business fields. We hope that these consequences and the many potential contributions of marketing to the
success of acquisitions are an impetus to not abandon the study of acquisitions to other disciplines.

Methodologically, this research highlights new metrics from finance that could be used to capture the long-term effects of other marketing-related assets (see also Rust, Moorman, and Dickson 2002). These measures present two advantages over alternate accounting or survey-based measures of performance: They are forward looking, and they measure the impact of only new, unexpected information associated with an event after the event unfolds. The forward-looking nature of these metrics enables researchers to evaluate expected economic rents years before they materialize in actual cash flows or earnings. Their ability to capture only new information associated with events enables researchers to disentangle the rents associated with specific events better than, perhaps, more traditional measures can. We detail the theoretical and empirical underpinnings of these metrics in the hope that others will use them to expand current work on the marketing–finance interface and to emphasize further the strategic role of marketing in the firm.

APPENDIX: ASSESSING THE RELATIONSHIP BETWEEN DEPLOYMENT AND PERFORMANCE

When an acquisition is announced, investors adjust stock prices on the basis of (1) expectations about how the acquisition will be deployed in the long run and (2) deal-specific information (e.g., premium paid, method of payment) that becomes available at time t, the time of the acquisition announcement. Therefore, we can write the short-term market reaction, measured as the short-term abnormal returns (Brown and Warner 1985), as a function of two components: anticipated deployment and variables whose values are known at time t:

\[(A1) \quad \text{Short-term returns}_{i,j,t} = \alpha_0 + \alpha_1 \text{Anticipated deployment}_{i,j,t} + \gamma S_{i,j,t},\]

where t is the time of the acquisition announcement. Short-term returns are the cumulated abnormal returns calculated over a five-day window surrounding the acquisition of target j by firm i. Anticipated deployment is the anticipated (at time t) deployment of target j by acquirer i, and S1, ..., Sk are other deal-specific variables whose values are known at time t.

Realized deployment, which we measure one year after an acquisition, has two unobserved components: The anticipated component is based on investor expectations of how deployment will unfold and is captured in the short-term stock market reaction; the unanticipated component is the difference between the realized deployment and the anticipated deployment:

\[(A2) \quad \text{Unanticipated deployment}_{i,j,t} = \text{Realized deployment}_{i,j,t} - \text{Anticipated deployment}_{i,j,t}.\]

Within an efficient market paradigm, short-term returns capture the effect of all variables whose values are known at time t and the effect of the anticipated deployment. Consequently, the only variable that can affect long-term returns is the unanticipated deployment:

\[(A3) \quad \text{Long-term performance}_{i,j,t} = v_0 + v_1 \text{Unanticipated deployment}_{i,j,t} + \epsilon_{i,j,t} + \nu.\]

Subsequently, we show that we can use the residuals from a regression in which realized deployment is the dependent variable and short-term returns are the independent variable as a measure of unanticipated deployment. When we use this measure as an independent variable in Equation A3, the unanticipated deployment is measured with error; however, we show that the consequence of this measurement error is that the coefficient \(v_1\) in Equation A3 is biased toward zero. Therefore, a significant result is a conservative test of a significant relationship between unanticipated deployment and long-term performance.3

To simplify the exposition, we present the mathematical derivation for a single, deal-specific variable, S, whose values are known at time t. Equation A1 becomes

\[(A1') \quad \text{Short-term returns}_{i,j,t} = \alpha_0 + \alpha_1 \text{Anticipated deployment}_{i,j,t} + \gamma S_{i,j,t}.\]

From Equations A1’ and A2, it follows that

\[(A4) \quad \text{Realized deployment}_{i,j,t} + m = \frac{\alpha_0}{\alpha_1} \text{Short-term returns}_{i,j,t} - \frac{\gamma}{\alpha_1} S_{i,j,t} + \text{Unanticipated deployment}_{i,j,t} + m.\]

If we estimate Equation A4 using OLS, with realized deployment as the dependent variable and short-term returns as the independent variable, the residual will be

\[(A5) \quad \text{Residual}_{i,j,t} + m = \text{Unanticipated deployment}_{i,j,t} + m + f(S_{i,j,t}).\]

where \(f(S_{i,j,t})\) is a linear function of the deal-specific variables.

Using this residual as a proxy for unanticipated deployment in Equation A3 means that unanticipated deployment is measured with an error \(u_{i,j,t} = f(S_{i,j,t})\), where

\[(A6) \quad u_{i,j,t} \sim [u, \sigma_u],\]

\[\text{cov}(u_{i,j,t}, \text{Unanticipated deployment}_{i,j,t} + m) = 0, \text{ and} \]

\[\text{cov}(u_{i,j,t}, \text{Long-term performance}_{i,j,t} + \nu) = 0.\]

The covariance between \(u_{i,j,t}\) and unanticipated deployment is zero because a systematic relationship between \(S_{i,j,t}\) and deployment would be already incorporated into the short-term returns; thus, there is no relationship between \(S_{i,j,t}\) and

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3This approach follows from our prior assumption of structural uncertainty. If investors had full structural knowledge of Equation 1b, we would use the residuals from that equation to obtain a proxy for unanticipated deployment. However, using a Monte Carlo simulation, we show that if investors do not know the functional form of Equation 1b, the use of residuals from that equation would introduce an additional bias toward zero and further reduce the power of the tests. We omit the results of the simulation for brevity, but they are available on request.
unanticipated deployment. The covariance between \( u_{i,j,t} \) and long-term performance is zero because all information about \( S_{i,j,t} \) is available at the time of the acquisition announcement; therefore, its effect is incorporated in the short-term returns.

For ease of exposition, we use the following notation:

Long-term performance \( \text{performance}_{i,j,t+n} = Y \);

Unanticipated deployment \( \text{deployment}_{i,j,t+n} = X; f(S_{i,j,t}) = u \).

Then, the true coefficient \( v_1 \) in Equation A3 is given by

\[
(\text{A7}) \quad v_1 = \frac{\text{cov}(X, Y)}{\text{var}(X)}
\]

If we use the residual described in Equation A5 as an instrument for unanticipated deployment in Equation A3, the coefficient \( v_1 \) becomes (also using Equation A6)

\[
(\text{A8}) \quad v'_1 = \frac{\text{cov}(X + u, Y)}{\text{var}(X + u)} = \frac{\text{cov}(X + u, Y - Y)}{\text{var}(X + u) + \text{var}(u)} = \frac{\text{cov}(X, Y) + \text{cov}(u, Y)}{\text{var}(X) + \text{var}(u) + 2\text{cov}(X, u)}
\]

Equation A8 shows that the coefficient \( v'_1 \) is biased toward zero compared with the \( v_1 \) coefficient. Therefore, the significance of \( v'_1 \) constitutes a conservative test of a significant relationship between unanticipated deployment and long-term performance.

REFERENCES


Financial Institutions Center, the Wharton School, University of Pennsylvania.


