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CHOOSING THE RIGHT TARGET: RELATIVE PREFERENCES FOR RESOURCE SIMILARITY AND COMPLEMENTARITY IN ACQUISITION CHOICE

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Research summary: *Corporate acquisition is a popular strategic option for firms seeking new resources. However, little research exists on the question of why one firm is chosen over another. We develop a model relating characteristics of similarity and complementarity between acquirers' and target firms' key resources, including their products and R&D pipelines, to the likelihood of the acquirers choosing a particular firm. We construct measures of similarity and complementarity between and across products and R&D pipelines, and test their effects using a novel application of the choice model. Findings reveal that acquirers view similarity and complementarity differently, based on the resource they are comparing. When making comparisons to their own R&D pipelines, acquirers prefer similarity over complementarity whereas when making comparisons to their product portfolios, they prefer complementarity over similarity.*

Managerial summary: *Corporate acquisition is a popular way for firms to grow and obtain innovative resources. However, we know little about why acquirers choose one firm over another. We capture the influence of similarity and complementarity between acquirers' and target firms' products (current innovative value) and R&D pipelines (future innovative value) on whether a particular target firm is acquired. Insights from the pharmaceutical industry reveal that acquirers value similarity and complementarity in target firms differently, based on whether the comparison being made is with respect to their products or their R&D pipelines. Regarding their R&D pipelines, acquirers prefer that the target firm has similar, rather than complementary, resources. However, the opposite is true concerning their own products: acquirers prefer that the target firm has complementary, versus similar, resources.*

INTRODUCTION

Corporate acquisitions have become a popular strategic option for firms to grow and acquire new resources to meet the rapidly changing demands of a competitive global marketplace. In 2012 alone, more than 37,000 merger and acquisition deals were made worldwide, valued at an astonishing $2.2 trillion (Cody, 2013). In the United States alone, merger and acquisition activity totaled $865.1 billion in the first nine months of 2013, representing a 39 percent increase compared to the same period a year before and the highest nine-month total since 2008 (Burrows, 2013). Some of the largest acquisitions in recent years have included Google's purchase of Motorola Mobility for $12.3 billion, Japan's Dainippon Sumitomo's purchase of Boston Biomedical for $2.63 billion, and IBM's purchase of Kenexa for $1.3 billion.

Keywords: acquisition; similarity; complementarity; innovation; choice model
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Given the enormous volume of acquisitions taking place and their steep financial costs, a wealth of academic research has been dedicated to examining whether acquisitions are, indeed, successful, and if so, what drives their success. For example, the literature is replete with work on the more immediate financial and performance outcomes of acquisitions (e.g., Datta, 1991; Harrison *et al.*, 1991; Kim and Finkelstein, 2009; Mukherji *et al.*, 2011; Prabhu, Chandy, and Ellis, 2005; Schijven and Hitt, 2012; Wan and Yiu, 2009), while other work has examined the long-term financial consequences of acquisitions (e.g., Sorescu, Chandy, and Prabhu, 2007). Some research has focused on innovation outcomes of acquisitions, such as R&D efficiency (e.g., Cassiman *et al.*, 2005), patent volume (e.g., Ahuja and Katila, 2001), and patent quality (e.g., Makri, Hitt, and Lane, 2010; Valentini, 2012). While informative, past work is largely limited to an understanding of what happens *after* an acquisition has been announced or has already occurred, resulting in the concern of selection bias because the decision of whom to acquire is not modeled. Some work (e.g., Higgins and Rodriguez, 2006) has examined what motivates a firm to enter the acquisition market, though we are still left with an inadequate understanding of what influences *whom* the acquirer chooses. Select research (e.g., Capron and Shen, 2007) has made important advancements in modeling target firm selection. Building on this work, we focus on the dyadic characteristics between acquiring firms and target firms, such as the extent to which resources between them relate or differ. It is important to consider dyadic information (Wang and Zajac, 2007) in this setting because firms often make acquisition decisions based on who the potential target firms are in relation to themselves, and not simply considering target firms in isolation.

We examine how acquiring firms use different resource comparisons to make decisions about whom to acquire. Central to our thesis is the notion that similarity will be preferred to complementarity with respect to certain resources of the acquiring firm, whereas complementarity will be preferred to similarity with respect to other resources of the acquirer. We focus on the degree of similarity and complementarity between acquiring and target firms' commercialized products and R&D pipelines, which constitute current and future sources of revenue, respectively. We measure parallel product development or "same-stage" similarity and complementarity (i.e., product-to-product and R&D pipeline-to-R&D pipeline) and, in what represents a novel departure from past research, we measure nonparallel or "across-stage" resource comparisons (i.e., product-to-R&D pipeline and R&D pipeline-to-product). We implement these ideas using data from the pharmaceutical industry on hundreds of pairs of public firms for thousands of products and R&D pipeline projects between 1988 and 2008.

We make several contributions to the strategic management literature. This is one of a small set of papers that examines target firm selection and what leads an acquirer to choose a particular firm. We find that acquirers prefer resource similarity to complementarity under some conditions, but not others. In particular, when it comes to its own products, an acquirer is more likely to choose a target firm with greater resource complementarity than similarity. However, when it comes to its own R&D pipeline, the reverse is true: an acquiring firm is more likely to choose a target firm with greater resource similarity than complementarity. These findings demonstrate a differential preference for similar or dissimilar resources based on the specific resources to which an acquirer compares (e.g., current vs. future innovation potential). In addition, to the best of our knowledge, our research is the first to measure across-product development stages of similarity and complementarity. By studying product portfolios alongside R&D pipelines, we are able to differentiate the role of comparing resources in the same stage of product development and those in different stages to see how acquirers view current and future innovation-potential when making acquisition decisions. Further, our new mathematical measures of similarity and complementarity go beyond existing measures in that they: (1) are calculated using third party objective data instead of survey data, (2) measure the degree of similarity and complementarity at the level of the product and project as opposed to the industry-level which uses a simple binary classification (e.g., whether the firms are within the same industry), (3) measure comparisons between and across product portfolios R&D pipelines, and (4) significantly explain variance in target selection above and beyond the effects of more simple measures. Finally, we modify the choice model to deal with a large choice set and apply it to a novel and important context. We suggest that future research consider employing similar modifications to broaden the appeal of the standard choice model.

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THEORY AND HYPOTHESES

Since its introduction, the resource-based view of the firm has received considerable support in the strategy literature. Resource-based theory suggests that competitive advantage lies in the resources and capabilities of the firm (Barney, 1991; Conner, 1991; Peteraf, 1993; Teece, Pisano, and Shuen, 1997). This view is based on an assumption that resources are both heterogeneous across firms and imperfectly mobile (Barney, 1991; Capron and Hulland, 1999; Hunt and Morgan, 1995). Firm resources (e.g., R&D projects, products) are stocks of knowledge and other tangible and intangible factors that a firm owns and controls, accumulated in a firm-specific and path-dependent manner (Swaminathan, Murshed, and Hulland, 2008). Due to the difficulty and cost of in-house new product development, firms often view the option of acquiring new product resources as their only viable means to achieve a competitive market advantage (Capron and Hulland, 1999). Further, since firms' resources are not readily exchanged on the market, acquisitions evolve as primary mechanisms for bringing in bundles of resources to the firm (Mitchell, 1994; Teece *et al.*, 1997; Wernerfelt, 1984).

Using theoretical arguments from the resource-based view of the firm, we propose that an acquirer will prefer (and therefore, choose) a target firm among alternatives based on, among other things, the similarity and complementarity between its resources and those of the target firm. Central to our hypotheses is the argument that similarity will be preferred to complementarity with respect to the acquirer's R&D pipeline, whereas complementarity will be preferred to similarity with respect to the acquirer's products.

Products and R&D pipelines as valuable resources

Innovation is a central motivator of acquisitions (Puranam, Singh, and Zollo, 2003). Two significant innovation-based resources that represent attractive opportunities for acquisition include a firm's R&D pipeline (innovation inputs) and its commercialized products (innovation outputs). The addition of products and R&D pipelines to an acquiring firm's resources matters insofar as they create current and future economic value, and in many circumstances, generate synergies where the value of the combination of these resources is greater than the sum of the value of these resources when the firms act independently (Barney, 1988; St. John and Harrison, 1999). A target firm with a strong R&D pipeline may not only augment an acquirer's own stream of innovations, but also add to its existing products by creating a steady stream of projects at various stages of the product development process. Further, acquiring firms have an interest in gaining commercialized products because they not only represent a current source of revenue, but also allow the acquirer to penetrate an existing market or enter a new one (Bharadwaj, Varadarajan, and Fahy, 1993; Lichtenthaler and Ernst, 2012; Srivastava, Shervani, and Fahey, 1998).

Similarity and complementarity between R&D pipelines and products

Acquirers can make two broad resource comparisons when deciding whether to acquire a firm: the extent to which a target firm's resources overlap with its existing resources (similarity) and the extent to which a target firm's resources add to its existing resources (complementarity). Dozens of studies have examined the effects of similarity on acquisition performance (e.g., Anand and Singh, 1997; Chung, Singh, and Lee, 2000; Kaplan and Weisbach, 1992; Lubatkin, 1987; Walker, 2000). A common finding is that similarity allows acquirers to leverage synergy in management style, culture, and administrative processes (Palich, Cardinal, and Miller, 2000; Robins and Wiersema, 1995), and is therefore a good thing. However, other studies show that related acquisitions do not outperform unrelated acquisitions (e.g., Matsusaka, 1993; Mukherji *et al.*, 2011; Seth, 1990) and go further to demonstrate that similarity can lead to redundancies and waste (Makri *et al.*, 2010).

Other scholars have argued that complementarity, and not similarity, between the acquirer and target firm is one of the most significant factors driving acquisition success (Capron, Dussauge, and Mitchell, 1998; Harrison *et al.*, 1991; Wang and Zajac, 2007). Complementarity can offer opportunities for expansion and value-enhancing resource redeployment (Cassiman and Veugelers, 2006). However, assimilating complementary resources to the firm can be difficult as it can increase integration costs, decrease knowledge transfer, and cause human resource disruptions (Bowman and Helfat, 2001; Chang and Singh, 2000).

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Overall, it is clear that the effects of similarity and complementarity found in past research are decidedly mixed, with little clarity on when an acquirer would benefit from similarity or from complementarity in resources. Further, while past research has hinted at a trade-off between the two resource comparisons, we know little about when an acquirer would prefer similarity *over* complementarity, and vice versa. These gaps compel us to further examine resource conditions for which acquirers would prefer similarity and those for which they would prefer complementarity. In particular, we examine resource comparisons between and across the R&D pipelines and products of acquiring and target firms. For example, we consider whether an acquirer would prefer greater similarity (vs. complementarity) between the target firm's R&D pipeline and its own R&D pipeline (i.e., the same-stage of product development) as well as between the target firm's products and its R&D pipeline (i.e., across stages of product development). This allows us to examine the impact of a broader set of resource configurations taken into account by acquirers when deciding whom to acquire. Figure 1 illustrates our conceptual framework and hypotheses.

A preference for similarity over complementarity

The success of an R&D project is often precarious, with only a very few projects actually reaching the market. Acquirers frequently augment their R&D pipelines with additional (and related) projects that improve the chance of any one project making it through the pipeline to commercialization. This is chiefly important in industries where products coming off of patent protection represent huge losses in revenue. Consider the pharmaceutical industry, where failure rates of drugs are notoriously high and the cost of transitioning an idea to a marketable drug can reach an astounding $5 billion (Herper, 2013). Mistakes are unambiguously costly. For example, Merck & Co., Inc., the once hugely successful pharmaceutical company in the mid-1980s, started facing problems with its R&D pipeline. It grew dangerously thin with its existing projects failing to ensure a replacement of revenue losses from drugs coming off of patent protection (Seiden, 1998). In response, Merck acquired several business units and firms with R&D pipelines comprised of similar resources (e.g., scientists with similar knowledge, projects in shared therapeutic areas) to leverage co-specialized assets (Chan, Nickerson, and Owan, 2007) and increase the odds of success in the market (Bellucci, 2005).

Thus, to hedge their bets and minimize inherent risks associated with any one project in their pipeline, acquirers are likely to acquire target firms with projects in similar areas, bolstering the chances of commercializing a product in a given area. In addition, since projects in the R&D pipeline are considered an expense, there might be an inherent desire to lower additional costs associated with integrating vastly different R&D projects from the target firm.

A relationship that is less understood, but equally noteworthy, is the relationship between the

Figure 1. Conceptual framework: resource comparisons and acquisition choice. **Notes:** S > C indicates that resource similarity (S) will increase the likelihood of the target firm being acquired and that resource complementarity (C) will decrease this likelihood. C > S indicates that resource complementarity will increase the likelihood of the target firm being acquired and that resource similarity will decrease this likelihood

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acquiring firm's R&D pipeline and the target firm's products. We contend that an acquiring firm will look to bolster its R&D pipeline with a greater number of similar (vs. complementary) products. Commercialized products within the same area or category represent current revenues that can help subsidize expenses associated with R&D projects. Additionally, if the acquirer can purchase a firm that has a related product already serving the market it intends to serve, then it can decide to abandon its projects in the pipeline or continue to invest in them if the acquired product's exclusivity agreements expire. Ostensibly, acquiring related products will allow the acquirer to "buy time" to decide what to do with its internal R&D projects, many of which represent considerable expenses and few of which are eventually marketable. In the pharmaceutical industry, for example, firms that end up with few candidate drugs in their R&D pipeline will be more likely to acquire firms whose drugs are well matched with their own cospecialized assets (Chan, Nickerson, and Owan, 2007), suggesting a preference for products similar to their R&D pipelines. Therefore, we hypothesize:

Hypothesis 1a: The acquirer will be more likely choose a target firm with greater similarity in R&D pipeline to its own R&D pipeline and less likely to choose a target firm with greater complementarity between these resources.

Hypothesis 1b: The acquirer will be more likely choose a target firm with greater similarity in commercialized products to its own R&D pipeline and less likely to choose a target firm with greater complementarity between these resources.

A preference for complementarity over similarity

When it comes to the acquiring firm's products, acquiring analogous products serving similar customers with comparable needs will not be in the firm's best interest. Indeed, it would be inadvisable for the firm to acquire competing products. Less obvious is the effect of similar, but not competing products, although even those are likely to create redundancies in an area where redundancies are less useful (Bahadir, Bharadwaj, and Srivastava, 2008). Redundancies in R&D assets and resources, as hypothesized in Hypotheses 1a and 1b, will help increase the chance of any one project reaching commercialization. However, redundancies in products already in the market are likely to create a high degree of overlap in served markets, decreasing synergy realization and possibly leading to cannibalization (Berry and Waldfogel, 2001). Thus, integrating a similar product, one that potentially competes with an acquiring firm's product, will be less attractive than adding complementary products that can increase the acquirer's reach in the marketplace and create unique synergies when the two firms are integrated (Barney, 1988, 1991).

Similarly, an acquirer is less likely to acquire a target firm with an R&D pipeline that is similar to its products, and instead, may prefer complementary R&D projects. A clear objective of creating and managing an R&D pipeline is to create a product that can be commercialized. If the acquirer already has a product that addresses a certain need in the marketplace, it may prefer to acquire R&D projects that address new, complementary areas. This will allow the acquirer to add to its innovative capabilities and create new products in the future in noncompeting areas. However, given that patent expiration is a looming, and inevitable, threat to many firms' current products, especially in the pharmaceutical sector, it is possible that acquirers may want to add R&D projects in areas to similar to their own products to preserve their revenue-streams and leverage common cospecialized assets once their patents expire.

This implies that when it comes to an acquirers' own products, relative preferences in the target firm's R&D pipeline are more ambiguous than for some of the other preferences we propose. Nonetheless, we conjecture that it is more likely that acquirers will prefer R&D pipelines that are complementary (versus similar) to their own products because of the new and added value that such projects offer. In cases where patent expiration is a threat, acquirers may prefer both similarity and complementary, suggesting that overall, there exists a relative preference for complementarity. In sum, we propose:

Hypothesis 2a: The acquirer will be more likely to choose a target firm with greater complementarity in commercialized products to its own products and less likely to choose a target firm with greater similarity between these resources.

Hypothesis 2b: The acquirer will be more likely choose a target firm with greater complementarity in R&D pipeline to its own products and less

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likely to choose a target firm with greater similarity between these resources.

Which resource comparison should the acquirer pursue?

Based on what we have described, an acquirer would plausibly choose a target firm with products similar to its R&D pipeline, but with products complementary to its products. Further, it could choose a target firm with an R&D pipeline similar to its R&D pipeline, but with an R&D pipeline complementary to its products. This might raise the question of whether it is possible to reconcile a preference for such different resource configurations in a single choice. To do so makes the assumption that a firm's R&D pipeline is distinct from its products so that one is better off with similarity while the other is better off with complementarity. We believe that this is not only plausible but likely. A firm is a bundle of resources (Barney, 1991), and its R&D pipelines can be similar to its own products and different from them, allowing resource comparisons with target firms to be different for its pipeline and for its products. Consider, for example, a pharmaceutical firm that has a cholesterol drug in the market. While the firm is likely to have a few cholesterol-related projects in its pipeline to replenish revenues once patent protection has expired, it is also likely to have R&D projects related to other, noncholesterol diseases, such as hypertension. This firm can choose to acquire a target firm with R&D projects and products related to hypertension, which inadvertently might be complements to the firm's cholesterol drug. It can also choose to acquire a firm with hypertension drugs already in the market, which are related to the acquirer's R&D pipeline but are complements to the acquirer's current products. Further, it is conceivable that an acquirer will select a target firm based on either its R&D pipeline or based on its products, and possibly, not both, depending on its priorities at the time. We infer from our sample that some acquisitions are intended to augment the acquirer's pipeline, while others are intended to add to the firm's drug portfolio. Overall, our hypotheses are intended to theorize relationships between acquirers and target firms in a very complex environment in which some resource comparisons might be more appropriate than others, depending on circumstances surrounding the firm and its industry.

METHOD

Empirical context

We empirically tested our hypotheses using data from the pharmaceutical industry, which is an ideal context for several reasons. In 2013 alone, the pharmaceutical industry generated $840 billion in worldwide sales with sales in the United States comprising $330 billion (Statista.com, 2014). This industry is one of the largest and most well-established and knowledge-intensive sectors in the U.S. economy, and is vitally important from both business and social perspectives. Further, it heavily depends on product innovation. The difficulty of developing new products through in-house efforts alone means that firms in this industry are constantly looking for such resources 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 an attempt to respond to multiple calls for a formal study of acquisitions in this commercially important industry (Danzon, Epstein, and Nicholson, 2003). Restricting our empirical context to a specific industry allows for comparability across acquisitions and helps address concerns of internal validity.

Data

We utilized three primary sources of data to conduct our empirical analysis: (1) information on the acquisition deal, (2) accounting and financial information for the acquirers and potential target firms,[1] and (3) product and R&D pipeline information. Table 1 details the specific data sources used for this study. Next, we summarize our data collection process (please refer to Online Appendix S1 for greater detail on data collection).

Our dataset consists of information on acquisition deals between January 1988 and June 2008, during which the acquiring and potential target firms were public pharmaceutical companies in the United States (SIC code 283X). The study is restricted to companies in the United States because

[1] We define *Potential target firms* as firms that are available for acquisition. *Alternative target firms* are those that are available for acquisition but are not chosen. Finally, *Chosen target firms* are those that are chosen for acquisition out of the consideration set of potential target firms.

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Table 1. Data sources

Information description	Variables	Data source
Acquisition deal-related information	Deal date, acquirer and target firm name, public status, industry SIC code, deal purpose, etc.	SDC Platinum[a]M&A
Financial information	Sales, assets, liabilities, market value, etc.	Compustat
Choice set of target firms	List of public pharmaceutical firms from 1988 to 2008	Compustat
Product and R&D pipeline information	Each firm's approved and pipeline drugs in each stage of the clinical trial process.	*NDA Pipeline*, Inteleos,[b] Capital IQ
Alliance information	Dummy for alliance history.	Strategic Alliance within SDC Platinum, Capital IQ

[a] SDC Platinum is a professional dataset offered by Thomson Financial.
[b] *NDA Pipeline* is an annual publication provided by Elsevier that tracks the drug development activity from late-stage preclinical through launch and post-marketing studies. Inteleos™ (online version of *NDA Pipeline*) is a commercial database that is updated daily and has coverage of more than 8,000 drugs from more than 1,200 companies.

it is difficult to get comprehensive and comparable information on non-U.S. pharmaceutical companies. We limited our sample to publicly traded firms because financial information is readily available for public firms, but not necessarily for private. However, we conducted individual and joint multivariate variance analysis (MANOVA) tests on public and private samples based on four financial ratios: sales ratio, total assets ratio, current assets ratio, and liability ratio (calculated as target value/acquirer value). None of the tests reject the null hypothesis that the means of the two samples are equal, suggesting that the sample of public firms was not statistically different from the sample of private firms.

We also limited the sample to deals that achieved more than 80 percent of the ownership transfer, therefore excluding acquisition deals with minority target stakes. We did not follow a particular precedent for this cutoff. The reason is that the shareholding percentages after the acquisition occurred followed a bimodal distribution with a heavy concentration at both extremes. Among the acquisitions that satisfied our other constraints, more than 90 percent either maintained less than 10 percent shares or over 90 percent shares after the deal. Only four percent of the total deals resulted in between 50 and 90 percent of the shareholdings of the target firm. We picked 80 percent as the cutoff since it appeared to be a reasonable number, and moving this cutoff in either direction was not likely to change the sample significantly. Finally, we deleted acquisition deals for which no product and R&D pipeline information could be found. After completing these steps, we arrived at 53 acquisition deals. Though seemingly small in number, these 53 deals have a total deal value of $225 billion, more than 70 percent of the value of public deals in the sample period.

Choice set construction

The primary goal of this article is to examine how resource similarity and complementarity in products and R&D pipelines between an acquirer and a consideration set of potential targets influence which target firm will be chosen. One challenge in applying the choice model to the acquisition setting is that researchers do not observe the other choice alternatives. Knowledge of the chosen target firm says little about which other firms were considered for the same deal.[2] In theory, the choice set should contain all pharmaceutical firms existing at the deal announcement date, which includes approximately 500 firms (range in our sample: 248 firms in 1988 to 602 firms in 2008). However, it is unlikely that an acquirer would consider all public firms for a given deal nor is it feasible to include all of them in the model estimation.

[2] Following Chou *et al.* (2015), we tried collecting information on rumored acquisition deals but rarely found rumors involving the same acquiring firm and more than one potential target firm. Most rumored deals in the SDC Platinum database, and anecdotal evidence featured in the popular press, only covered deals that were in the process of or had already gone through an acquisition. Thus, potential target firms considered by top executives or those discussed during board meetings were unknown to researchers.

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Given these limitations, we constructed our choice sets for each acquisition using a random sampling method. This method has been widely used in the choice modeling literature for situations in which the true consideration set is not observable and the possible alternatives are too numerous (e.g., Feather, 2003; McFadden, 1977; Parsons and Kealy, 1992; Parsons and Needelman, 1992; Train, McFadden, and Ben-Akiva, 1987). For each acquisition deal, we randomly sampled nine alternative (nonchosen) target firms from the pool of firms that excluded the chosen target firms. Combined with the chosen target firm, this created a consideration set of up to 10 potential target firms for a given deal. We imposed constraints on the sampling set to obtain a set of alternative firms that were distributed around the size of the chosen target firm (and thus, the constructed set was plausibly representative of the true consideration set). Specifically, we required that the total assets of the alternative target firms be within 0.3 and two times that of chosen target firm's total assets. We conducted a simulation to examine the ability of the model to recover parameters with different sample sizes and a different number of alternative firms (for a similar simulation method, see Train, 2003: 68). The simulation results support our use of this method and are available upon request.

Among the nine alternative target firms for each deal, some firms were dropped due to missing financial and product/R&D pipeline information. Our final choice sets ranged from 3 to 9 alternative firms for each deal, generating a sample of 238 alternative target firms and a total sample of 291 potential target firms (53 chosen target firms + 238 alternative target firms).

Model specification

We used the random utility discrete choice model (Hoetker, 2007; McFadden, 1973; Wiersema and Bowen, 2009) to model acquisition choice. To the best of our knowledge, this article is the first to apply choice modeling to the study of acquisitions. In our model, acquirer j faces a choice among K potential target firms $(1, \ldots K)$ in period t and chooses the firm that provides the highest utility $U_{jkt} > U_{jdt}, \forall\, d \neq k; d, k \in (1, \ldots K), t = 1, \ldots, T$. The utility can be decomposed as $U_{jkt} = V_{jkt} + \varepsilon_{jkt}$ where V_{jkt} captures the deterministic part and ε_{jkt} captures the unobserved part (i.e., random error). We assumed ε_{jkt} to follow iid extreme value distribution. Under these assumptions, the probability that acquirer j chooses target firm k is: $P_{jkt} = \text{prob}\left(U_{jkt} > U_{jtd}, \forall d \neq k\right) = \frac{e^{V_{jkt}}}{\sum_d e^{V_{jdt}}}$. We estimated the model using the maximum likelihood method. The log-likelihood of the estimation is: $\sum_j \sum_t \sum_k y_{jkt} \ln P_{jkt}$, where y_{jkt} is an indicator variable taking value 1 when k is the actual choice (i.e., the chosen or acquired firm) in time t. We formulated the utility of acquirer firm j from choosing target firm k among a consideration set of potential target firms at time t as:

$$U_{jkt} = \sum_{n=1}^{N} \beta_n \phi_{jknt} + \sum_{l=1}^{L} \gamma_l x_{jklt} + \varepsilon_{jkt}, \qquad (1)$$

where ϕ_{jknt} is n-th measure of similarity or complementarity between acquirer j and potential target firm k at time t. N is the total number of similarity and complementarity measures, which we describe in greater detail subsequently. The l-th control variable for acquirer j and potential target firm k at time t is x_{jklt}. We had L measures of control variables. We note that not all control variables pertain to firm j; however, we include the subscript j to accommodate those that do. The β coefficients measure the impact of the eight resource comparisons between the acquirers and potential target firms on target firm selection. Finally, γ measures the impact of the control variables on target firm selection. Our goal was to test the significance of the impact of the β coefficients.

Resource comparison measures

We propose a new method for creating the eight focal measures of similarity and complementarity, which feature resource comparisons between acquirers and potential target firms. The measures include: R&D Pipeline-to-R&D Pipeline Similarity, R&D Pipeline-to-R&D Pipeline Complementarity, R&D Pipeline-to-Product Similarity, R&D Pipeline-to-Product Complementarity, Product-to-Product Similarity, Product-to-Product Complementarity, Product-to-R&D Pipeline Similarity, and Product-to-R&D Pipeline Complementarity. The measures are described in the context of the pharmaceutical industry, for example, approved drugs (products), pipeline drugs (R&D pipeline projects), and therapeutic areas (markets served), though they can be generalized to other contexts. To begin, we used a "tree" of therapeutic areas, or

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Figure 2. An illustration of the therapeutic tree

diseases, provided by the Inteleos database, which includes all diseases that are treated by all of the approved and pipeline drugs in the pharmaceutical industry. The tree enabled us to identify the therapeutic areas, or markets served, corresponding to acquiring and potential target firms' drugs and pipeline projects to identify which were similar and which were distinct. This allowed us to compute the eight resource comparisons measures. The number of therapeutic areas treated by each drug serves as a proxy for its commercial value or potential: the more diseases a drug treats, the more patients it can be marketed to and the higher its commercial value.[3]

The tree has 22,372 therapeutic areas and 10 levels of hierarchy. More general therapeutic areas (e.g., digestive tumors) are placed on higher levels of the tree and more specific therapeutic areas (e.g., a specific kind of digestive tumor) are placed on lower levels. Thus, the tree structure represents relationships between various related therapeutic areas. (See Figure 2 for an example of a section of the tree.) We identified the drugs and pipelines of each acquirer and potential target firm in our sample and matched them with the therapeutic areas. After we identified the therapeutic areas that each firm's drugs and pipeline projects treated or intended to treat, we mapped them on to the tree to identify the distances between the acquirers' and target firms' therapeutic areas. These distances were used to calculate the similarity and complementarity measures. We describe the measure construction more generally below and in greater detail in Online Appendix S2.

Assume that the set of all drugs, $D = \{D_1, D_2, \ldots, D_{O+M}\}$, is comprised of approved drugs $P = \{P_1, \ldots, P_O\}$ and pipeline drugs $= \{R_1, \ldots, R_M\}$, where $D = P$. Because each drug can potentially treat multiple diseases and each disease can represent a group of patients (i.e., potential markets), we use the therapeutic areas as proxies for markets and denote them as $C = \{C_1, \ldots, C_h\}$. Given firm *i*'s portfolio of drugs $D^i = P^i \cup R^i$, we first identified which therapeutic areas they treated using information provided by Inteleos, and then calculated the market potential that firm *i* has in each therapeutic area C_o, which we denoted as its *product score*, $S_p(C_o, i)$. The market potential of each drug was assigned a value between 0 and 1. If the drug had been approved, then we assigned the product score a value of 1. For approved drugs that had lost patent protection and faced heavy competition from generic drugs, we assigned them a value of 0.1.[4] Regarding the pipeline drugs, not

[3] Ideally, we would have used the estimated market size (in dollar sales) for each disease area, but this information was not available for each disease area.

[4] It is common for firms to lose 70–90 percent of market share in the first three years of patent expiration. Ideally, we would calculate the market value of a drug as a function of the number of years since its patent loss. However, there is often more than one patent associated with a particular drug and determining the exact date of patent loss can be complicated. For simplicity, we use 0.1

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all of them reached the commercialization stage. Research projects in the later stages of clinical trials have a better chance of commercialization than those in the earlier stages. To account for this, we used the clinical probability of FDA approval as a proxy for the market potential, or *R&D pipeline score*, denoted as $S_r(C_o, i)$, of the pipeline drugs.[5] The product and R&D pipeline scores were used to create the eight resource comparison measures of similarity and complementarity. The measures were operationalized as weighted summations of the product scores and pipeline scores of the acquirers and potential target firms. The mathematical expressions for each of these measures can be found in Online Appendix S2.

Principal component regression

Some of the resource comparison measures shared commonalities (with correlations exceeding 0.70), while others had much less in common (the correlations ranged between 0 and 0.20). Still, we needed to address the impact of higher correlations among some of the independent variables, since a high degree of multicollinearity among independent variables (X) makes the matrix X^TX difficult to invert and causes the coefficient estimates to be unreliable. Further, small changes in the model or data can cause erratic responses in the coefficient estimates (Gujarati, 2003).

There are multiple ways to solve this multicollinearity problem, such as standardizing the independent variables, mean centering the predictor variables, obtaining more data, dropping one or more of the collinear variables, or using principal component regression. We standardized and mean-centered the independent variables, but the high correlations remained. Obtaining more data was difficult since we had already used all of the possible deals in the pharmaceutical industry during the sample time period. Lengthening the sample time frame and collecting more data would have been extremely labor-intensive, given the type of data we would have needed to collect. Further, additional data may not have solved the problem of multicollinearity. Since all eight resource comparison variables have theoretical significance and are subject to hypothesis testing, we could not drop any single variable easily. Thus, we went with the commonly used statistical approach of principal component regression (PCR: Hotelling, 1957; Jeffers, 1967; Jolliffe, 1982; Kendall, 1957) to solve this problem.

The PCR method has been used in various empirical contexts, including medicine (Barker and Brown, 2001), genomics (Pant *et al.*, 2010), economics and management (Chan and Park, 2005), marketing (Posselt and Gerstner, 2005), chemistry (Reinsberg *et al.*, 2011), and social development (Sufian, 2005). We follow the method specification used by Sufian (2005) in our estimation due to its clarity of exposition and contextual similarity. Essentially, PCR replaces the original regressor variables with their principal components; thus, orthogonalizing the regression problem and making the computations easier and more stable (Gunst and Mason, 1980; Mardia, Kent, and Bibby, 1979). After the regression estimation (in our case, logistic regression), the parameter estimates of the principal components are converted back to the original variables and are reported accordingly.

To conduct PCR, we first standardized our eight resource comparison variables. Second, we conducted principal component analysis (PCA), a method widely used in the strategy literature (e.g., Klingebiel and Rammer, 2014; Shafique, 2013) for variable reduction and converting a set of correlated variables into a set of values of linearly uncorrelated variables (principal components). Third, we used a subset of the principal components to replace the original resource comparison variables. To determine the number of components to comprise our subset, we examined the eigenvalues and variance of the independent variables accounted for by the components. We found that the first three components explained close to 80 percent of the total variance among the resource comparison variables. However, in order to lose as little information as possible, we kept seven out of eight principal components, which collectively explained 98.75 percent of the variation. We dropped the last component because it explained very little variance (almost zero) and because at least one component needs to be dropped in PCR. Further, dropping the last component hardly affected the log likelihood of the model. If we had kept all eight components, then the parameter estimates (after converting them

as the market potential for drugs that have lost patent protection. Variations in this assumption can be tested in future extensions of this research.

[5] Following Higgins and Rodriguez (2006), we capture all four phases of drug development: preclinical, phase I, phase II, phase III, and pending approval. The clinical probabilities of approval in these phases are 0.07, 0.22, 0.30, 0.69, and 0.90, respectively.

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back to the original variables) would have been identical to the regression analysis without PCR, but the multi-collinearity problem would have persisted, which would suppress the true effects of several of the variables (Gujarati, 2003; Sufian, 2005). Thus, we neither lost any information nor did we introduce bias by dropping the eighth component. Finally, the parameter estimates of the principal components from the regression analysis were converted back to the original variables using the factor loading matrix from the PCA. We provide greater detail on the PCR method and why we chose this approach in Online Appendix S3.

Control variables

In accordance with past research on acquisitions, we included several financial and nonfinancial control variables in our model. We controlled for *target debt to assets ratio* by dividing the potential target firms' total debt by their total assets. If this ratio is high, then the firm may face the risk of financial distress; but if the ratio is low, then it may not be fully utilizing the tax shield of debt (Rao, Mahajan, and Varaiya, 1991). We measured a binary dummy variable, *target biotech area*, to control for whether the potential target firms belonged to the biotechnology industry, which has been shown to have a large effect on acquisition outcomes in the pharmaceutical industry (Chesbrough, 2003; Higgins and Rodriguez, 2006). We controlled for another ratio (Wiseman, 2009), the relative size of the target firm (*acquirer-target assets ratio*: ratio of potential target firm total assets to acquirer total assets), to account for the fact that larger firms have very different organizational cultures than smaller firms (Prabhu *et al.*, 2005; Shleifer and Vishny, 1990; Sorescu *et al.*, 2007). We also measured *acquirer-target biotech match*, a dummy variable indicating whether the acquirer and potential target were both biotechnology firms. Biotech firms have a higher technology content in their research and production processes than traditional pharmaceutical firms, and a match between firms is likely to improve the post-acquisition integration process. Finally, we included a binary classification for *acquirer-target alliance history* to control for whether there existed a prior alliance relationship between the acquirer and potential target firm (Higgins and Rodriguez, 2006). A history of partnership is likely to increase the chance of acquisition.

RESULTS

Summary statistics

We compare the summary statistics for the chosen target firms and the alternative firms (firms in the consideration set for acquisition but which were not acquired) in Table 2. From the summary statistics, it appears that the chosen target firms aren't systematically different from the alternative

Table 2. Summary statistics of potential target firms

	Chosen target firms (n = 53)		Alternative target firms (n = 238)	
Variables	Mean	Std. dev.	Mean	Std. dev.
R&D pipeline-to-R&D pipeline similarity	0.17	1.20	−0.04	0.95
R&D pipeline-to-R&D pipeline complementarity	−0.01	1.14	0.002	0.97
R&D pipeline-to-product similarity	0.07	1.09	−0.02	0.098
R&D pipeline-to-product complementarity	−0.08	0.71	0.02	1.05
Product-to-product similarity	−0.05	0.38	0.01	1.20
Product-to-product complementarity	0.03	1.20	−0.01	1.11
Product-to-R&D pipeline similarity	0.03	0.92	−0.01	1.02
Product-to-R&D pipeline complementarity	0.17	1.38	−0.04	0.89
Target debt to assets ratio	0.39	0.55	0.44	0.50
Target biotech area	0.32	0.34	0.37	0.48
Target-acquirer assets ratio	0.14	0.20	0.12	0.20
Target-acquirer biotech match	0.15	0.36	0.10	0.30
Target-acquirer alliance history	0.17	0.38	0.01	0.09

Notes: Chosen Target firms pertains to the firms that were chosen and acquired and *Alternative target firms* refers to the firms that were not acquired but were in the acquirers' consideration sets.

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target firms. For example, except for the variable alliance history, all of the control variables are comparable between two samples. However, significant variability exists between the two samples in terms of the eight resource comparison measures. Further, both samples have considerable variance in all of the measures, suggesting that we could not draw conclusions from mean statistics alone and needed to perform a formal analysis of the data.

Model fit analysis

To demonstrate the value of each resource comparison variable and the need for PCR, we conducted a step-by-step analysis by adding pairs of variables, one at a time, to a baseline model of control variables and then compared their log likelihoods. We also compared a full model without PCR to one with PCR (our hypothesized version). We found that the incremental addition of the resource comparison variable pairs led to increases in the log likelihood (i.e., the values became less negative), indirectly verifying the explanatory power of the hypothesized variables ($LL_{\text{Baseline Model}} = -71.76$, $LL_{\text{One Added Pair}} = -69.01$, $LL_{\text{Two Added Pairs}} = -67.11$, $LL_{\text{Three Added Pairs}} = -62.33$, $LL_{\text{Full Model}} = -60.81$). The log likelihood of the full model without PCR was identical to that of our PCR model (both had $LL = -60.81$), and the signs of the coefficients were identical, confirming that PCR neither negatively affected model fit nor changed the directional conclusions of the analysis. The main difference between the full model with PCR and without PCR was the significance of the resource comparison variable coefficients: more variables gained significance in the PCR analysis. This is because reducing multi-collinearity among independent variables, which the PCR achieved, helps recover parameter significance by reducing the standard errors (Hotelling, 1957; Jeffers, 1967; Jolliffe, 1982; Kendall, 1957; Sufian, 2005). The variables were not significant in the model without PCR because of the high correlation among the variables, which when left untreated, suppresses their true effects (Gujarati, 2003).

The results of the principal component logit model estimation are reported in Table 3.

Control variables results

Several controls, such as acquirer-target alliance history, target biotech area, and target biotech match, had significant effects in the expected directions. Others, including acquirer-target assets ratio and target debt to assets ratio, were not significant. While these control variables are not a focus of this research, we take a moment to discuss their nonsignificance. It is likely that the target firm's size, as opposed to the relative size of the target, will influence whether the target is chosen. Still, we kept relative size in the model to comply with past research. The nonsignificance of the target firm's debt-to-asset ratio is surprising. It might be the case that some acquirers favor a potential target firm with relatively low debt, while others are able to tolerate relatively high debt from the target firm (for reasons laid out in previous sections), so the two effects canceled out each other.

Effects of similarity and complementarity in R&D pipelines

To test Hypothesis 1a, we compared the effect of R&D pipeline-to-R&D pipeline similarity on target firm choice to the effect of R&D pipeline-to-R&D pipeline complementarity. Similarity has a positive effect on the likelihood of acquiring a target firm ($\beta = 0.89$, $p < 0.03$), whereas complementarity has a negative effect ($\beta = -1.17$, $p < 0.01$). Taken together, these results reveal that acquirers will choose target firms with greater similarity (vs. complementarity) in R&D pipelines, supporting Hypothesis 1a. In fact, while similarity in R&D pipelines increases the likelihood of the target firm being chosen, complementarity actually decreases the chance of acquisition. This not only demonstrates a preference for similarity but also an aversion to complementarity.

Effects of similarity and complementarity between acquirers' R&D pipelines and target firms' products

To test Hypothesis 1b, we compared the across-product development stage effects of R&D pipeline-to-product similarity and R&D pipeline-to-product complementarity on target firm selection. Here, similarity has a positive effect on the likelihood of acquisition ($\beta = 4.48$, $p < 0.09$), whereas complementarity has a negative effect ($\beta = -3.56$, $p < 0.09$). Similar to the previous results, this demonstrates a preference for similarity and an aversion to complementarity. Taken together, and in support of Hypothesis 1b,

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Table 3. Estimation results from the principal component logit model

Independent variables	Hypothesized direction: Similarity	Hypothesized direction: Complementarity	Parameter estimate	Standard error	p-value	Hypothesis support
Comparisons to acquirers' R&D pipeline (acquirer R&D pipeline-to-target firm resources)						
R&D pipeline-to-R&D pipeline similarity	+		0.89	0.41	<0.03	Yes
R&D pipeline-to-R&D pipeline complementarity		−	−1.17	0.46	<0.01	
R&D pipeline-to-product similarity	+		4.48	2.69	<0.09	Yes
R&D pipeline-to-product complementarity		−	−3.56	2.11	<0.09	
Comparisons to acquirers' products (acquirer product-to-target firm resources)						
Product-to-product similarity	−		−4.98	2.77	<0.07	Partial
Product-to-product complementarity		+	0.32	0.47	>0.49	
Product-to-R&D pipeline similarity	−		−0.05	0.24	>0.84	Partial
Product-to-R&D pipeline complementarity		+	0.91	0.47	<0.05	
Control variables						
Target debt to assets ratio			−0.37	0.38	>0.32	
Target biotech area			−0.87	0.51	<0.09	
Target-acquirer assets ratio			−1.27	1.17	>0.28	
Target-acquirer alliance history			4.29	1.17	<0.00	
Target-acquirer biotech match			1.89	0.84	<0.02	
Fit statistics						
Log likelihood of null model			−87.74			
Log likelihood of hypothesized model			−60.81			

the results demonstrate that acquirers are more likely to choose target firms with greater similarity (vs. complementarity) between the target firms' products and their own R&D pipeline.

Effects of similarity and complementarity in products

To test Hypothesis 2a, we compared the effect of product-to-product similarity to the effect of product-to-product complementarity on target firm selection. Here, similarity has a significant and negative effect on the likelihood of acquiring a target firm ($\beta = -4.98$, $p < 0.07$), whereas complementarity has a directionally positive but nonsignificant effect ($\beta = 0.32$, $p > 0.49$). These results suggest that complementarity alone does not appear to increase the likelihood of acquiring a target firm; rather, similarity decreases this likelihood, demonstrating partial support for Hypothesis 2a. Thus, while acquiring firms may not prefer complementarity between products, they appear to dislike similarity, and as a result, the *relative* preference is for complementarity.

Effects of similarity and complementarity between acquirers' products and target firms' R&D pipelines

To test Hypothesis 2b, we compared the across-stage effects of product-to-R&D pipeline similarity and product-to-R&D pipeline complementarity on target firm selection. Here, similarity has a directionally negative but nonsignificant effect on the likelihood of acquiring the target firm ($\beta = -0.05$, $p > 0.84$), whereas complementarity has a significant and positive effect ($\beta = 0.91$, $p < 0.05$). These results reveal that similarity between the target firm's R&D pipeline and the acquirer's products alone does not appear to decrease target selection;

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rather, complementarity between the two resources has a positive effect, demonstrating partial support for Hypothesis 2b. Thus, while acquiring firms may not be averse to similarity between target firms' R&D pipelines and their products, they have a clear preference for complementarity, resulting in a *relative* preference for complementarity. Taken together with the results of Hypothesis 2a, we find that an acquirer is less likely to choose a target firm with similar products to its own products and is more likely to choose a target firm with a complementary R&D pipeline to its own products.

Summary of results

Overall, the results demonstrate that acquirers are more likely to choose target firms with greater similarity (vs. complementarity) between the target firms' R&D pipelines/products and their own R&D pipelines. This relative preference for similarity stems from a penchant for similarity and an aversion to complementarity. Alternatively, acquirers are more likely to choose target firms with greater complementarity (vs. similarity) between the target firms' R&D pipelines/products and their own commercialized products. Here, the relative preference for complementarity stems from an aversion to similar products and a preference for complementary R&D pipelines.

CONCLUSION

Corporate acquisitions have become a popular strategic option for firms to acquire new resources to meet the rapidly changing demands of a competitive marketplace. Our research begins to answer the important question of why acquiring firms choose one target firm over another. To answer this question, we examined how acquirers use information about similarity and complementarity between their resources and those of potential target firms to decide which firms to acquire. In doing so, we were able to examine resource-based conditions for which acquirers prefer similarity relative to complementarity, and conversely, when they prefer complementarity relative to similarity.

Much past research on resource comparison has favored the examination of resource similarity at the expense of complementarity. In this article, we examine both resource comparisons and assess whether there is a relative preference for one over the other and under which resource-based conditions of the acquiring firm. Our findings reveal that, when it comes to their own products, acquirers are more likely to choose target firms with greater resource complementarity relative to similarity. Alternatively, when it comes to their own R&D pipelines, the reverse is essentially true: they prefer target firms with greater similarity relative to complementarity. These findings not only demonstrate a relative preference for one resource comparison over another, but also they show that acquiring firms differentiate between their current (i.e., products) and future (i.e., R&D pipelines) innovation potential when deciding whom to acquire.

By studying product portfolios alongside R&D pipelines, we were able to see whether acquiring firms, in fact, consider how their own R&D pipelines (products) compare to the target firms' products (R&D pipelines) or whether they simply consider more expected relationships (e.g., R&D pipeline-to-R&D pipeline and product-to-product). Our hypotheses centered on the notion that acquirers differentiate between their own R&D pipelines and products when considering a potential target firm, but treat the target firms' R&D pipelines and products similarly. For example, and in line with our hypotheses, we found that, when it comes to their own R&D pipelines, acquirers are more likely to choose target firms with similar R&D pipelines and products, and are less likely to choose target firms with complementary R&D pipelines and products. Thus, acquirers seem to be treating target firms' resources, whether they are R&D projects or commercialized products, in the same way. However, we found that, when considering their own products, acquirers appear to be treating potential target firms' R&D pipelines differently from their products, even though the acquirers still have a relative preference for resource complementarity. For example, we found that acquirers are less likely to choose a target firm with products similar to their own products, but product complementarity doesn't have a significant effect. Alternatively, acquirers are more likely to choose a target firm with a complementary R&D pipeline to their own products, but similarity does not appear to have a significant effect. Thus, the relative preference for complementarity still remains, but not because preferences for similarity and complementarity move in opposite directions. Rather, it is because one effect is nonsignificant and the other is significant so that a relative preference still arises. This raises the question of whether a

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greater number of resource preferences (and aversions) surround the acquirer's R&D pipeline more than its products. Future research might investigate whether an acquirer's R&D pipeline or its product portfolio is comparatively driving acquisition decisions and whether firms tend to prioritize one over the other.

Future researchers might consider adopting our measures of similarity and complementarity. They were calculated using third-party (objective) data of firms' product and R&D pipeline information, instead of using survey data typically used in past research. They measure the degree of similarity and complementarity at product/project-levels as opposed to classifying them using a more simple binary measure at the industry-level. This distinction is important since two firms can operate in the same industry but have very different product and research profiles. The case of the merger of Celgene and Gilead Sciences, two top biopharmaceutical firms that operate in the same SIC area, is revealing. Given former definitions of similarity, these two firms would be considered as similar. However, in reality, these two firms are far from similar because of the types of drugs each one markets; Celgene produces drugs that treat various types of cancer, whereas Gilead Sciences produces drugs that treat HIV, AIDS, hepatitis B, and so on. They have completely different products, different pipelines, and different markets. Therefore, it is necessary to take into account the nature of firms' actual commercialized products and pipelines of innovation projects as opposed to a more general affiliation, such as industry-specific membership. In addition, our measures capture resource comparisons between and across acquirers' and target firms' product portfolios and R&D pipelines, allowing a greater number of resource configurations to be measured. Finally, they significantly explain variance in target selection above and beyond the effects of some simpler measures such as industry classification.

Our choice modeling approach in the acquisition context can be extended to the study of other managerial decisions in the business-to-business context, such as alliances, joint ventures, and ad agency selection. The model also can be generalized to many nonbusiness settings, such as dating and social networking. This article also suggests a new direction for the empirical mergers and acquisitions literature. Instead of studying the acquisition outcome unconditionally, this article suggests that it might be better to condition the outcome on acquisition motive (suggested by target selection criteria), to help scrutinize each step in the acquisition process and improve future practices. Future research might jointly examine target selection and the performance outcomes of such selection criteria to assess whether synergies are created on account of whom the acquirer chooses and whether this choice generates performance rewards. Further, future researchers might consider combining acquisition deal-related data with some contemporaneous data collected from managers doing acquisitions to incorporate the effects of motives and perceptions, in addition to the resource comparison measures we proposed.

Some limitations of this article are worth noting. First, this study was conducted using data from a single industry. While the pharmaceutical industry is undoubtedly an important and prominent industry, especially considering the prevalence of its large-scale acquisition activity, applying our approach to multiple industries where acquisitions are more prevalent (e.g., high-technology sectors) to capture industry differences is a promising avenue for future research.

Second, due to data constraints, we were limited to using data from public firms, causing us to miss out on acquisition activity among private firms. This concern is reduced to some extent by the fact that 80 percent of the total deal value across the acquisitions in our sample could be attributed to public deals whereas only four percent could be attributed to deals between private firms (the remaining deal value could be attributed to subsidiaries and joint ventures). However, if possible, it would be worthwhile to examine whether the same selection criteria are employed by private firms and whether any differences emerge.

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SUPPORTING INFORMATION

Additional supporting information may be found in the online version of this article:

Appendix S1. R&D pipeline and product data collection details.
Appendix S2. Construction of resource comparison measures.
Appendix S3. Addressing multi-collinearity with principal components regression (PCR).

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