

**Counting Chickens before the Eggs Hatch:  
On the Valuation of New Drug (Product) Development  
Portfolios in the Pharmaceutical Sector**

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## **Counting Chickens before the Eggs Hatch: On the Valuation of New Drug (Product) Development Portfolios in the Pharmaceutical Sector**

### **ABSTRACT**

New drug development is the lifeline of pharmaceutical firms—a critical source of life sciences innovation in the healthcare industry. Pharmaceutical firms maintain their competitiveness by continuously developing and introducing new drugs, which requires an efficient new drug portfolio management process. However, current literature does not elaborate on new drug (product) portfolio (i.e., portfolio of drugs under development) strategies, nor does it provide the means to distinguish objectively between good and bad portfolios. To address this problem, the authors propose generic descriptors of new drug portfolios (i.e., breadth, depth, blockbuster versus shotgun, and emphasis on different stages of development) and relate these descriptors to Tobin's  $q$ , a forward-looking measure of firm value based on the efficient markets paradigm in finance. The results from a latent class regression analysis show that the stock market generally favors diversified new drug portfolios that consist of potential blockbusters. For a majority of firms, the stock market focuses on the final stage of new drug development and deemphasizes portfolio depth. In contrast, for a minority of mostly small firms, stock markets seem to value the earlier stages of the new drug development process with stress on portfolio depth.

## 1. Introduction

Considering that healthcare expenditures constitute 8–15% of gross domestic product for most developed countries (Shankar 2007), research advancing the management of healthcare and life science technologies is considered vital for progress. More than any other component of the healthcare industry, the pharmaceutical sector has grown in terms of both expenditures and innovations. Consequently, proponents of healthcare innovation increasingly focus on the pharmaceutical sector, a major source of advances in life science and healthcare technologies.

The pharmaceutical sector is expanding at a remarkable rate, with global sales increasing from \$317 billion in 2000 to \$550 billion in 2004 (Trombetta 2005). This growth results from massive investments in research and new drug development, which extend to approximately 20–30% of the revenues of pharmaceutical firms. Continuous introductions of new products address new forms of diseases, and massive numbers of diseases remain in desperate need of remedy, so new drug development represents the lifeline of most pharmaceutical firms. However, managing the development of new drugs in the pharmaceutical industry remains extremely challenging due to the complexities of the development process and government regulations. The new drug (product) development process in the pharmaceutical industry consists of multiple stages, exogenously defined by federal regulations for human drug development. Specifically, *in vitro* analysis identifies a potential drug candidate as a treatment for a given disease; preclinical tests then are conducted with animals. If the results of the preclinical tests are promising, the firm files an application with the Federal Drug Administration (FDA) to test the drug on human subjects (clinical trials). The clinical trial stage comprises three phases: Phase I tests the drug in a small number of healthy human subjects for safety, phase II tests it for efficacy and potential side effects on an average-sized sample of a few hundred patients, and phase III tests the drug for dosage guidelines and establishes a detailed clinical profile using thousands of patients. Finally, the test results are submitted to the FDA for evaluation

and possible approval. New drug development in the pharmaceutical industry is costly (several estimates put the average cost at \$800 million–\$1 billion per drug), risky (only 1 in 50,000 compounds tested becomes a drug), and lengthy (10–12 years average development time), and the market payoff is time sensitive (on average, patent protection ends 10 years after the introduction of a drug). Therefore, the management and structure of the new drug development process cannot be considered trivial.

In increasingly risky environments across industries, firms turn to portfolio management to develop new products and maintain sustainable competitive advantages and long-term profitability (Cooper, Edgett, & Kleinschmidt 2004). Specifically, new product portfolio management, defined as a “dynamic decision process, whereby a business’s list of active new product projects is constantly updated and revised,” serves to optimize resource allocation among new product projects at various stages of development and targeted toward diverse markets (Cooper, Edgett, & Kleinschmidt 1998, p. 3). The management of a portfolio of new drugs under development otherwise referred to as a *new drug portfolio* remains one of the most important components of corporate strategy for pharmaceutical firms. Most firms also maintain formal portfolio management teams to create optimal new drug portfolio strategies. Yet portfolio management successes have been adequate at best (Slade 2006), and it should come as no surprise that many firms, including pharmaceutical companies, struggle to distinguish between good and bad new drug (product) portfolio strategies.

The challenge in assessing the quality and value of portfolios of new products under development stems from their valuation, which can refer only to expected future income; new product portfolios themselves do not generate any current income. Furthermore, it is impossible to evaluate portfolios on the basis of their historical performance—akin to counting chickens before the eggs hatch. Unfortunately, no objective measures of the quality and value of new product portfolios are available, though such measures would represent powerful tools for distinguishing

between good and bad new drug portfolio strategies. Decisions about individual projects often rely on a net present value analysis to make go/no-go decisions. Although similar techniques could be adapted for portfolios, incorporating synergies and complementarities would be difficult, and managerial judgments about revenues, expenses, and synergies across the projects in a portfolio would remain necessary, which means judgment biases would still exist (e.g., Sharma & Lacey 2004).<sup>1</sup>

We believe financial markets might help overcome this lack of objectivity in value assessments of new drug portfolio strategies. The efficient market hypothesis in finance literature suggests that financial markets integrate all relevant knowledge to arrive at a stock price and can absorb new information about the current value of uncertain future income quickly, as reflected in updated stock prices (e.g., Fama, Fisher, Jensen, & Roll 1969). Forward-looking measures are common (e.g., Goldenberg, Libaib, Moldovanc, & Mullerb 2007), especially stock price-based measures, which are increasingly popular for assessing the value of market-based assets (e.g., Rust, Ambler, Carpenter, Kumar, & Srivastava 2004). According to the framework we propose, the efficient market hypothesis implies that a measure based on stock price can assess the value of new drug portfolio strategies, provided that information about the strategies is publicly available. Due to federal regulations, information about new drug developments is made public by the FDA, which makes this industrial sector ideal for evaluating the efficacy of new product portfolios.

Evaluation of the efficacy of new drug portfolios requires a description of various portfolio strategies. We propose descriptors of new drug portfolios that capture four key strategy dimensions, namely, breadth (number of different major markets targeted), depth (allocation of effort in each

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<sup>1</sup> As summarized by Cooper et al.'s (1998) work, several scholars define a new product portfolio as effective if it meets the following conditions: (1) it aligns with business objectives, (2) it includes high-value projects, (3) there is congruence between spending on projects and business strategy, (4) projects are completed in a timely manner, (5) projects are balanced, and (6) it includes an appropriate number of projects. Following these criteria, managers can collect perception data using Likert scales and assess the extent to which their portfolios are effective.

targeted market), blockbuster versus shotgun (size distribution of the individual product markets targeted), and emphasis on different (early versus late) new drug development stages. The new products literature in general supports the use of some of these dimensions, such as breadth and depth (e.g., Bordley 2003). In turn, we hope to capture these four dimensions of a firm's new drug portfolio and relate them to Tobin's  $q$ , a stock market-based measure of firm value (Wernerfelt & Montgomery 1988).

Because systematic work in new product portfolio valuation is lacking, as are relevant historical results in the domain of healthcare innovation and management, we recognize that our research is largely exploratory. Nonetheless, we seek to make several important contributions to innovation management literature in general and the domain of life sciences and healthcare in particular. Because we study new drug portfolios for the pharmaceutical sector, we offer substantive contributions in terms of understanding portfolio valuation in this strategically and economically important sector. By providing an objective assessment of the value of new drug portfolios, we also offer a means to identify best practices among pharmaceutical firms. Finally, we use a measure based on stock price (Tobin's  $q$ ; e.g., Simon & Sullivan 1993) to assess the value of new drug (product) portfolios and thus respond to calls by scholars suggesting marketing should “engage in a meaningful dialogue with financial and top management” and focus on issues critical to shareholders (Srivastava, Shervani, & Fahey 1999, p. 168; see also Rust et al. 2004).

We organize the remainder of this article as follows: In the next section, we provide a conceptual background of existing innovation research set in the context of the pharmaceutical industry. Against this overview, we describe several new drug portfolio strategies and theoretically explore their effects on financial market valuation. Next, we examine how financial markets value new drug portfolios according to a latent class regression analysis (to account for the possibility of

multiple regimes<sup>2</sup>). We conclude with discussions of the limitations of the study and its implications for further research.

## **2. Conceptual Background**

### **2.1. Innovation in the pharmaceutical sector**

Innovation and new drug development form the crux of life sciences and healthcare-related research in the pharmaceutical sector. A broad range of studies examine (1) new drug development decisions, (2) interfirm alliances for new drug development, and (3) the economics of new drug development. Together, these studies provide valuable guidelines for managing a creative and dynamic new drug development strategy.

Research on new drug development decisions consists of two broad streams: the new drug development process and new drug portfolios. A broad range of theoretical perspectives serves to suggest improvements in the new drug development process and related innovations. On the basis of a valuable decision model that reveals the ideal size or number of new drugs on the market, Ding & Eliashberg (2002) show that leading firms under spend on new drug development during clinical trials. They further suggest that firms need different new drug development pipelines for different development problems. Applying a problem-solving perspective, Chandy, Hopstaken, Narasimhan, & Prabhu (2006) explain that though pharmaceutical firms suffer extreme pressures to develop and release new drugs, a strong focus on rapid innovation and varied new drug concepts may harm firms by lowering their ability to convert these concepts into commercial products. In contrast, the use of control theory mandates that, irrespective of the size or number of new drugs, formal behavioral and output control mechanisms should enable the effective implementation of the new drug development process (Cardinal 2001).

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<sup>2</sup> In our empirical analysis, different segments or regimes of firms might exist for which the coefficients of interest differ in magnitude, direction, and statistical significance. Such different regimes result from the inherent heterogeneity among firms, which makes certain associations valid for some firms and invalid for others (see the Appendix).

Several scholars investigate portfolios of new drugs under development, instead of simply the number of drugs. As drug research has advanced, it has become more dependent on a broad array of scientific disciplines (Henderson & Cockburn 1995); as a result, considerable diversity exists in new drug concepts and development processes (Cardinal 2001). A new drug portfolio diversified across many diseases (i.e., product categories) seems to reduce the variation in firm performance because of the low probability associated with successful drug development (Powell, Koput, & Smith-Doerr 1996). Diversity in the new drugs under development also leads to innovation and improved productivity (Cardinal & Hatfield 2000b). Such diversity may be maintained by investing in separate knowledge creation centers or research facilities rather than maintaining single research facilities (Cardinal & Hatfield 2000a). Research also suggests that firms seek to increase diversity in new drug projects by forming development alliances that pool the financial and technological resources of the partner firms (Bower 1993).

Such alliances have become a vital source of innovation in the pharmaceutical industry. Wuyts, Dutta, & Stremersch (2004) study the effect of a pharmaceutical firm's alliances with biotechnology firms on innovation and profitability and find that firms that focus on radical innovation invest in technologically diverse portfolios in which they repeatedly contract with the same partners to facilitate complex knowledge transfers. New drug development through alliances also achieve higher probabilities of success in clinical trials, especially if the partner is a large firm (Danzon, Nicholson, & Pereira 2005 ). As a caveat to this line of research, Kalaignanam, Shankar, & Varadarajan (2007) show that though alliances are popular for new drug development, an excessive focus on underlying knowledge and technologies often increases the chances of alliance termination and thus should be avoided. Therefore, it remains important to understand both the costs and the potential returns of any strategy deployed for new drug development and innovation.

The economics of new drug development in the pharmaceutical industry often serve as guidelines for research and development (R&D) resource allocations. DiMasi, Hansen, & Grabowski (2003) estimate an average preapproval cost of a drug at \$802 million, including out-of-pocket costs of \$403 million. Scherer (2001) emphasizes that only 21–23% of new chemical entities that enter the last phases of clinical trials emerge with commercialization approval. The uncertainty in terms of the total costs of development and commercialization, as well as the returns from new drugs, becomes further aggravated by the differential rates at which new drugs diffuse and penetrate among markets (Desiraju, Nair, & Chintagunta 2004), which is not surprising, because every market has unique features that influence the differential growth of new products (Stremersch & Tellis 2004). The elaborate and expensive nature of the new drug development process prompts several scholars to try to estimate returns to investments in new drug development. For example, Sorescu, Chandy, & Prabhu (2003) evaluate shareholder returns on radical new drug innovations versus market or technological innovations; the financial value of a radical innovation is much greater than those of market or technological breakthroughs. Grabowski, DiMasi, & Vernon (2002) use a capital asset pricing model to study returns on R&D for new drugs and find that the mean industry rate of return is greater than the cost of capital; the R&D costs, number of new drugs, and contribution margins in the 1990s also appear significantly higher than they were in the 1980s.

In our investigation of stock market assessments of various new drug portfolio strategies, we provide additional insights into how a new drug development process should be structured in terms of its portfolio and the financial returns on that portfolio. Therefore, our research contributes to research in both new drug development decisions and the economics of drug development.

## **2.2. New drug (product) portfolio descriptors**

Consider, as an illustration, the example of Pfizer in 1999, which then possessed 40 new drug candidates. In addition to the sheer number of candidates, several other factors contributed to

the complexity of Pfizer's new drug portfolio (SG Cowen 1999). First, its drug candidates (new products) targeted a wide variety of therapeutic categories. To further complicate matters, the drug candidates from each category may or may not have targeted the same disease (i.e., market). Second, each drug candidate resided in a different stage of new product development. Third, the competitive scope of the market changed constantly for each disease, mainly because patents on existing drugs expired and competitors moved new drug candidates through different development stages. To uncover the value of such complex new drug portfolios, it is essential to develop summary descriptors that provide information about portfolio strategies and thereby concisely delineate their various features.

**2.2.1. Portfolio breadth.** Portfolio breadth refers to the extent to which a firm's product portfolio is diversified across different product categories. As new product alliances propagate and scientific diversity increases, a firm's product portfolio must spread across a variety of markets (Bordley 2003). In the context of a pharmaceutical firm's new drug portfolio, we can define portfolio breadth as the number of different markets that the firm intends to target with its new drug portfolio (e.g., Leendersa & Wierenga 2008). Pharmaceutical firms develop and market new drugs for a large variety of diseases that can be grouped into therapeutic categories on the basis of their similarities. GlaxoSmithKline, for example, groups its new drug candidates into the following therapeutic categories: cardiovascular, urogenital, metabolic, viral, microbial, musculoskeletal, neurological and psychiatric, gastrointestinal, and respiratory diseases. For each therapeutic category, GlaxoSmithKline provides a line of drug candidates that targets different diseases. For example, the firm's new drug projects target depression, schizophrenia, HIV, and asthma. Thus, as opposed to a focused portfolio, portfolio breadth is equivalent to the diversity or number of therapeutic categories, as well as diseases, that the firm targets with its new drug portfolio.

**2.2.2. Portfolio depth.** According to research on product lines (e.g., Bordley 2003; Putsis & Bayus 2001), product portfolio depth refers to the variations in distribution of resources across different markets. Although depth may refer to the intensity with which the firm allocates resources to any particular targeted market, the multiplicity of such markets requires a summary description, which may rely on the unevenness in the distribution of resources across various therapeutic categories or markets. Greater variation in the distribution of resources across therapeutic categories means the portfolio is differentiated to a greater extent, such as deep in some therapeutic categories and shallow in others. With smaller variation, the portfolio is more evenly balanced across therapeutic categories. For example, within the neurological and psychiatric diseases category, GlaxoSmithKline Beecham's new drug projects target depression, schizophrenia, bipolar disorder (manic depression), anxiety disorders, sleep disorders, drug dependence (nicotine and alcohol), hypoactive sexual desire disorder, smoking cessation, and premenstrual dysphoric disorder. Within the respiratory therapeutic category, the firm targets asthma, chronic obstructive pulmonary disease, bronchospasm, and rhinitis. In the viral category, its projects target HIV, hepatitis, genital herpes, sores, and chickenpox. The obvious variations or differentiation in the number of diseases in each therapeutic category indicate the difference in focus and therefore the resource allocations toward various therapeutic categories. Controlling for the number of therapeutic categories and number of diseases a firm targets, greater variation means the firm has adopted a differentiated depth strategy rather than a balanced depth strategy.

**2.2.3. Blockbuster versus shotgun strategy.** With a blockbuster strategy, the firm focuses solely on a few diseases with high market potential, whereas with a shotgun strategy, it emphasizes the development of new products with varying potential (low, medium, and high). Whether a new drug candidate will garner blockbuster sales after commercialization remains speculative during the development stages, so when we use a blockbuster versus shotgun strategy to describe a new drug

portfolio, we refer to the expected market potential of the diseases targeted by the new drugs under development. The expected market potential for such diseases often can be specified a priori by pharmaceutical firms. A portfolio of a few new drug candidates designed to treat diseases with high expected market potential indicates a blockbuster rather than a shotgun strategy.

**2.2.4. Stage of new drug development.** In the context of the pharmaceutical industry, the four stages of the new drug development process consist of preclinical trials and phases I–III of clinical trials. These stages generally are similar to the stage gate process of new product development followed in firms that implement best practices (Griffin 2007), though they do not capture very nascent stages of the development process, in which molecular prototypes or new chemical entities are proposed as potential treatments. As described in prior research (Danzon et al. 2005; DiMasi, Hansen, Grabowski, & Lasagna 1995; Ding & Eliashberg 2002), our four stages of development capture the testing and repeated modification process, which begins with early preclinical tests with animals. Thus, they reflect the extent to which a drug candidate likely will be commercialized. The likelihood that a drug candidate will result in a commercialized identity increases as the drug candidate enters the later stages of development.

### **2.3. Valuation of new drug (product) portfolio strategies**

To evaluate new drug portfolio strategies, we require a robust stock price–based measure, such as Tobin’s  $q$ , which has been used in finance (e.g., Chung & Pruitt 1994), management (e.g., Bharadwaj, Bharadwaj, & Konsynski 1999), and various applications in marketing (e.g., Simon & Sullivan 1993; Srinivasan 2006). Tobin’s  $q$  offers several benefits, namely, that it (1) derives from a firm’s stock price and thus is a forward-looking measure, (2) reflects a firm’s long-term profitability because it captures the link between the replacement cost of the firm’s tangible assets and its market value, and (3) can compare firms across industries because it is not affected by accounting conventions (e.g., Lee & Grewal 2004). On the basis of the efficient market hypothesis, Mizik &

Jacobson (2003) and others (e.g., Kumar & Petersen 2005) claim they can gauge the value of market-based assets and marketing strategies from the excess future returns that the strategies generate.

In the context of new drug portfolios, the firm value accounted for by new drug portfolio strategies therefore should reflect the value of the new drug portfolio. However, it seems feasible that the value descriptors vary across firms. For example, some firms might attain value for the earlier stages of new drug development, others for the final stages.<sup>3</sup> Thus, consistent with the efficient market hypotheses, we capture the current value of future rent with measures of firm value and recognize the possibility of the existence of multiple regimes explaining the value generated by new drug portfolio strategies.

**2.3.1. Portfolio breadth.** The breadth of new drug portfolios captures the extent of diversity in the number of markets targeted by the firm. Focused portfolios enable specialization and the development of deep but narrow knowledge stores (e.g., Miles & Snow 1978; Postrel 2002), whereas diversified portfolios allow for economies of scope and hedged risks (e.g., Kim, Hwang, & Burgers 1993; Luo 2002). Anecdotal evidence supports existing research claims about specialization and diversification (e.g., Miles & Snow 1978) and suggests that financial markets can evaluate both focused and diversified new drug portfolio strategies positively. For example, in the pharmaceutical industry, financial markets value the focused drug development strategy of Wyeth Pharmaceuticals but also appreciate the diversified new drug pipelines of Pfizer.<sup>4</sup> By focusing on a narrow market, firms become experts in the particular domain and reap the benefits of specialization, but by “putting all their eggs in one basket,” they also face a huge downside if the selected focus does not work. The diversification strategy, in contrast, separates the risks associated with new drug

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<sup>3</sup> Similarly, in contexts other than new product portfolios, financial markets may evaluate firms in terms of their current profitability, their future profit potential, or a completely different set of indicators, such as revenue growth.

<sup>4</sup> As we elaborate subsequently, we use latent class regression models to identify structural relationships, which potentially enable us to uncover two (or more) regimes, one that values a focused strategy and another that prefers a diversified strategy. Thus, the modeling framework may offer support for two seemingly contradictory strategies.

development, such that the ultimate outcome (i.e., successful new product) does not depend on a few gambles. As a result, a medium return level appears the most likely scenario for a large portfolio breadth or diversification strategy, but the likelihood of a worst-case scenario decreases.

**2.3.2. Portfolio depth.** A differentiated portfolio depth strategy targets more diseases in a few therapeutic categories and fewer diseases in other therapeutic categories. In contrast, a more even or balanced portfolio depth strategy targets similar numbers of diseases across all therapeutic categories. The former requires firms to pick the markets (therapeutic categories) in which they intend to compete and then invest heavily, whereas the latter pushes product decisions to a later development stage (e.g., Sanchez 1999; Sanchez 1995). Differentiated depth eliminates future strategic options but also can be valuable if financial markets regard the chosen therapeutic categories as potentially beneficial (e.g., Bowman & Hurry 1993). In contrast, though a balanced depth strategy creates future strategic options and thus should be valued, its significant opportunity costs may outweigh the benefits derived from strategic options (e.g., Evans 1991; Grewal & Tansuhaj 2001).

**2.3.3. Blockbuster versus shotgun strategy.** Industry observers suggest that the drug development market should value portfolios with potential blockbuster drug candidates (Outlook 2003, Tufts Center for the Study of Drug Development). A potential blockbuster drug, by definition, is innovative and offers great potential market, which virtually guarantees its long-term, large payoff. Blockbuster drugs also might be valued more as a result of the relatively large size of the several well-known pharmaceutical companies that tend to develop them. Industry experts predict that pharmaceutical companies will grow approximately 20% (or at least at double-digit rates) each year, and with current revenues of more than \$10 billion, such growth can be achieved only through strategies that focus more on potential blockbuster drugs. Finally, two critical drivers of new

drug development, uncertainty and cost, remain relatively similar regardless of the market payoff, which makes potential blockbuster candidates more attractive.

**2.3.4. Stage of new drug development.** On the one hand, the proportion of new drugs at various stages of development may not remain totally under a firm's control. The inherent uncertainty in the process and the extensive timelines for each stage of development may result in uniformly distributed portfolios at each stage of development or a skewed distribution. On the other hand, some firms may acquire others to expand their new drug portfolios, thereby strategically adding to their portfolios. In any case, investors typically are shortsighted and make investment decisions on the basis of publicly available information. Therefore, according to the observable information about a firm's current distribution of new drugs in various stages of development, financial markets should place more value on the final stages of new drug development, in which new drugs approach commercialization. However, financial markets also may value early development stages for certain inventions, which typically are newsworthy and have tremendous potential upsides. In the presence of contrasting arguments about the valuation of stages of development, we contend that several firm-related factors may divert the attention of the financial market to certain stages over others. For example, some firms, such as start-ups or small biotechnology and pharmaceutical firms, lack the slack needed to drive the development of new drugs through all stages of development. Such firms focus more on earlier stages of development and usually enter agreements with larger firms to conduct the final phase of clinical trials and subsequent commercialization. In such conditions, the financial market might focus on earlier stages of development rather than later stages to assign a value to these firms. All such sources of firm-level heterogeneity thus get reflected in multiple regimes of valuation by financial markets, which we proceed to estimate in the following sections.

### 3. Method and Results

#### 3.1. Data sources and variable operationalization

We use Pharmaprojects, a leading database that tracks the new drug development process in the pharmaceutical industry, as a source of data about drugs at various stages of the development process. When we acquired the database, we gained access to information about approximately 29,000 drug candidates under development by 1,451 firms on December 31, 2002. We use the database to create a list of drug candidates from 388 firms, the stage of development for each drug, and the disease the drug was being developed to treat.

**3.1.1. Portfolio breadth.** The breadth or diversity of a new drug portfolio refers to the number of different therapeutic categories and number of different diseases targeted by a pharmaceutical firm's new drug portfolio. We define the total number of therapeutic categories ( $T_{fk}^C$ ) for which firm  $f$  has at least one drug candidate at stage  $k$  as

$$(1) \quad T_{fk}^C = \sum_{c=1}^C N_{fkc} ,$$

where  $N_{fkc}$  is a dummy variable that equals 1 if firm  $f$  has at least one drug candidate under development in stage  $k$  for any disease in therapeutic category  $c$  and 0 otherwise. Similarly, we define the total number of diseases ( $T_{fk}^I$ ) for which firm  $f$  has a drug candidate at stage  $k$  as:

$$(2) \quad T_{fk}^I = \sum_{c=1}^C \sum_{i=1}^{I_c} N_{fkc_i} .$$

These two measures thus capture the breadth of a firm's new product portfolio. As we display in Table 1, out of the six firms, Schering targets a much broader or more diverse range of therapeutic categories and diseases at any stage of development than the other firms.

[Insert Table 1 about here]

**3.1.2. Portfolio depth.** Because depth refers to the extent of variation in the kind of resource allocation or number of diseases targeted across different therapeutic categories, we propose a measure called cross-category variance, which reflects how evenly a firm distributes its resources across therapeutic categories, such that when we control for the number of therapeutic categories and number of diseases, greater variance means the firm adopts a differentiated depth strategy and the portfolio is deep in some therapeutic categories but shallow in others. Assuming at least one drug candidate in a therapeutic category at a given stage, we define the cross-category variance ( $V_{fk}$ ) for development stage  $k$  of firm  $f$  as:

$$(3) \quad V_{fk} = \sum_{c=1}^C \left\{ N_{fkc} \left( \sum_{i=1}^{I_c} N_{fkc_i} - \frac{T_{fk}^I}{T_{fk}^C} \right)^2 \right\}.$$

$T_{fk}^I / T_{fk}^C$  captures the average number of diseases targeted within any therapeutic category at stage  $k$ , and  $\sum_{i=1}^{I_c} N_{fkc_i}$  indicates the total number of diseases in therapeutic category  $c$  targeted by the firm at stage  $k$ . As in any total variance calculation, the difference between the total and the average number of diseases in a therapeutic category is squared and summed across the number of therapeutic categories targeted by the firm at stage  $k$ . For example in Table 1, compared to Ribapharm, both Schering and Corixa provide more differentiated portfolios in at least the first two stages of development. In the first three stages, Schering achieves much greater portfolio depth than the others. The negligible cross-category variation for Ribapharm and Alfacell indicates that they have balanced portfolio depth strategies, with general uniformity in the number of diseases targeted across therapeutic categories.

**3.1.3. Blockbuster versus shotgun strategy.** In the blockbuster strategy, the firm focuses solely on a few diseases with high expected market potential, whereas the shotgun strategy emphasizes the development of various new products with varying potential levels (low, medium,

and high). After controlling for the number of therapeutic categories, the total expected market potential of the new drug portfolio and the number of diseases targeted should provide a measure of the strategy adopted by the firm. If the total expected market potential of the new drug portfolio is high and the number of targeted diseases is low, the numbers reflect a blockbuster strategy.

In calculating the total expected market potential of the new drug portfolio, we take into consideration the risks associated with achieving that potential in the future. For example, for a given disease, because of the risks associated with new drugs in earlier development stages, early-stage drugs should have a lower probability of success than those in the later stages. Therefore, risk-adjusted expected market potential, not simply market potential, becomes critical for evaluating and summarizing the total expected market potential of a firm's new drug portfolio at any stage of development. The risk-adjusted expected market potential ( $M_{fk}$ ) at stage  $k$  for firm  $f$  can be written as follows:

$$(4) \quad M_{fk} = \sum_{c=1}^C \sum_{i=1}^{I_c} m_{ci} N_{fkc i} P_{kci},$$

where  $c = 1, \dots, C$  denotes the number of therapeutic categories;  $i = 1, \dots, I_c$  represents the number of diseases in therapeutic category  $c$ ;  $m_{ci}$  represents the market potential for a drug targeting disease  $i$  in therapeutic category  $c$ ;  $N_{fkc i}$  is a dummy variable that equals 1 if firm  $f$  has a drug candidate under development in stage  $k$  for disease  $i$  in therapeutic category  $c$  and 0 otherwise; and  $P_{kci}$  is the probability that the drug will clear all remaining stages for a  $k$ -stage candidate targeting disease  $i$  in therapeutic category  $c$ .

The Pharmaprojects database also classifies each drug candidate on the basis of its projected market size: means of \$250 million, \$1,250 million, \$3,500 million, \$7,500 million, and \$10,000

million.<sup>5</sup> We use these market size values to represent the market potential for disease  $i$  in category  $c$  ( $m_{ci}$ ). Following existing research (DiMasi et al. 1995), we then calculate the therapeutic category-specific probability of success on the basis of the historical data in the database. The probability that a drug candidate in category  $c$  will survive stage  $k$  ( $p_{kc}$ ) equals the percentage of drug candidates tested in this category that have survived stage  $k$  since 1980. Because of our data constraints, we assume that  $p_{kci} = p_{kc}$  for all  $i$  in category  $c$ .<sup>6</sup> The probability that a stage- $k$  drug candidate in category  $c$  clears all remaining stages ( $P_{kc}$ ) equals the product of the probabilities of it surviving all remaining stages (including  $k$ ), that is, the  $J$ -stage product development process,  $P_{kc} = \prod_{j=k}^J p_{jc}$ .

**3.1.4. Stages of development.** Instead of adding a unique measure for this construct, we rely on the statistical significance of the coefficients of the other constructs in each development stage. For example, if most of the coefficients are statistically significant for Stages 1 and 2 as opposed to Stages 3 and 4, we may conclude that the stock market emphasizes the earlier stages of development rather than the later stages.

**3.1.5. Tobin's q.** For the 388 publicly traded firms for which we have new product portfolio information, we collect data to calculate the Tobin's q as follows (see Chung & Pruitt 1994):

$$(5) \quad TQ = \frac{MVE + PS + DEBT}{TA},$$

where

$$TQ = \text{Tobin's q,}$$

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<sup>5</sup> In the Pharmaprojects database, the market potential for each drug candidate consists of five intervals. By definition, the market potential is not category or disease specific; however, two drugs that target the same disease likely have the same market potential. Pharmaprojects indicates that the information about target markets for drug candidates comes from the firms directly (e.g., firm Web sites, annual reports, press releases). Every firm with an entry in the database is asked to verify the details on their records.

<sup>6</sup> In conversations with high-level R&D executives in pharmaceutical firms, we learned that most firms use the average probability across all therapeutic categories when they calculate the probability of a drug candidate passing a certain stage of the drug development process. To our knowledge, they employ no firm-specific probabilities in practice, and no public data on these probabilities exist.

MVE	= (Closing price of shares at the end of the financial year) × (Number of common shares outstanding),
PS	= Liquidation value of the firm's outstanding preferred stock,
DEBT	= (Current liabilities – Current assets) + (Book value of inventories) + (Long-term debt), and
TA	= Book value of total assets.

For these 388 firms, we obtain information for the 2002 Tobin's q and control variables from the COMPUSTAT database; however, incomplete data reduced our sample to 308 firms.

### 3.2. Control variables

Because variables other than a firm's new product portfolio strategy might influence the value of Tobin's q, we control for a firm's financial strategy, as reflected by a parsimonious summary of its efficiency, liquidity, and leverage ratios, to assess its financial strength. Several studies confirm that these financial ratios can distinguish unhealthy from healthy firms (e.g., Kahya 1997). Financial efficiency, which we measure according to net income (e.g., Black 1980), captures current firm profitability; in most circumstances, firm value tends to increase as efficiency increases (e.g., Platt & Platt 1991). Liquidity ratios, such as current assets to current liabilities, or the current ratio, represent a firm's ability to raise credit in the short term, which may be a slack resource that improves flexibility (Evans 1991) to implement strategies effectively.<sup>7</sup> Finally, leverage ratios, such as the debt-to-equity ratio we use herein, reflect the firm's ability to raise low-interest money to fund future projects, including those related to new drugs. Firms with greater leverage can fund projects that might yield future rents, whereas those with lower leverage have greater flexibility to fund future rent-generating projects.

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<sup>7</sup> In some cases, liquidity could relate negatively to firm performance if the firm does not use its liquid resources to invest in growth opportunities or incurs opportunity costs associated with liquid resources (e.g., Grewal & Tansuhaj 2001; Vorberg & Ulrich 1987). As we elaborate subsequently, we use latent class regression analysis as the data analytic framework (Wedel & Kamakura 2000) and therefore may find multiple regimes (latent segments) that experience different effects of liquidity. Latent class regression analysis should identify those regimes in which the effect is positive versus negative.

We also control for the R&D expenditures (Mizik & Jacobson 2003) and the number of patents issued to a firm in the year 2002 (Griliches 1984), both of which influence the financial market valuations of firms. However, because these two constructs are highly correlated, and because the number of patents often indicates the productivity of R&D expenditures (Dutta, Narasimhan, & Rajiv 1999), we use the constructs separately. To tabulate R&D expenditures, we rely on the COMPUSTAT database; for the number of patents, we obtain information from the U.S. Patent and Trademark Office database.

Competition is an important contingency to take into account when assessing the value of new product strategies (e.g., Carbonella & Rodriguez 2006). We control for competitors' portfolios of new drugs under development, which should affect the value of a given firm's portfolio. For example, a drug candidate adds less value to a firm's portfolio if its competitors already have candidates that target the same disease. To control for such competitive effects, we define the risk-adjusted market potential of all competitors ( $M_{fk}$ ) for firm  $f$ 's stage- $k$  portfolio as:

$$(6) \quad M_{fk} = \sum_{c=1}^C \sum_{i=1}^{I_c} \left[ m_{ci} N_{fki} P_{kci} \left( \sum_{h=1}^F N_{hki} - 1 \right) \right],$$

where  $F$  is the total number of firms.

As this equation shows, we subtract the risk-adjusted expected market potential of the new drug portfolio of the focal firm from the total risk-adjusted expected market potential of the new drug portfolios of all pharmaceutical firms to obtain the risk-adjusted expected market potential of the competitors to the focal firm.

### 3.3. Model specification

Consistent with the preceding discussion, we operationalize a firm's new drug portfolio strategies with portfolio descriptors, namely, number of therapeutic categories, number of diseases, cross-category variance, and risk-adjusted market potential. If our logic holds, we should be able to

identify the aspects of a new drug portfolio strategy that increase and decrease the firm's market valuation. Specifically, we study the following model specification:

$$\begin{aligned}
 TQ_f = & \alpha_0 + \alpha_1 INC_f + \alpha_2 CR_f + \alpha_3 DE_f + \alpha_4 RD_f + \sum_{k=1}^4 \alpha_{5k} CMP_{kf} + \sum_{k=1}^4 \alpha_{6k} NG_{kf} \\
 & + \sum_{k=1}^4 \alpha_{7k} NI_{kf} + \sum_{k=1}^4 \alpha_{8k} CCV_{kf} + \sum_{k=1}^4 \alpha_{9k} MP_{kf} + \varepsilon_f
 \end{aligned} \tag{7}$$

where TQ, INC, CR, DE, RD, CMP, NG, NI, CCV, and MP stand for Tobin's q, net income, current ratio, debt-to-equity ratio, R&D expenditures (in a separate regression, we use the number of issued patents instead of R&D expenditures), competitors' new drug portfolio risk-adjusted market potential, the number of therapeutic categories, number of diseases (indications), cross-category variance, and the firm's new drug portfolio risk adjusted market potential, respectively. The regression parameters are denoted by  $\alpha$ s, the random error by  $\varepsilon$ , and the four stages of new drug development by  $k$ . We present the descriptive statistics in Table 2.

[Insert Table 2 here]

### 3.4. Model estimation strategy

Because we have one year of data from 308 firms, we use ordinary least squares to obtain the best linear unbiased estimate. However, such an aggregate approach rules out the presence of multiple regimes (e.g., Bijmolt, Paas, & Vermunt 2004; Kamakura, Wedel, & Agrawal 1994), which may suggest that the stock market evaluates groups of firms in several different manners. Multiple regimes can exist for firm valuation and, by extension, the valuation of new drug portfolios. Thus, to allow for the presence of multiple regimes, we use latent class regression analysis (see the Appendix). Specifically, for Equation 7, we use the following specification:

$$(8) \quad TQ_f = \sum_{r=1}^R \sum_{a=0}^9 [\alpha_{ar} X_{af} + \varepsilon_{rf}],$$

where  $R$  denotes the number of empirically determined regimes,  $\alpha$  is the vector of regime-specific parameter estimates, and  $X$  is the matrix of explanatory variables, including the constant term.

## 4. Results

### 4.1. Model selection

We provide results for three models. The first does not control for R&D expenditures and number of issued patents, the second controls for R&D expenditures, and the third controls for the number of issued patents. The consistent Akaike information criterion (CAIC) values show that in all three models, two regimes ( $CAIC_{\text{model1}} = 1655$ ,  $CAIC_{\text{model2}} = 1687.12$ ,  $CAIC_{\text{model3}} = 1690.83$ ) outperform models with just one ( $CAIC_{\text{model1}} = 2131$ ,  $CAIC_{\text{model2}} = 2144.60$ ,  $CAIC_{\text{model3}} = 2150.43$ ) or three ( $CAIC_{\text{model1}} = 1708$ ,  $CAIC_{\text{model2}} = 1749.74$ ,  $CAIC_{\text{model3}} = 1777.03$ ) regimes. In the two-regime solution, the first regime consists of 90% of the firms, and its entropy of separation value falls in the range of .86–.93, which implies good separation between the latent regimes and enhances confidence in the model. Because Regime 1 includes the majority of the firms in our data set for the two-regime solutions, it appears that the market is generally efficient and uses similar criteria to value most firms.

### 4.2. Estimation results

In Tables 3 and 4, we present the results for Regimes 1 and 2, respectively. Although we add the theoretically important controls of R&D expenditures and number of issued patents one at a time, we do not find any substantial differences in the direction or statistical significance of coefficients across the three models, which suggests the robustness of our results.

[Insert Tables 3 and 4 here]

**4.2.1. Regime 1 results.** In terms of control variables, a higher current ratio tends to decrease the market valuation of firms ( $b = -.414$ ,  $p < .01$ ; we refer to Model 2 from Table 3, which includes R&D expenses as a control variable). None of the other control variables, including R&D

expenses, has any statistically significant influence on the firm's market valuation. An emphasis on more therapeutic categories, which signals new drug portfolio diversification, increases market valuation ( $b = .704, p < .05$ ) in the later stages (stage 4) of development. However, more targeted diseases reduces market valuation in the later stages of development, especially stage 4 ( $b = -.528, p < .10$ ).

The new drug portfolios of almost all firms in Regime 1 have significant expected market potential, as evidenced by their large mean values and small standard deviations (Stage 1:  $m = 909.93, sd = 77.34$ ; Stage 2:  $m = 755.52, sd = 102.52$ ; Stage 3:  $m = 1458.48, sd = 169.24$ ; Stage 4:  $m = 1569.31, sd = 210.80$ ). Thus, even though we do not find any statistically significant effect for risk-adjusted expected market potential, its effect may be captured in the intercept term for Regime 1 ( $b = 1.958, p < .01$ ). Fewer targeted diseases implies that the average risk-adjusted expected market potential per disease should be quite high. Because we control for the sum of risk-adjusted expected market potential of the new drug portfolio, this preference for fewer diseases ( $b = -.528, p < .10$ ) indicates a general stock market preference for concentration of fewer diseases with greater risk-adjusted expected market potential for every disease. That is, the stock market values a firm that follows a blockbuster portfolio strategy. Finally, as most of the statistically significant coefficients emerge in stage 4 of new drug development, we conclude that the stock market prefers new drugs in the later stages of development in this regime.

**4.2.2. Regime 2 results.** In terms of financial variables, as net income increases, so does market valuation ( $b = .664, p < .01$ ). In addition, a higher debt-to-equity ratio tends to increase the market valuation of firms in Regime 2 ( $b = 2.568, p < .05$ ). For the competitor variables, we find negative effects of the total risk-adjusted market potential of competitors' new drug portfolios in stage 2 on market valuation ( $b = -.015, p < .01$ ). Although a significant negative effect for this competitor variable emerges in stage 4 ( $b = -.034, p < .05$ ), the effect disappears when we control

for R&D expenditures and number of patents. Unlike in Regime 1, in Regime 2, both R&D expenditures ( $b_{\text{model } 2} = .088, p < .10$ ) and number of issued patents ( $b_{\text{model } 3} = .001, p < .10$ ) indicate significant positive influences on market valuation.

The stock market values more therapeutic categories in stage 2, that is, the beginning of clinical trials ( $b = 73.321, p < .01$ ). In terms of the number of diseases however, the stock market prefers fewer in stage 2 ( $b = -78.523, p < .01$ ). The results also seem to suggest that the stock market strongly favors greater cross-category variance (portfolio depth). In other words, a well-differentiated portfolio depth strategy strongly increases a pharmaceutical firm's market valuation ( $b = 447.986, p < .01$ ) in stage 2 among firms in Regime 2. A similar positive effect appears in stage 3 ( $b_{\text{model } 1} = 82.66, p < .10$ ), though it becomes statistically insignificant when we control for R&D expenditures and number of patents. Higher risk-adjusted expected market potential of a new drug portfolio increases its market valuation in stage 4 ( $b = .029, p < .01$ ); when we control for this risk-adjusted expected market potential, we find that the stock market prefers fewer diseases (refer to result for number of diseases). Therefore, similar to Regime 1, in Regime 2, the stock market prefers a blockbuster portfolio strategy that focuses on a few diseases with greater average risk-adjusted expected market potential. Finally, most of the statistically significant coefficients occur in stage 2, so we infer that for firms in Regime 2, the stock market prefers new drugs to be in earlier stages of development.

## **5. Discussion**

Our exploratory research describes new drug portfolio strategies in terms of their breadth or diversity in new therapeutic categories and diseases, depth or variation in the number of diseases targeted in each therapeutic category, blockbuster versus shotgun strategies, and stages of new drug development. Financial markets know the importance of portfolio management and will increase or decrease a firm's stock value or market valuation on the basis of its new drug portfolio strategies.

Overall, a firm's market valuation increases with a broader and more diversified portfolio that targets multiple therapeutic categories. A blockbuster strategy also appears valued by financial markets. The financial market further recognizes interfirm differences and values certain firms differently from others. For most firms in our sample, financial markets favor broad portfolios that target multiple therapeutic categories in later stages of development, but prefer a limited number of diseases to be distributed across these therapeutic categories. However, for 31 firms, the markets want a broad portfolio with multiple targeted therapeutic categories and few diseases, though only in the earlier stages of development. In addition, for these 31 firms, the financial market emphasizes a differentiated depth strategy, with more targeted diseases in some therapeutic categories and fewer in others.

[Insert Table 5 here]

If the financial market differentiates between firms in terms of valuation, how do the profiles of the firms in the two regimes of valuation differ? In Table 5, we provide a list of differentiation factors; firms in Regime 1 are significantly larger in terms of number of employees ( $\text{mean}_{\text{Regime1}} = 6.54$ ,  $\text{mean}_{\text{Regime2}} = .12$ ), older ( $\text{mean}_{\text{Regime1}} = 30$ ,  $\text{mean}_{\text{Regime2}} = 18$ ), and have higher liquidity ( $\text{mean}_{\text{Regime1}} = 7.20$ ,  $\text{mean}_{\text{Regime2}} = 2.00$ ). We do not find a corresponding difference in net sales, primarily because Regime 1 comprises both very large firms and small firms, so the variance in net sales is dramatic. Firms in Regime 1 range from mega-pharmaceutical firms, such as Pfizer, Aventis, and Merck, to small biotech companies, such as Imclone Systems Inc. and Ligand Pharmaceuticals.

Not only are firms in Regime 2 much smaller, but the time since their incorporation is much shorter than those in Regime 1. The products in their development pipelines suggest that most new drugs under development remain in the preclinical stage or phase I of clinical trials. As an example, Alfacell Corporation targets eight diseases in two therapeutic categories, that is, oncology and viral. Of these eight diseases, drug candidates for only two have progressed to phase III of clinical trials,

and the rest are in the preclinical stage or phase I. Amylin Pharmaceutical's product pipeline shows three developmental projects that have yet to reach phase II of clinical trials. All five new drug candidates of Manhattan Pharmaceutical, across its targeted categories of dermatology and immunology, remain in their preclinical stage. Similarly, about 70% of the new drug candidates created in-house by Insite Vision have yet to reach phase II of clinical trials.

The primary difference in valuation between the regimes depends on the focus on different stages of development and portfolio depth. If we pool the observations for firms in Regime 2, we can infer that their extremely small sizes and corresponding lack of resources prevents these firms from pushing their own innovations through the final stages of development. Prior research reveals that very small firms, such as start-ups, often form cooperative agreements with larger, more established firms to improve the success rates of their innovations, especially in the biotechnological and pharmaceutical domains (Shan, Walker, & Kogut 1994). Because the definition of a start-up firm varies, with some scholars suggesting size as a demarcation and others recommending organizational experience or age (e.g., Barkema & Vermeulen 1998), we cannot establish firmly whether the small firms in Regime 2 are start-ups. However, we can conclude that these firms are smaller and younger than firms in Regime 1, which means they have greater capability to invent new chemical entities and test their functionalities on a small scale compared with that for pushing through expensive and large-scale later-stage clinical trials on humans. Therefore, it is not surprising that the financial market pays attention to the earlier stages of development rather than the later stages among these firms.

The considerably larger values of Tobin's  $q$  enjoyed by firms in Regime 2 imply that their market values far exceed the value related to their tangible assets, primarily because of the intangible value ascribed to their product market assets (Srivastava, Shervani, & Fahey 1998), of which the new drug (product) portfolio is a part. The intangible value of these small and young firms increases

because of the level of expertise they display in certain subsets of therapeutic categories. The differentiated depth strategy of these firms also reflects the types of platform technologies they deploy to research specific therapeutic categories intensively. Hemispherx, a small biopharmaceutical firm, has developed a platform technology that includes large and small agent components and that enables it to extract multiple treatments for several viral infections. Unigene Laboratories focuses on the oral and nasal delivery of peptide drugs, which can be adopted easily to treat many different diseases. Similarly, NovaDel Pharmaceutical owns a lingual spray technology with applications for several drug candidates. Inspire Pharmaceutical has patented many innovations related to the discovery and synthesis of nucleotides that could be important for treating diseases involving deficiencies in the body's mechanisms to protect mucosal surfaces.

By attempting to count the chickens before the eggs hatch, our exploratory study into the market valuation of new drug portfolios that remain under development offers several implications for managers. First, most pharmaceutical firms get valued in a similar fashion; in that most belong to Regime 1. Because the later stages of the new drug portfolio are valued more highly in this regime, the recent frenzy to acquire firms with products close to the final stages of their new development process makes sense. Pfizer, for example, has undergone two mega-mergers in the past two years, mostly to supplement its late-stage new drug pipeline. Second, smaller biotechnology and pharmaceutical firms can enjoy the support of shareholders and raise more money from the financial market by developing expertise and depth in certain therapeutic categories, as well as by concentrating on the pipeline of new drug candidates during early development stages. Third, having a portfolio of potential blockbuster drug candidates increases the prospects of long-term profitability, which suggests that smaller firms with blockbuster strategies represent the ideal candidates for acquisition by larger and more established firms.

## **6. Limitations and Future Research Opportunities**

In our description of new drug portfolio strategies, we do not include the level of innovativeness, or the proportion of radical new products relative to incremental new products in a portfolio. Although it may provide an important descriptor of new product portfolios in general (Voss, Montoya-Weiss, & Voss 2006), according to repeated surveys by the Product Development and Management Association, the innovativeness of a product portfolio structure actually does not differ between the best performing firms and others (PDMA 2004). Financial markets thus may overlook this aspect of a new drug (product) portfolio and focus instead on the descriptors included in our research. Nevertheless, the level of innovativeness of a new drug portfolio provides an important future research area.

Our research deals with an important financial consequence of structuring new drug portfolios, especially in relation to the overwhelming call to integrate marketing with shareholder value creation. However, substantial potential exists in the investigation of other relevant financial consequences. For example, a broad new drug portfolio may provide strategic options or a hedge against uncertainties, while it also restricts the firm's potential to extract maximum returns from any particular therapeutic category because of its distributed resource allocations. We recognize the possible trade-offs in creating a specific type of new drug portfolio in terms of the risks, market share growth, and revenue optimization. A study of such trade-offs would provide an interesting extension of this research.

Finally, due to lack of data across multiple years, we could provide results for only the year 2002. The Pharmaprojects database is unique, in that it precludes observers from moving back in time, which prevents us from conducting a longitudinal study. However, the use of cross-sectional data is fairly common as a means to assess relationships between marketing constructs and shareholder value, as in the context of consumer good brands (Kerin & Sethuraman 1998) and

global expansion (Christophe & Lee 2005). Yet a longitudinal data set would have enabled us to track the extent to which new drug portfolios change over time, as well as the corresponding impacts on financial values. Therefore, we encourage additional research that explores the dynamic relationship between a firm's changing new drug portfolio and its financial consequences.

**Table 1**  
**Examples of Portfolio Breadth and Portfolio Depth**

	Number of Therapeutic Categories				Number of Diseases				Portfolio Depth or Cross-Category Variance			
	S1	S2	S3	S4	S1	S2	S3	S4	S1	S2	S3	S4
Alfacell	1	0	0	1	1	0	0	1	0	0	0	0
Corixa	5	2	1	3	12	3	1	4	3	1	0	1
Novadel	6	0	4	0	8	0	5	0	2	0	1	0
Pfizer	11	5	9	6	24	7	14	11	1	1	1	1
Ribapharm	0	2	2	0	0	2	2	0	0	0	0	0
Schering	12	9	11	6	29	24	31	6	6	2	5	0

Notes: S1 is Stage 1, S2 is Stage 2, S3 is Stage 3, and S4 is Stage 4. As indicated by our estimation, Corixa, Pfizer, and Schering are members of Regime 1, and Alfacell, Novadel, and Ribapharm are members of Regime 2.

**Table 2**  
**Descriptive Statistics**

Variables	Mean	Standard Deviation
Tobin's q	2.99	6.11
Sales (\$ million)	1587.37	6636.89
Net income (\$ million)	174.87	1010.48
Current ratio	6.67	9.14
Debt to equity ratio	.31	3.03
R&D expenditures (\$ million)	231.14	749.84
Number of patents	14.94	52.37
Stage 1: Competitors' risk-adjusted market potential (\$ million)	106047.42	145824.36
Stage 2: Competitors' risk-adjusted market potential (\$ million)	10089.22	25936.88
Stage 3: Competitors' risk-adjusted market potential (\$ million)	17960.69	34497.61
Stage 4: Competitors' risk-adjusted market potential (\$ million)	8738.82	22346.37
Number of therapeutic categories (stage 1)	2.27	2.24
Number of therapeutic categories (stage 2)	.85	1.41
Number of therapeutic categories (stage 3)	1.20	1.65
Number of therapeutic categories (stage 4)	.73	1.25
Number of diseases (stage 1)	3.40	4.41
Number of diseases (stage 2)	1.08	2.23
Number of diseases (stage 3)	1.61	2.92
Number of diseases (stage 4)	.92	1.82
Cross-category variance (stage 1)	.44	1.35
Cross-category variance (stage 2)	.04	.19
Cross-category variance (stage 3)	.12	.53
Cross-category variance (stage 4)	.06	.34
Stage 1: Risk-adjusted market potential (\$ million)	878.79	1253.42
Stage 2: Risk-adjusted market potential (\$ million)	714.56	1638.83
Stage 3: Risk-adjusted market potential (\$ million)	1390.52	2700.12
Stage 4: Risk-adjusted market potential (\$ million)	1445.57	3358.53

**Table 3**

**Market Valuation of New Drug Portfolio Strategies for Regime 1**

Variable Category	Explanatory Variables	Regime 1		
		Model 1 Coefficient (t-value)	Model 2 Coefficient (t-value)	Model 3 Coefficient (t-value)
Control variables	Constant	1.994*** (12.359)	1.958*** (12.894)	2.012*** (12.021)
	Net income <sup>a</sup>	.002 (1.303)	0.002 (1.603)	0.002 (1.613)
	Current ratio <sup>a</sup>	-.429*** (-5.066)	-0.414*** (-4.762)	-0.435*** (-5.128)
	Debt-to-equity ratio	-.009 (-.325)	-0.074 (-0.275)	-0.009 (-0.325)
	R&D		-0.001 (-.471)	
	Patents			-0.001 (-0.741)
Competitors' risk-adjusted market potential	Stage 1 <sup>a</sup>	-.000 (-1.245)	-.000 (-1.422)	-.000 (-1.3581)
	Stage 2 <sup>a</sup>	.000 (.681)	.000 (0.692)	.000 (0.5342)
	Stage 3 <sup>a</sup>	-.000 (-1.301)	-.000 (-1.463)	-.000 (-1.3971)
	Stage 4 <sup>a</sup>	-.000 (-1.052)	-.000 (-0.845)	-.000 (-0.8772)
Number of therapeutic categories	Stage 1	-.119 (-1.063)	-0.115 (-1.047)	-0.126 (-1.128)
	Stage 2	.044 (.192)	0.039 (0.157)	0.032 (0.126)
	Stage 3	.174 (1.001)	0.157 (0.918)	0.189 (1.075)
	Stage 4	.788** (2.508)	0.704** (2.245)	0.726** (2.281)
Number of diseases	Stage 1	-.071 (-.841)	-0.067 (-0.800)	-0.065 (-0.766)
	Stage 2	.063 (.278)	0.062 (0.271)	0.064 (0.275)
	Stage 3	.041 (.254)	0.061 (0.388)	0.039 (0.248)
	Stage 4	-.596* (-2.066)	-0.528* (-1.837)	-0.566* (-1.921)

Cross-category variance (portfolio depth)	Stage 1	-.017 (-.216)	-0.0163 (-0.208)	-0.022 (-0.278)
	Stage 2	.131 (.144)	0.0355 (0.037)	0.0529 (0.0546)
	Stage 3	-.381 (-1.496)	-0.376 (-1.376)	-0.384 (-1.376)
	Stage 4	.207 (.666)	0.0726 (0.222)	0.087 (0.263)
Risk-adjusted market potential	Stage 1 <sup>a</sup>	.003 (1.195)	0.004 (1.320)	0.004 (1.309)
	Stage 2 <sup>a</sup>	-.002 (-1.412)	-0.002 (-1.390)	-0.002 (-1.263)
	Stage 3 <sup>a</sup>	.001 (.681)	0.001 (0.820)	0.001 (0.794)
	Stage 4 <sup>a</sup>	.001 (1.292)	0.001 (1.104)	0.001 (1.219)
Profiling variables	Constant	.946*** (8.786)	.927*** (8.825)	.914*** (8.403)
	Sales <sup>a</sup>	.007 (1.299)	.003 (1.342)	.003 (1.040)
Pseudo R-square		.221	.223	.223

\*\*\*  $p < .01$ . \*\* $p < .05$ . \* $p < .10$ .

a) For ease of presentation, we multiply the estimated coefficient and standard error by 10.

Notes: Because R&D expenditures and number of issued patents are highly correlated, we incorporate these two variables, one at a time, into the basic regression model (model 1).

**Table 4**  
**Market Valuation of New Drug Portfolio Strategies for Regime 2**

Variable Category	Explanatory Variables	Regime 2		
		Model 1 Coefficient (t-value)	Model 2 Coefficient (t-value)	Model 3 Coefficient (t-value)
Control variables	Constant	27.753*** (7.186)	29.929*** (7.227)	25.324*** (5.988)
	Net income <sup>a</sup>	.505** (2.094)	.664*** (2.949)	.667*** (2.654)
	Current ratio <sup>a</sup>	1.923 (.283)	.467 (.290)	.219 (.098)
	Debt-to-equity ratio	2.124** (2.182)	2.568** (2.030)	2.443* (1.687)
	R&D		.088* (1.661)	
	Patents			.001* (1.681)
Competitors' risk-adjusted market potential	Stage 1 <sup>a</sup>	-.000 (-.852)	.000 (.901)	.000 (.908)
	Stage 2 <sup>a</sup>	-.014** (-2.185)	-.015*** (-2.486)	-.015*** (-2.513)
	Stage 3 <sup>a</sup>	-.003 (-1.256)	-.002 (-.473)	-.001 (-.411)
	Stage 4 <sup>a</sup>	-.034** (-1.902)	-.001 (-.735)	-.062 (-1.230)
Number of therapeutic categories	Stage 1	-1.223 (-.218)	-2.268 (-.340)	-1.956 (-.483)
	Stage 2	57.864* (1.681)	73.321*** (2.357)	73.346** (1.982)
	Stage 3	9.906 (.803)	6.501 (.620)	6.038 (.945)
	Stage 4	-74.388 (-1.237)	-34.697 (-.556)	-44.60 (-.209)
Number of diseases	Stage 1	-3.360 (-.706)	-2.592 (-.429)	-2.633 (-.629)
	Stage 2	-61.587* (-1.829)	-78.523*** (-2.488)	-78.730*** (-2.840)
	Stage 3	-9.538 (-.742)	-8.132 (-.651)	-8.312 (-.258)
	Stage 4	61.667 (1.024)	20.986 (0.322)	21.523 (.160)

Cross-category variance (portfolio depth)	Stage 1	.916 (.161)	.535 (.102)	1.252 (.091)
	Stage 2	377.631*** (3.318)	447.986*** (2.565)	446.872*** (2.631)
	Stage 3	82.666* (1.966)	59.557 (1.370)	59.246 (1.699)
	Stage 4	-42.076 (-1.245)	-25.860 (-.714)	-24.850 (-.713)
Risk-adjusted market potential	Stage 1 <sup>a</sup>	.002 (.036)	.001 (.227)	.000 (.248)
	Stage 2 <sup>a</sup>	-.029 (-.193)	-.003 (-.276)	-.003 (-.0.272)
	Stage 3 <sup>a</sup>	.057 (.794)	.004 (.548)	.190 (.731)
	Stage 4 <sup>a</sup>	.315*** (4.337)	.029*** (4.070)	.118*** (4.529)
Pseudo R square		.651	.666	.692

\*\*\*  $p < .01$ . \*\* $p < .05$ . \* $p < .10$ .

a) For ease of presentation, we multiply the estimated coefficient and standard error by 10.

Notes: Because As R&D expenditures and number of issued patents are highly correlated, we incorporate these two variables, one at a time, into the basic regression model (model 1). This table presents results for Regime 2, so there are no concomitant profiling coefficients, because we treat Regime 2 as the base.

**Table 5**  
**Statistically Significant Differences in Firm Profiles across Regimes**

Variables	Regime 1 mean (s.e)	Regime 2 mean (s.e)
Current Ratio	7.20 <sup>***</sup> (.57)	2.00 <sup>***</sup> (.58)
Stage 1: Competitors risk-adjusted expected market potential (in \$ million)	11151.40 <sup>**</sup> (8912.35)	57188.40 <sup>**</sup> (20037.85)
Stage 4: Competitors risk-adjusted expected market potential (in \$ million)	9523.46 <sup>*</sup> (1401.77)	1727.70 <sup>*</sup> (1220.37)
Stage 2: Number of therapeutic categories	.90 <sup>*</sup> (.09)	.45 <sup>*</sup> (.17)
Stage 4: Number of therapeutic categories	.79 <sup>**</sup> (.08)	.19 <sup>**</sup> (.07)
Stage 1: Number of diseases	3.54 <sup>*</sup> (.27)	2.13 <sup>*</sup> (.48)
Stage 4: Number of diseases	.99 <sup>**</sup> (.11)	.23 <sup>**</sup> (.09)
Stage 4: Risk-adjusted expected market potential	1569.31 <sup>*</sup> (1569.31)	339.83 <sup>*</sup> (158.45)
Number of employees	6.54 <sup>*</sup> (21.11)	.12 <sup>*</sup> (.20)
Age (in years)	30 <sup>*</sup> (761.70)	18 <sup>*</sup> (29.01)
Tobin's q	1.73 <sup>***</sup> (1.90)	15.31 <sup>***</sup> (255.6)

\*\*\* Mean value between Regime 1 and Regime 2 is statistically different at  $p < .01$ .

\*\* Mean value between Regime 1 and Regime 2 is statistically different at  $p < .05$ .

\* Mean value between Regime 1 and Regime 2 is statistically different at  $p < .10$ .

Notes: We include only variables for which statistical differences exist across Regime 1 and Regime 2.

## APPENDIX LATENT CLASS REGRESSION ANALYSIS

We take the following modeling approach to account for the possibility of multiple regimes, as specified in Equation 8:

$$(A1) \quad TQ_f = \sum_{r=1}^R \sum_{a=0}^9 [\alpha_{ar} X_a + \varepsilon_r].$$

To estimate this multiregime model, we use a finite mixture of linear regressions, also known as latent class regressions (DeSarbo & Cron 1988; Hutchinson, Kamakura, & Lynch 2000; Wedel & Kamakura 2000), based on finite mixture distribution theory (Everitt & Hand 1981; Titterton, Smith, & Makov 1985). We use the Bayes rule to calculate the posterior probability that regime  $r$  will be representative of firm  $f$ ; that is:

$$(A2) \quad P[f \in r | TQ_f] = \frac{\delta_{r|f} L_{f|r}}{\sum_{r=1}^R \delta_{r|f} L_{f|r}},$$

where  $\delta_{r|f}$  denotes the prior probability that firm  $f$  belongs to regime  $r$ , and  $L_{f|r}$  is the likelihood that firm  $f$  belongs to regime  $r$ .

Consistent with extant literature (Dayton & MacReady 1988; Kamakura et al. 1994), we use the logit formulation to specify the prior probabilities:

$$(A3) \quad \delta_{r|f} = \frac{e^{\kappa_r}}{\sum_{r=1}^R e^{\kappa_r}},$$

We estimate  $\kappa_r$  for each regime. Again, we can standardize Equation A3:

$$(A4) \quad \delta_{r|f} = \frac{e^{\kappa_r}}{[1 + \sum_{r=1}^{R-1} e^{\kappa_r}]}$$

Thus, we treat the last regime as the base and must estimate only  $R - 1$  parameters.

Consistent with the concomitant variable approach (e.g., Dayton & MacReady 1988; Kamakura et al. 1994), we use firm size (indicated by sales) as a determinant of regime membership. The likelihood of each regime may be specified on the basis of the standard normal density, as follows:

$$(A5) \quad L_{f|r} = \phi^*(\varepsilon_r),$$

where  $\phi^*(\cdot)$  is the standardized normal density function, and  $\varepsilon_r$  is the residual error, such that  $\varepsilon_r \sim N(0, \sigma_r)$ .

Thus, the likelihood function can be written as

$$(A6) \quad L = \prod_{f=1}^F \sum_{r=1}^R \theta_{r|f} L_{f|r},$$

where, we have  $F$  firms in the data set and estimate the relationship for  $R$  regimes.

We maximize natural logarithm of Equation A6 to obtain parameter estimates for the  $R$  regime solution. Specifically, we use the E-M algorithm with 50 random start values to obtain the parameter estimates. To determine the number of the regimes, we use CAIC (Bozdogan 1987) and compare the model with  $r$  regimes with a model with  $r + 1$  regimes,  $\forall r = 1, 2, \dots$ , until model fit stops improving. We calculate the CAIC as follows:

$$(A8) \quad CAIC = -2 * LL + K * (1 + \ln(N)),$$

where  $LL$ ,  $K$ , and  $N$  stand for the log-likelihood value, number of parameters, and sample size, respectively.

We also report an entropy measure of separation (ES) to assess the extent of separation of the clusters (Wedel & Kamakura 2000). We calculate ES (bound to the range 0–1, such that a value closer to 1 indicates good separation of regimes) as:

$$(A9) \quad ES = 1 - \frac{\sum_{n=1}^N \sum_{r=1}^R -p_{n|r} \ln(p_{n|r})}{N \ln(R)},$$

where  $p_{n|r}$  is the probability of unit  $n$  belonging to regime  $r$ , which we calculate using the Bayes rule specified in Equation A2.

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