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Counting chickens before the eggs hatch: Associating new product development portfolios with shareholder expectations in the pharmaceutical sector

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ABSTRACT

Drug development is the lifeblood of pharmaceutical firms and a critical source of 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, the current literature does not elaborate on strategies pertaining to these new drug (product) portfolios (i.e., portfolios of drugs under development), nor does it provide the means with which to understand the future cash flow-generating potential of these portfolio strategies. To address this problem, we propose a set of generic descriptors of new drug portfolio strategies (i.e., portfolio breadth, portfolio depth, blockbuster strategy, and stages of the drug development process) and relate these descriptors to Tobin's q , a forward-looking measure of shareholder expectations. The results of a latent class regression analysis show that shareholder expectations of firms with broad new drug portfolios and potential blockbusters are positive. For most firms, shareholders focus on the final stage of the drug development process and deemphasize portfolio depth. In contrast, for a minority of mostly small firms, shareholders seem to value the earlier stages of the drug development process and stress portfolio depth.

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1. Introduction

Considering that healthcare expenditures constitute 8–15% of the gross domestic product in most developed countries (Shankar, 2007), research advancing the management of healthcare and life science technologies is considered vital for progress. The pharmaceutical sector has grown more than any other component of the healthcare industry, both in terms of expenditure and innovation. 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). Much of the growth is sustained by the continuous introduction of new products addressing diseases in desperate need of remedies. The development of new drugs is the lifeblood of most pharmaceutical firms, and it is no wonder that pharmaceutical firms spend approximately 20–30% of their revenues on research and drug development.

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. Drug development is also costly, costing \$800 million–\$1 billion per drug, and extremely risky, as only 1 in 50,000 chemical entities gen-

erated in the earliest stages of development ultimately qualify as a new drug candidate that moves into the later stages of development. In addition, the development time of a new drug is quite lengthy (10–12 years on average), as each drug must clear multiple stages during the development process.

The multiple stages of the drug (product) development process in the pharmaceutical industry comprise the following: *in silico* and *in vitro* analyses identify a potential drug candidate as a treatment for a given disease, after which preclinical animal tests are conducted. If the preclinical tests yield promising results, the firm files an application with the Federal Drug Administration (FDA) to test the drug on human subjects through a series of clinical trials. The clinical trial stage comprises three phases. In phase I the drug is tested in a small number of healthy human subjects for safety; in phase II the drug is tested for efficacy and potential side effects on an average-sized sample of a few hundred patients; and in phase III the drug is tested for dosage guidelines and a detailed clinical profile using thousands of patients is established. Finally, the test results are submitted to the FDA for evaluation and possible approval.

In increasingly risky industry environments, such as the pharmaceutical sector, 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’ list of active new product projects is constantly updated and revised,” optimizes resource allocation among new product projects at various stages of development and is aimed at

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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 the corporate strategy of pharmaceutical firms. However, 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 assess the revenue-generating potential of their portfolio strategies.

The challenge in assessing 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 assess portfolios on the basis of their historical performance – akin to counting chickens before the eggs hatch. Unfortunately, no objective measures of the future revenue-generating potential of new product portfolios exist, though such measures would represent powerful tools for distinguishing among new drug portfolio strategies. Decisions regarding individual projects often rely on a net present value analysis to make go/no-go decisions for product development projects. Although similar techniques could be adapted for portfolios, incorporating synergies and complementarities would be difficult, and managerial judgments regarding 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).¹

We believe that shareholder expectations, as expressed through stock market-based indicators, might help overcome this lack of objectivity in understanding the firm's future cash flows accruable to new drug portfolio strategies. The efficient market hypothesis found in the 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 an uncertain future income quickly, as reflected in rapidly updated stock prices (e.g., Fama, Fisher, Jensen, & Roll, 1969). Forward-looking measures are common (e.g., Goldenberg, Libai, Moldovan, & Muller, 2007); especially stock price-based indicators, which are increasingly popular for assessing the value of market-based assets (e.g., Rust, Ambler, Carpenter, Kumar, & Srivastava, 2004). Consistent with the efficient market paradigm, we propose that the association of new drug portfolio strategies and a stock price-based measure can assist in understanding shareholder expectations of a firm's future cash flows accruable to its new drug portfolio strategies. We also clarify that we do not intend to make generalized claims about the effectiveness of new drug portfolio strategies, but rather to explore their relationships with stock price-based measures. Due to federal regulations, information about drugs under development is made public by the FDA. Hence, the pharmaceutical sector is ideal for research into the connections between new drug portfolio strategies and stock price-based measures of firm valuation.

We propose descriptors of new drug portfolios that capture four key strategic dimensions, namely portfolio breadth (number of different markets targeted), portfolio depth (variation in allocation of resources among different targeted markets), blockbuster strategy (a portfolio with a high expected market potential and few targeted diseases), and the stage of drug development (earlier versus later). The literature on product policy supports the use of some of these descriptors, such as breadth and depth (e.g., Bordley, 2003). In turn, we hope to capture these four descriptors of a firm's new drug

portfolio strategies and relate them to Tobin's q , a stock market-based indicator of a firm's value (Wernerfelt & Montgomery, 1988).

Because both systematic studies on product portfolio valuation and relevant historical results in the area of healthcare innovation and management are lacking, we recognize that our research is largely exploratory. We further characterize this research as exploratory because we claim only associations between the four descriptors of new drug portfolio strategies and Tobin's q , not causal effects of the descriptors on Tobin's q . Nonetheless, we seek to make several important contributions to the general innovation management literature 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 the economic potential of portfolios in this strategically important sector. By providing an objective assessment of shareholder expectations of new drug portfolios, and consequently of the firm, we make it easier to identify the most favorable practices among pharmaceutical firms. Finally, we use a measure based on stock prices (Tobin's q ; e.g., Simon & Sullivan, 1993) to understand the economic value of new drug (product) portfolios and thus respond to requests by scholars who suggest that 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, Ambler, Carpenter, Kumar, & Srivastava, 2004).

We organize the remainder of this article as follows: in the following section, we provide a background of the previously conducted innovation research set in the context of the pharmaceutical industry. Based on this overview, we discuss four descriptors of new drug portfolio strategies and theoretically explore their associations with Tobin's q . Next, we examine these associations by a latent class regression analysis to account for the possibility of multiple regimes². 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 drug development form the crux of life sciences and healthcare-related research in the pharmaceutical sector. A broad range of studies examine (1) drug development decisions, (2) interfirm alliances to develop new drugs, and (3) the economics of drug development. Together, these studies provide valuable guidelines for managing a creative and dynamic drug development strategy.

Research on drug development decisions focuses on two broad areas: the drug development process and the new drug portfolios. A broad range of theoretical perspectives serves to suggest improvements to the drug development process and related innovations. On the basis of a valuable decision model that reveals the ideal extent or number of new drugs on the market, Ding and Eliashberg (2002) showed that leading firms underspend on drug development during clinical trials and suggested that firms need different drug development pipelines for different development problems. Applying a problem-solving perspective, Chandy, Hopstaken, Narasimhan, and Prabhu (2006) explained that though pharmaceutical firms are under extreme pressure 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 extent or number of new drugs,

¹ As summarized by Cooper et al. (1998), several scholars define a new product portfolio as effective if it meets the following criteria: (1) it aligns with business objectives, such as maximizing financial returns, (2) it includes high-value projects, (3) it achieves resource efficiencies through congruence between project spending and business strategies, (4) projects reach completion in a timely manner, (5) projects are balanced, and (6) it includes an appropriate number of projects. Following these criteria, managers can collect perceptual data using Likert scales and assess the extent to which their portfolios are effective.

² 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 segments result from the inherent heterogeneity among firms, which makes certain associations valid for some firms and invalid for others (see the Appendix).

formal behavioral and output control mechanisms should enable the effective implementation of the drug development process (Cardinal, 2001).

Several scholars have investigated portfolios of drugs under development instead of simply the number of drugs. As drug research advances, it depends more on a broad array of scientific disciplines (Henderson & Cockburn, 1994), and a considerable diversity now exists in the field of new drug concepts and development (Cardinal, 2001). A new drug portfolio diversified across many diseases (i.e., product categories) seems to reduce the variation in firm performance by increasing the probability of successful drug development (Powell, Koput, & Smith-Doerr, 1996). Diversifying drug development also leads to innovation and improved productivity (Cardinal & Hatfield, 2000b), which may be maintained by investing in separate knowledge creation centers or research facilities rather than maintaining a single research facility (Cardinal & Hatfield, 2000a). Research also suggests that firms seek to increase drug project diversity 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, and Stremersch (2004) studied the effects of a pharmaceutical firm's alliances with biotechnology firms on its innovation and profitability. They found that firms focusing on radical innovation invest in technologically diverse portfolios, in which they repeatedly contract with the same partners to facilitate complex knowledge transfers. Drug development through alliances also achieves a higher probability of success during clinical trials, especially if the partner is a large firm (Danzon, Nicholson, & Pereira, 2005). As a caveat, Kalaiganam, Shankar, and Varadarajan (2007) showed that although alliances are popular when developing new drugs, an excessive focus on the underlying knowledge and technologies often increases the chances of alliance termination and thus should be avoided. It remains important to understand both the costs and the potential returns of any strategy deployed for drug development and innovation.

The economics of drug development in the pharmaceutical industry often serve as guidelines when determining research and development (R&D) resource allocations. DiMasi, Hansen, and Grabowski (2003) estimated an average drug preapproval cost of \$802 million, including out-of-pocket costs of \$403 million. Scherer (2001) emphasized that only 21–23% of new drug candidates 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 potential returns from new drugs becomes further aggravated by the differential rates at which new drugs diffuse in and penetrate markets (Desiraju, Nair, & Chintagunta, 2004). These differential rates are not surprising, as every market has unique features that influence the differential growth of new products (Stremersch & Tellis, 2004). The elaborate and expensive nature of the drug development process has prompted several scholars to estimate returns from investments in drug development. For example, Sorescu, Chandy, and Prabhu (2003) evaluated shareholder returns from radical new drug innovations compared to market or technological innovations; the financial value of a radical innovation is much greater than those of market or technological breakthroughs. Grabowski, Vernon, and DiMasi (2002) used a capital asset pricing model to study the returns from R&D in drug development and found 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 the 1980s.

In our investigation of the connections between the descriptors of new drug portfolio strategies and shareholder evaluations, we provide insights into shareholder expectations of the future cash flows of firms accruable to their new drug portfolio strategies. Therefore, our research mostly contributes to research on the economics of drug development.

2.2. 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 , as used in finance (e.g., Chung & Pruitt, 1994), management (e.g., Bharadwaj, Bharadwaj, & Konsynski, 1999), and marketing (e.g., Simon & Sullivan, 1993; Srinivasan, 2006). Tobin's q offers several benefits. In particular, Tobin's q (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 and Jacobson (2003) and others (e.g., Kumar & Peterson, 2005) claimed that stock price-based indicators reflect the expectations of a firm's shareholders and can thus be used to gauge the future potential of market-based assets and marketing strategies. We investigate the associations between descriptors of a firm's new drug portfolio strategies and Tobin's q to obtain insights into shareholder expectations of the firm's future cash flows accruable to its new drug portfolio strategies.

2.2.1. Portfolio breadth

Portfolio breadth refers to the number of different markets targeted by a firm's new drug portfolio. In the context of the pharmaceutical industry, markets refer to therapeutic categories in which the firm focuses its research efforts on various related diseases. Therefore, a therapeutic category is a broad market that concerns numerous related ailments. The greater the number of therapeutic categories targeted by a firm, the wider is its portfolio breadth. The new drug portfolio of GlaxoSmithKline Beecham (GSK), for example, targets the following therapeutic categories: cardiovascular, urogenital, metabolic, viral, microbial, musculoskeletal, neurological and psychiatric, gastrointestinal, and respiratory diseases. Within the market represented by neurological and psychiatric diseases, GSK targets depression, schizophrenia, bipolar disorder (manic depression), anxiety disorders, and sleep disorders.

Firms with a wider portfolio possess a broad strategic scope, as they have multiple opportunities to leverage their resources and technologies across various markets (Leenders & Wierenga, 2008). As new product alliances propagate and scientific diversity increases, a firm increases its efficiency by spreading its product portfolio across a variety of markets (Bordley, 2003). By targeting numerous therapeutic categories, the firm also develops diverse competencies that enable it to satisfy the needs and wants of heterogeneous customer groups (Quelch & Kenny, 1994). A wide portfolio also may create entry barriers for new firms due to the large scale of resources involved (Putsis & Bayus, 2001). In addition, a wide portfolio distributes the risks associated with drug development across various markets, such that the ultimate outcome (i.e., a successful new product) does not depend on the fortunes of just a few endeavors (Kim, Hwang, & Burgers, 1993; Luo, 2002). Therefore, unlike a narrow portfolio, in which specialized research efforts target limited markets, a wide portfolio should facilitate a consistent future cash flow, as failures in some markets may be compensated for by successes in others. In contrast, narrow portfolios would dramatically magnify the impact of a future loss from any single market, perhaps threatening firm survival. Due to the multiple potential benefits accruable to a wide portfolio, shareholders should develop positive expectations of a firm's future cash flow obtained from the new drug portfolio. Therefore, we propose:

H1. The relationship between portfolio breadth and Tobin's q is positive.

2.2.2. Portfolio depth

Portfolio depth refers to the extent to which resource allocation varies across different markets or therapeutic categories. In other words, if resource allocations are intensive in some therapeutic categories and relatively shallow in others, the firm has greater portfolio

depth than a firm that allocates its resources evenly among different therapeutic categories. Although depth in a traditional sense refers to the intensity of the resource allocation in any particular market, the multiplicity of such markets requires a summarized description of depth, for which, in the context of new drug portfolios, we rely on variations in the distribution of resources across various markets (consistent with extant research on product lines; e.g., Bordley, 2003; Putsis & Bayus, 2001). The number of diseases targeted by each therapeutic category provides a good indicator of the extent of resources allocated to a particular therapeutic category, because the scale and variety of specialized skills, knowledge, and technical resources required to find remedies for each disease is distinct. As a result, the resources allocated to therapeutic categories that differ in the number of diseases targeted would vary. The portfolio depth of a firm with large variations in the number of diseases targeted across therapeutic categories would be much greater than the portfolio depth of a firm with a uniform number of diseases targeted across its therapeutic categories. For example, GSK possesses a deep new drug portfolio, as reflected by the varying number of diseases it targets in different therapeutic categories. Within the category of neurological and psychiatric diseases, GSK has new drug candidates for nine diseases. In the respiratory category, however, GSK has new drug candidates for four diseases, and in the viral category, it targets five diseases.

As portfolio depth increases, a firm's greater focus on certain markets (therapeutic categories) leads to heavy investments in those markets, possibly at the cost of diminished investments in other markets (e.g., Sanchez, 1999). Because of resource limitations, such heavy investments in selective markets would reduce the firm's flexibility to recover and redeploy resources in the event of new drug failures within the heavily supported markets. In contrast, because firms usually invest more in markets with a higher expected market potential (Mahmoud, Danzon, Barton, & Mugerwa, 2006), new drug successes in such markets could result in financial windfalls (e.g., Bowman & Hurrey, 1993). In the pharmaceutical industry, in which drug development costs are high, the potential advantages of recovering costs and profiting from new drugs in a few markets (therapeutic categories) with high expected market potential may compensate for the risks, such as a loss of flexibility, inherent in such a strategy. Therefore, not allowing for sufficient portfolio depth may create significant opportunity costs that could outweigh the benefits derived from retaining flexibility through shallower portfolios (e.g., Sanchez, 1995). Because shareholders are interested in strategies that potentially maximize returns, they should value deeper new product portfolios more than shallower ones. Thus, we propose:

H2. The relationship between portfolio depth and Tobin's q is positive.

2.2.3. Blockbuster strategy

With a blockbuster strategy, a firm exclusively allocates its resources to a few diseases with a high expected market potential rather than distributing resources among diseases with varying expected market potentials. Whether a new drug candidate with a high expected market potential garners blockbuster sales after commercialization is largely speculative during the drug development process. Thus, when we use the term blockbuster strategy to describe a new drug portfolio, we refer to the expected market potential of the diseases targeted by the new drug candidates; a portfolio of a few targeted diseases with high expected market potential indicates a blockbuster strategy. The blockbuster strategy differs from portfolio depth in several ways. First, unlike portfolio depth, a blockbuster strategy refers to the level of diseases rather than therapeutic categories. A firm not only decides to focus on particular therapeutic categories but also, because each therapeutic category comprises multiple diseases, must determine the number and kind of diseases on which to focus its research efforts. Second, whereas portfolio depth refers to higher resource allocations in some therapeutic categories and lower resource allocations in others, a

blockbuster strategy devotes exclusive attention to a few diseases with a high expected market potential and totally ignores other possible diseases with relatively lower expected market potential.

In summarizing the reasons for product portfolio management cited by senior managers, Cooper, Edgett, and Kleinschmidt (2001) emphasize that firms should develop new product portfolios that allow for efficient allocations of scarce resources and maximize financial returns. New drug candidates targeting diseases with high expected market potential offer great potential sources of cash flow, which virtually guarantees their long-term payoff. A blockbuster strategy that allocates resources among selective diseases based on their expected market potential should therefore represent an efficient way to distribute resources to maximize financial returns. Industry observers suggest that the drug development market should value portfolios that comprise potential blockbuster drug candidates (Arlington, Barnett, Hughes, & Palo, 2006).

In addition to the tremendous potential upside of the blockbuster strategy, the potential downside represents an extreme. Scarce resources allocated to a few diseases tend to become increasingly specialized and is dictated by the specifications of a disease (e.g., Krishnan & Ulrich, 2001). Such specialization at the disease level severely constrains the firm's ability to redeploy resources across diseases and, to a greater extent, across therapeutic categories. The inability to move a resource when required severely affects flexibility if a new drug candidate fails after commercialization; a scenario not unlikely in the pharmaceutical industry (Henderson & Cockburn, 1994). Thus, even though the expected returns from a blockbuster strategy may be immense, the strategy reduces the certainty with which shareholders may expect consistent future cash flows.

In summary, shareholder expectations concerning blockbuster strategies may be either positive or negative, as shareholders are interested in not only the magnitude of the firm's expected cash flows but also their stability. Therefore, we offer two contrasting hypotheses:

H3a. The relationship between blockbuster strategy and Tobin's q is positive.

H3b. The relationship between blockbuster strategy and Tobin's q is negative.

2.2.4. Stages of drug development

In the context of the pharmaceutical industry, the four stages of the drug development process consist of preclinical trials and phases I–III of the clinical trials. These four stages are generally similar to the stage gate process of product development followed in firms that implement the best practices for product development (Griffin, 2007), though they do not capture the 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 (e.g., Danzon, Nicholson, & Pereira, 2005; DiMasi, Hansen, Grabowski, & Lasagna, 1995; Ding & Eliashberg, 2002), the four stages of drug development describe the part of the process during which the drug candidates, after having evolved from several new chemical entities as candidates for further development, are repeatedly tested to determine dosage, safety, and improved functionality.

As a drug candidate passes through the four stages of the drug development process, the uncertainty about its true quality declines, as issues concerning its efficacy are gradually resolved. Also, drug candidates move closer to FDA approval and possible commercialization as the drug makes its way through the stages of the development process. A firm should be able to continually replenish its repertoire of drugs in the market if it maintains an adequate number of drug candidates in the later stages of development, such that at least a few of these candidates will be commercialized in time to replace mature product lines. Consequently, a firm that emphasizes maintaining new drug candidates in the later stages of development may be able to

sustain its cash flows in the near future by continually replenishing its products on the market. Shareholders, interested in the consistency of a firm's future cash flows, should emphasize the final, rather than the earlier, stages of drug development. Thus, we propose:

H4. The associations among stages of drug development and Tobin's q will more likely be positive for the later stages of the drug development process than for the earlier ones.

2.2.5. Multiple regimes of firm valuation

Because firms typically are heterogeneous, shareholders may prioritize some descriptors of drug portfolio strategies, depending on the characteristics of the firm. For example, in the pharmaceutical industry, the two most common types of firms are mature pharmaceutical firms and start-up biotechnology firms. Mature pharmaceutical firms, such as Pfizer, have immense experience in drug development, large-scale clinical trials, and activities that follow commercialization, such as marketing and sales. Mature firms are able not only to extract the market potential of commercialized drug candidates, but also to combine development resources across various drug development projects over time. In contrast, start-up biotechnology firms suffer from a severe lack of resources and clinical capabilities, which confines their efforts to only earlier stages of drug development such as the discovery and testing of new chemical entities on a small scale (Powell & Brantley, 1992). The differences in the range of development activities that the two types of firms can perform suggest that shareholders may develop different expectations for such firms, which would be reflected in the shareholders' valuation of the firm in multiple regimes.

These multiple regimes manifest themselves in any empirical analysis as groups of firms, with a firm only belonging to a single group. The regression coefficients vary between these groups (e.g., Grewal, Lilien, & Mallapragada, 2006). For example, start-up biotechnology firms lack resources, such as clinical capabilities, needed to drive the development of drugs through all stages of the drug development process. As a result, these firms focus on the earlier stages of drug development with the objective of demonstrating the potential of the new drug candidate and usually enter agreements with larger firms in order for them to conduct the later phases of clinical trials and subsequent commercialization. Under such conditions, the shareholders might focus on the earlier stages of the drug development process rather than the later ones when valuating start-up biotechnology firms. In contrast, mature pharmaceutical firms do not need to focus as much on the earlier stages of development, as they can easily license new drug candidates from start-ups and/or through alliances with other firms. With their capabilities, mature firms can execute later-stage clinical trials and implement subsequent commercialization efforts for the new drug candidates that they license or acquire. As a result, shareholders may emphasize the later stages of drug development when assessing the future cash flow potential of mature firms. Therefore, mature pharmaceutical firms may comprise one regime in which only the later stages of drug development process may be associated with Tobin's q , while start-up biotechnology firms may comprise a second regime in which only the earlier stages of drug development process may be associated with Tobin's q .

3. Methods and results

3.1. Data sources and variable operationalization

We use Pharamaprojects, a leading database that tracks drug development processes in the pharmaceutical industry, as a data source for drugs at various stages of the development process. Through the database, we have access to information about approximately 29,000 drug candidates that were under development by 1451 firms on December 31, 2002. We use the database to create a list of drug candidates for 388 public firms, the stage of development of each drug, and the disease the drug was being developed to treat.

Because new drug candidates must pass through each of the four stages of drug development, every stage of development will invariably have drug candidates that target various therapeutic categories and underlying diseases. In addition, the measures of new drug portfolio strategies across the different stages of drug development may not be correlated, as new drug candidates are frequently eliminated, purchased, or licensed from other firms, and the portfolio breadth and depth in one stage of development may be quite different from that in other stages. Therefore, the measures of most of the descriptors of new drug portfolio strategies should differ across the four stages of drug development. We therefore calculate measures of portfolio breadth, portfolio depth, and blockbuster strategy at each of the four stages of drug development and determine not only shareholders' expectations of a firm's future cash flows from its portfolio strategies, but also whether these expectations depend on how far along in the development process the drug is.

3.1.1. Portfolio breadth

Portfolio breadth refers to the number of different therapeutic categories targeted by a 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:

$$T_{fk}^c = \sum_{c=1}^C N_{fkc}, \tag{1}$$

where N_{fkc} is a Boolean 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.

In Table 1, we provide examples of new drug portfolio descriptors, such as portfolio breadth and portfolio depth, calculated for six randomly selected firms in our sample. As Table 1 suggests, of the six firms, Schering targets a much wider range of therapeutic categories at any stage of development than any of the other firms and therefore has a wider portfolio.

3.1.2. Portfolio depth

Portfolio depth refers to the extent to which resource allocation or the number of targeted diseases varies across different markets or therapeutic categories. Our measure of variance should be such that when we control for the number of therapeutic categories, a greater variance means that resource allocation is intensive in some categories but shallow in others. Assuming at least one drug candidate in a therapeutic category at a given stage, we define the portfolio depth for development stage k of firm f in terms of variance as:

$$V_{fk} = \sum_{c=1}^C \left\{ N_{fkc} \left(\frac{\sum_{i=1}^C N_{fki} - T_{fk}^l}{T_{fk}^c} \right)^2 \right\}, \tag{2}$$

where T_{fk}^l represents the total number of diseases targeted by firm f at stage k .

Therefore, T_{fk}^l / T_{fk}^c captures the average number of diseases targeted within any therapeutic category at stage k , and $\sum_{i=1}^C N_{fki}$ indicates the

Table 1
Examples of portfolio breadth and portfolio depth

	Portfolio breadth				Number of diseases				Portfolio depth			
	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.

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 . As an example from Table 1, both Schering and Corixa have deeper portfolios than Ribapharm during the first two stages of the drug development process. For the first three stages, Schering achieves deeper portfolios than the other firms. The negligible variation within the portfolios of Ribapharm and Alfacell indicates that they have shallow portfolios with general uniformity in the number of diseases targeted across therapeutic categories.

3.1.3. Blockbuster strategy

In the blockbuster strategy, the firm focuses on a few diseases with a high expected market potential. 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 whether or not a firm pursues a blockbuster strategy. 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, since the average expected market potential per targeted disease would be high.

We define the number of targeted diseases (T_{fk}^I) for which firm f has a drug candidate at stage k as:

$$T_{fk}^I = \sum_{c=1}^C \sum_{i=1}^{I_c} N_{fckci} \quad (3)$$

where $\sum_{i=1}^{I_c} N_{fckci}$ describes the total number of diseases (I_c) in therapeutic category c , summed over all therapeutic categories.

In calculating the 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 greater uncertainty in determining the true quality of new drug candidates during the earlier stages of development, earlier-stage drug candidates should have a higher probability of being abandoned during the development process than those in the later stages. Therefore, we adjust the expected market potential for risk before evaluating and summarizing the expected market potential of a firm's new drug portfolio at any stage of development. The expected market potential (M_{fk}) adjusted for risk at stage k for firm f can be written as follows:

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

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_{fckci} is a Boolean 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 classifies each drug candidate on the basis of its projected market size, with means of \$250 million, \$1250 million, \$3500 million, \$7500 million, and \$10,000 million.³ We use these market size values to represent the market potential for disease i in category c (m_{ci}). Following existing research (DiMasi, Hansen, Grabow-

³ In the Pharmaprojects database, the market potential for each drug candidate consists of five intervals. By definition, the market potential is not specific to a category or disease. However, two drugs that target the same disease likely have the same market potential. Pharmaprojects indicates that the information regarding target markets for drug candidates comes from the firms directly (e.g., firm web sites, annual reports, press releases, etc.). Every firm with an entry in the database is asked to verify the details on their records.

ski, & Lasagna, 1995), we calculate the therapeutic category-specific probability of success on the basis of the historical data in the database. The probability P_{kc} that a drug candidate in category c will survive stage k is set equal to 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 .⁴ The probability P_{kc} that a stage- k drug candidate in category c clears all the remaining stages equals the product of the probabilities of it surviving each remaining stage (including k), that is, in a J -stage product development process, $P_{kc} = \prod_{j=k}^J p_{jk}$.

3.1.4. Stages of drug 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 stage of drug development to assess the influence of the stages of drug development. For example, if most coefficients are statistically significant for Stages 1 (preclinical trials) and 2 (phase I) as opposed to Stages 3 (phase II) and 4 (phase III), we may conclude that the shareholders focus on the earlier stages of drug 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 (Chung & Pruitt, 1994):

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

where

TQ	Tobin's q ,
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 the total assets.

For these 388 firms, we obtain information about Tobin's q for the year 2002 and control variables from the COMPUSTAT database. However, incomplete data reduce our usable sample to 308 firms.

3.2. Control variables

Because variables other than a firm's new product portfolio strategy might be associated with 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 and healthy firms (e.g., Kahya, 1997). Financial efficiency, which we measure by net income (e.g., Black, 1980), embodies the current firm profitability. Firm value tends to increase as efficiency increases (e.g., Platt & Platt, 1991). Liquidity ratios, such as the ratio of current assets to current liabilities (the current ratio), represent a firm's ability to raise short-term credit, which may be a slack resource that improves the flexibility to implement strategies effectively (Evans, 1991).⁵ Finally, leverage ratios,

⁴ From conversations with high-level R&D executives in pharmaceutical firms, we learned that most firms use the average probability across all therapeutic categories when calculating 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.

⁵ In some cases, liquidity could relate negatively to Tobin's q if the firm does not invest its liquid resources 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 both the regimes in which the effect is positive or negative.

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. On the one hand, firms with high leverage ratio cannot fund projects as easily as firms with low leverage ratio, as high leverage ratio firms have greater liabilities and are considered financially unstable. On the other hand, debt can be beneficial when the investments made from the borrowed money outweigh the cost of debt (Brealey & Myers, 2003). Therefore, the effect of leverage ratio (beneficial or detrimental) may vary across firms.

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 are associated with stock price-based measures of a firm. However, because these two constructs are highly correlated in that the number of patents often indicates the productivity of R&D investments (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., Carbonell & Rodriguez, 2006). We control for competitors' new drug portfolios, which should affect the association of a given firm's portfolio with Tobin's *q*. For example, a new 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 expected market potential M_{fk} (adjusted for risk) of all competitors for firm *f*'s stage-*k* portfolio as:

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

where *F* is the total number of firms.

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

3.3. Model specification

As per our theoretical exposition, we should be able to identify the aspects of new drug portfolio strategies that are associated either positively or negatively with Tobin's *q*. Specifically, we study the following model specification:

$$TQ_f = \alpha_1 + \alpha_2 EFF + \alpha_3 LIQ + \alpha_4 LEV + \alpha_5 RD + \sum_{k=1}^4 \alpha_{6k} CMP_k + \sum_{k=1}^4 \alpha_{7k} PB_k + \sum_{k=1}^4 \alpha_{8k} PD_k + \sum_{k=1}^4 \alpha_{9k} ND_k + \sum_{k=1}^4 \alpha_{10k} MP_k + \varepsilon_f \quad (7)$$

where TQ, EFF, LIQ, LEV, RD, CMP, PB, PD, ND, and MP stand for Tobin's *q*, efficiency, liquidity, leverage, R&D expenditures (in a separate regression, we use the number of issued patents instead of R&D expenditures), competitors' new drug portfolio expected market potential, portfolio breadth, portfolio depth, number of diseases, and the firm's new drug portfolio expected market potential, respectively.

The final two explanatory variables together reflect the degree to which the firm pursues a blockbuster strategy. The regression parameters are denoted by α parameters, the random error by ε , and the four stages of drug development by *k*. The descriptive statistics are presented in Table 2.

3.4. Model estimation strategy

Because we have one year of data from 308 firms, we use an ordinary least squares method to obtain the best linear unbiased

Table 2
Descriptive statistics

Variables	Mean	Standard deviation
Tobin's <i>q</i>	.99	6.11
Sales (\$ million)	1587.37	6636.89
Efficiency (\$ million)	174.87	1010.48
Liquidity	6.67	9.14
Leverage	.31	3.03
R&D expenditures (\$ million)	231.14	749.84
Number of patents	14.94	52.37
Stage 1: competitors' expected market potential (\$ million)	106,047.42	145,824.36
Stage 2: competitors' expected market potential (\$ million)	10,089.22	25,936.88
Stage 3: competitors' expected market potential (\$ million)	17,960.69	34,497.61
Stage 4: competitors' expected market potential (\$ million)	8738.82	22,346.37
Portfolio breadth (stage 1)	2.27	2.24
Portfolio breadth (stage 2)	.85	1.41
Portfolio breadth (stage 3)	1.20	1.65
Portfolio breadth (stage 4)	.73	1.25
Portfolio depth (stage 1)	.44	1.35
Portfolio depth (stage 2)	.04	.19
Portfolio depth (stage 3)	.12	.53
Portfolio depth (stage 4)	.06	.34
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
Stage 1: expected market potential (\$ million)	878.79	1253.42
Stage 2: expected market potential (\$ million)	714.56	1638.83
Stage 3: expected market potential (\$ million)	1390.52	2700.12
Stage 4: expected market potential (\$ million)	1445.57	3358.53

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 by several different criteria. Multiple regimes can exist for firm valuation and, by extension, for the association of descriptors of new drug portfolio strategies with Tobin's *q*. To allow for the presence of multiple regimes, we use latent class regression analysis (see the Appendix for estimation details). Specifically, for Eq. (7), we use the following specification:

$$TQ_f = \sum_{r=1}^R [\alpha_r X_{rf} + \varepsilon_{rf}] \quad (8)$$

where *R* denotes the number of empirically determined regimes, α is the vector of regime-specific parameter estimates, and *X* represents the vector of explanatory variables, including the intercept term.

4. Results

4.1. Model selection

We provide results based on three models. Model 1 does not control for R&D expenditures or the number of issued patents, Model 2 controls for R&D expenditures, and Model 3 controls for the number of issued patents. The consistent Akaike information criterion (CAIC) values show that in all three models, a two-regime model (CAIC_{model1} = 1655, CAIC_{model2} = 1687, CAIC_{model3} = 1691) outperforms models with just one regime (CAIC_{model1} = 2131, CAIC_{model2} = 2145, CAIC_{model3} = 2150) or three regimes (CAIC_{model1} = 1708, CAIC_{model2} = 1750, CAIC_{model3} = 1777). In the two-regime solution, the first regime consists of 90% of the firms, and its value of entropy of separation falls in the range of .86–.93, which implies a good separation and instills confidence in the models with two regimes. Because this first regime includes the majority of the firms in our data set for the two-regime solution, it appears that the market is generally efficient and uses similar criteria to value most firms. We explore the differences in firm characteristics between the two regimes at the end of the Results section.

4.2. Estimation results

In Tables 3 and 4, we present the results for Regimes 1 and 2 from Model 2 respectively, which includes R&D expenses as a control variable. Although we add the theoretically important controls of R&D expendi-

Table 3
Latent class regression results for regime 1

Variable category	Explanatory variables	Regime 1		
		Model 1	Model 2	Model 3
		Coefficient	Coefficient	Coefficient
		(t-value)	(t-value)	(t-value)
Control variables	Constant	1.994***	1.958***	2.012***
		(12.359)	(12.894)	(12.021)
	Efficiency ^a	.002	0.002	0.002
		(1.303)	(1.603)	(1.613)
	Liquidity ^a	-.429***	-.414***	-.435***
		(-5.066)	(-4.762)	(-5.128)
Leverage		-.009	-0.074	-0.009
		(-.325)	(-0.275)	(-0.325)
R&D		-	-0.001	-
			(-.471)	
Patents		-	-	-0.001
				(-0.741)
Competitors' expected market potential	Stage 1 ^a	-.000	-.000	-.000
		(-1.245)	(-1.422)	(-1.3581)
	Stage 2 ^a	.000	.000	.000
		(.681)	(0.692)	(0.5342)
	Stage 3 ^a	-.000	-.000	-.000
	(-1.301)	(-1.463)	(-1.3971)	
Portfolio breadth	Stage 4 ^a	-.000	-.000	-.000
		(-1.052)	(-0.845)	(-0.8772)
	Stage 1	-.119	-0.115	-0.126
		(-1.063)	(-1.047)	(-1.128)
	Stage 2	.044	0.039	0.032
	(.192)	(0.157)	(0.126)	
Portfolio depth	Stage 3	.174	0.157	0.189
		(1.001)	(0.918)	(1.075)
	Stage 4	.788**	0.704**	0.726**
		(2.508)	(2.245)	(2.281)
Number of diseases	Stage 1	-.017	-0.0163	-0.022
		(-.216)	(-0.208)	(-0.278)
	Stage 2	.131	0.0355	0.0529
		(.144)	(0.037)	(0.0546)
	Stage 3	-.381	-0.376	-0.384
	(-1.496)	(-1.376)	(-1.376)	
Expected market potential	Stage 4	.207	0.0726	0.087
		(.666)	(0.222)	(0.263)
	Stage 1	-.071	-0.067	-0.065
		(-.841)	(-0.800)	(-0.766)
	Stage 2	.063	0.062	0.064
	(.278)	(0.271)	(0.275)	
Profiling variables	Stage 3	.041	0.061	0.039
		(.254)	(0.388)	(0.248)
	Stage 4	-.596*	-0.528*	-0.566*
		(-2.066)	(-1.837)	(-1.921)
	Constant	.003	0.004	0.004
	(1.195)	(1.320)	(1.309)	
Expected market potential	Stage 2 ^a	-.002	-0.002	-0.002
		(-1.412)	(-1.390)	(-1.263)
	Stage 3 ^a	.001	0.001	0.001
		(.681)	(0.820)	(0.794)
	Stage 4 ^a	.001	0.001	0.001
	(1.292)	(1.104)	(1.219)	
Profiling variables	Constant	.946***	.927***	.914***
		(8.786)	(8.825)	(8.403)
	Sales ^a	.007	.003	.003
	(1.299)	(1.342)	(1.040)	
Pseudo R square		.221	.223	.223

***p<.01, **p<.05, *p<.10.

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

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

Table 4
Latent class regression results for regime 2

Variable category	Explanatory variables	Regime 2		
		Model 1	Model 2	Model 3
		Coefficient	Coefficient	Coefficient
		(t-value)	(t-value)	(t-value)
Control variables	Constant	27.753***	29.929***	25.324***
		(7.186)	(7.227)	(5.988)
	Efficiency ^a	.505**	.664***	.667***
		(2.094)	(2.949)	(2.654)
	Liquidity ^a	1.923	.467	.219
		(.283)	(.290)	(.098)
Leverage		2.124**	2.568**	2.443*
		(2.182)	(2.030)	(1.687)
R&D		-	.088*	-
			(1.661)	
Patents		-	-	.001*
				(1.681)
Competitors' expected market potential	Stage 1 ^a	-.000	.000	.000
		(-.852)	(.901)	(.908)
	Stage 2 ^a	-.014**	-.015***	-.015***
		(-2.185)	(-2.486)	(-2.513)
Stage 3 ^a		-.003	-.002	-.001
		(-1.256)	(-.473)	(-.411)
Stage 4 ^a		-.034**	-.001	-.062
		(-1.902)	(-.735)	(-1.230)
Portfolio breadth	Stage 1	-1.223	-2.268	-1.956
		(-2.18)	(-3.40)	(-4.83)
	Stage 2	57.864*	73.321***	73.346**
		(1.681)	(2.357)	(1.982)
Stage 3		9.906	6.501	6.038
		(.803)	(.620)	(.945)
Stage 4		-74.388	-34.697	-44.60
		(-1.237)	(-.556)	(-2.09)
Portfolio depth	Stage 1	.916	.535	1.252
		(.161)	(.102)	(.091)
	Stage 2	377.631***	447.986***	446.872***
		(3.318)	(2.565)	(2.631)
Stage 3		82.666*	59.557	59.246
		(1.966)	(1.370)	(1.699)
Stage 4		-42.076	-25.860	-24.850
		(-1.245)	(-.714)	(-.713)
Number of diseases	Stage 1	-3.360	-2.592	-2.633
		(-7.06)	(-4.29)	(-6.29)
	Stage 2	-61.587*	-78.523***	-78.730***
		(-1.829)	(-2.488)	(-2.840)
	Stage 3	-9.538	-8.132	-8.312
	(-7.42)	(-6.51)	(-2.58)	
Stage 4		61.667	20.986	21.523
		(1.024)	(0.322)	(.160)
Expected market potential	Stage 1 ^a	.002	.001	.000
		(.036)	(.227)	(.248)
	Stage 2 ^a	-.029	-.003	-.003
		(-.193)	(-.276)	(-0.272)
	Stage 3 ^a	.057	.004	.190
	(.794)	(.548)	(.731)	
Stage 4 ^a		.315***	.029***	.118***
		(4.337)	(4.070)	(4.529)
Pseudo R square		.651	.666	.692

***p<.01, **p<.05, *p<.10.

Notes: Because R&D expenditures and the 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, as this regime is used as a base.

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

tures and number of issued patents one at a time, we do not find any substantive differences in the direction or statistical significance of coefficients across the three models, which speak to the robustness of our results.

4.2.1. Regime 1

In terms of control variables, higher liquidity tends to relate negatively to Tobin's q ($b = -.414, p < .01$). None of the other control variables,

including R&D expenses, has any statistically significant association with Tobin's q . We find support for H1, as the portfolio breadth of these firms is positively associated with Tobin's q ($b = .704, p < .05$) in the later stages (Stage 4) of development. We do not find support for H2; all the coefficients with portfolio depth are statistically non-significant ($b_{\text{stage1}} = -.016, p > .38$; $b_{\text{stage2}} = .035, p > .29$; $b_{\text{stage3}} = -.376, p > .52$; $b_{\text{stage4}} = .072, p > .87$).

To assess the relationship between blockbuster strategy and Tobin's q , we look at two sets of results. First, as the number of targeted diseases increases, the value of Tobin's q decreases, especially in Stage 4 of the drug development process ($b = -.528, p < .10$). This result suggests that a higher number of targeted diseases are negatively associated with shareholder expectations of the firms' future cash flows accruable to new drug portfolios. Second, we do not find any statistically significant relationship for the expected market potential of the new drug portfolios. However, the mean value of the expected market potential of the new drug portfolios, especially in Stage 4, is not only large in magnitude (mean = 1569.31) but also significantly greater than the corresponding mean value for firms in Regime 2 (mean = 339.83, see Table 5). Because we find a high expected market potential of the new drug portfolio and a negative association between the number of targeted diseases and Tobin's q in Stage 4 ($b = -.528, p < .10$), we infer that shareholders have high expectations of a firm's future cash flows when a portfolio concentrates on fewer diseases with greater expected market potential (a blockbuster strategy). Therefore, we find support for H3a, which proposes a positive association between a blockbuster strategy and Tobin's q , but not for H3b. Finally, most of the statistically significant coefficients emerge in Stage 4 of drug development. We therefore conclude that shareholders focus more on the later stages of drug development in this regime, which is in support of H4.

4.2.2. Regime 2

In terms of financial variables, Tobin's q increases with the efficiency ($b = .664, p < .01$). In addition, a higher leverage ratio tends to be positively associated with Tobin's q for firms in Regime 2 ($b = 2.568, p < .05$). For the variables pertaining to the competitors, we

find negative associations of the total expected market potential of the competitors' new drug portfolios in Stage 2 and Tobin's q ($b = -.015, p < .01$). Although a significant negative association for this competitor variable emerges in Stage 4 ($b = -.034, p < .05$), the association disappears when we control for R&D expenditures and/or number of patents. Unlike in Regime 1, both R&D expenditures ($b_{\text{model 2}} = .088, p < .10$) and the number of issued patents ($b_{\text{model 3}} = .001, p < .10$) indicate a significant positive association with market valuation.

We again find support for H1; portfolio breadth is positively associated with Tobin's q in Stage 2, the beginning of clinical trials ($b = 73.321, p < .01$). The results also suggest that shareholders have high expectations of a Regime 2 firm's future cash flows when the new drug portfolio has greater depth in Stage 2 ($b = 447.986, p < .01$) and 3 ($b_{\text{model 1}} = 82.66, p < .10$), though this latter association becomes statistically non-significant when we control for R&D expenditures and number of patents. Regardless, we seem to find support for H2.

To evaluate the association of a blockbuster strategy with Tobin's q , we again look at two sets of results. First, in terms of the number of targeted diseases, the association with Tobin's q is significantly negative in Stage 2 ($b = -78.523, p < .01$). Second, a higher expected market potential of a new drug portfolio relates positively to Tobin's q in Stage 4 ($b = .029, p < .01$). Therefore, shareholders appear to expect greater future cash flows from a firm with a portfolio that targets fewer diseases and has a high expected market potential. Similar to Regime 1, shareholders in Regime 2 firms seem to favor a blockbuster portfolio strategy, in support of H3a but not H3b. Finally, in H4, we propose that shareholders focus on later rather than earlier stages of drug development. This hypothesis receives no support based on the data from Regime 2, as most of the statistically significant coefficients in this regime occur in Stage 2. Hence, we infer that for firms in Regime 2, shareholders pay more attention to the earlier stages of drug development than to the later stages.

4.2.3. Sources of heterogeneity among regimes

The results for the descriptors of new drug portfolio strategies in Regimes 1 and 2 are not similar. To understand why, we look at the sources of firm-level heterogeneity between the two regimes, as shown in Table 5. Firms in Regime 1 have a significantly larger number of employees (mean_{Regime1} = 6.54, mean_{Regime2} = .12), are older (mean_{Regime1} = 30, mean_{Regime2} = 18), and have higher liquidity (mean_{Regime1} = 7.20, mean_{Regime2} = 2.00). We do not find a corresponding difference in net sales, primarily because Regime 1 comprises both very large and small firms, so the variance in net sales is dramatic. For example, 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. Finally, the regimes differ in the average values of Tobin's q , as firms in Regime 2 enjoy much greater Tobin's q values than do firms in Regime 1 (mean_{Regime2} = 15.31, mean_{Regime1} = 1.73). In the next section, we relate these sources of heterogeneity to the differential associations between the descriptors of new drug portfolio strategies and Tobin's q across the two regimes.

5. Discussion

Our exploratory research describes new drug portfolio strategies in terms of portfolio breadth, portfolio depth, blockbuster strategy, and the stages of drug development. We also argue that shareholder expectations in Tobin's q are forward-looking, because they reflect financial market sentiments about the future streams of cash flow accruable to company strategies, such as new drug portfolio strategies (see Table 6 for a summary of this research). Overall, shareholder expectations of a firm's future cash flow potential relate positively to a wide portfolio that targets multiple therapeutic categories. A blockbuster strategy also appears important, as indicated by its positive association with Tobin's q . Shareholders recognize interfirm

Table 5
Statistically significant differences in firm profiles between regimes

Variables	Regime 1	Regime 2
	Mean (S.E)	Mean (S.E)
Liquidity	7.20*** (.57)	2.00*** (.58)
Stage 1: competitors expected market potential	11151.40** (8912.35)	57188.40** (20037.85)
Stage 4: competitors expected market potential	9523.46* (1401.77)	1727.70* (1220.37)
Stage 2: portfolio breadth	.90* (.09)	.45* (.17)
Stage 4: portfolio breadth	.79** (.08)	.19** (.07)
Stage 1: number of diseases	3.54* (.27)	2.13* (.48)
Stage 4: number of diseases	.99** (.11)	.23** (.09)
Stage 4: expected market potential	1569.31* (1569.31)	339.83* (158.45)
Number of employees	6.54* (21.11)	.12* (.20)
Age (in years)	30* (761.70)	18* (29.01)
Tobin's q	1.73*** (1.90)	15.31*** (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 between Regime 1 and Regime 2.

Table 6
Summary of descriptors of the new drug portfolio strategies, their operationalization, the hypotheses, and the results

Variable of interest	Definition	Operationalization	Hypotheses	Results
Tobin's q	Stock price-based measure of firm valuation.	(market capitalization+liquidation value of outstanding preferred stock+total debt)/book value of total assets.	–	–
Portfolio breadth	Number of different markets (therapeutic categories) targeted by a firm's new drug portfolio.	Total number of therapeutic categories targeted at each stage of development (see Eq. (1)).	H1: relationship with Tobin's q is positive.	– Supported in Regime 1. – Supported in Regime 2.
Portfolio depth	Variation in the number of diseases targeted across therapeutic categories.	Total variance in the number of diseases targeted across all therapeutic categories at each stage of development (see Eq. (2)).	H2: relationship with Tobin's q is positive.	– Not supported in Regime 1. – Supported in Regime 2.
Blockbuster strategy	Portfolio targeting a few diseases with high expected market potential.	– Total no. of diseases targeted at each stage of development (see Eq. (3)) and – Expected market potential of new drug portfolio at each stage of development (see Eq. (4))	H3a: relationship with Tobin's q is positive. H3b: relationship with Tobin's q is negative.	– Supported in Regime 1. – Supported in Regime 2. – Not supported in Regime 1. – Not supported in Regime 2.
Stages of drug development.	Earlier stages: preclinical trials, phase I of clinical trials. Later stages: phases II and III of clinical trials.	Statistical significance of coefficients of other constructs at each stage of development.	H4: relationship is stronger for later stages than earlier stages.	– Supported in Regime 1. – Significant but opposite association in Regime 2.

differences and alter expectations across firms accordingly. For most firms in our sample (Regime 1), shareholders assign importance to broad portfolios that target multiple therapeutic categories in the later stages of development, but they prefer a limited number of diseases to be targeted. However, for 31 firms (Regime 2), shareholders make positive associations with a broad portfolio targeting multiple therapeutic categories and few diseases, though only in the earlier stages of the drug development process. In addition, shareholders in these firms emphasize greater portfolio depth with considerable variability in the number of targeted diseases across the therapeutic categories.

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

The primary difference in shareholder expectations between the regimes stems from the differences in focus on the various stages of drug development and portfolio depth. If we pool together the observations for Regime 2 firms, we can infer that their extremely small sizes and corresponding lack of resources prevent these firms from pushing their own innovations through the final stages of the drug development process. 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 industries (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 or not the small firms in Regime 2 are start-ups. However, 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 than to push through expensive, large-scale, later-stage clinical trials on humans and eventually commercialize the drug. Therefore, it is not surprising that the shareholders of Regime 2 firms pay attention to the earlier stages of drug development rather than the later ones.

The considerably larger values of Tobin's q enjoyed by firms in Regime 2 imply that their market values far exceed the values 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, young firms is increased by the level of expertise they display in certain subsets of therapeutic categories, a fact which is reflected in their greater portfolio depth. Firms in Regime 2 also deploy platform technologies to research specific therapeutic categories intensively. Hemisphere, a small biopharmaceutical firm, has developed a platform technology comprising large and small agent components 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. 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 of the association of descriptors of new drug portfolio strategies with shareholder expectations, expressed as Tobin's q , offers several implications for managers. First, most pharmaceutical firms are valued in a similar fashion, in that most belong to Regime 1. Because the later stages of drug development are associated with Tobin's q in this regime, the recent frenzy to acquire firms with products close to the final stages of their development 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 concentrating on the pipeline of new drug candidates during early development stages. Third, 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 further research opportunities

In our description of new drug portfolio strategies, we do not include the level of innovation 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 does actually not differ between the best performing firms and others (PDMA, 2004). Financial markets may thus overlook this aspect of a new drug (product) portfolio, instead focusing on the descriptors included in our research. Nevertheless, the level of innovation of a new drug portfolio provides an important future research area.

In response to the overwhelming number of requests to integrate marketing and shareholder value creation, our research relates an important financial indicator to descriptors of new drug portfolio strategies. However, substantial potential exists for investigating other relevant financial indicators. For example, a broad new drug portfolio may provide strategic options or a hedge against uncertainties while restricting 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 and factors, such as risks, market share growth, and revenue optimization, which play a role when creating a specific type of new drug portfolio. A study of such trade-offs and factors would provide an interesting extension of this research.

Finally, due to a lack of data across multiple years, we provide results only for 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 goods (Kerin & Sethuraman, 1998) and global expansion (Christophe & Lee, 2005). Still, a longitudinal data set would have enabled us to track the extent to which new drug portfolios change over time, as well as their corresponding associations with financial indicators. Therefore, we encourage additional research that explores the dynamic relationship between a firm's changing new drug portfolio and its financial consequences.

Appendix A. Latent class regression analysis

We take the following modeling approach to account for the possibility of multiple regimes, as specified in Eq. (8):

$$TQ_f = \sum_{r=1}^R [\alpha_r X_{rf} + \varepsilon_{rf}] \tag{A1}$$

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* represents firm *f*; that is:

$$P[f \in r | TQ_f] = \frac{\delta_{rf} L_{f|r}}{\sum_{r=1}^R \delta_{rf} L_{f|r}} \tag{A2}$$

where δ_{rf} 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, Wedel, & Agrawal, 1994), we use the logit formulation to specify the prior probabilities:

$$\delta_{rf} = \frac{e^{\kappa_r}}{\sum_{r=1}^R e^{\kappa_r}} \tag{A3}$$

such that we estimate κ_r for each regime. Again, we can standardize Eq. (A3) as:

$$\delta_{rf} = \frac{e^{\kappa_r}}{\left[1 + \sum_{r=1}^{R-1} e^{\kappa_r} \right]} \tag{A4}$$

Thus, we treat the last regime as the base and must estimate only *R* - 1 parameters. Note that, 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:

$$L_{f|r} = \phi^*(\varepsilon_{rf}) \tag{A5}$$

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

Thus, the likelihood function can be written as:

$$L = \prod_{f=1}^F \sum_{r=1}^R \delta_{rf} L_{f|r} \tag{A6}$$

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

We maximize the natural logarithm Eq. (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 to a model with *r* + 1 regimes $\forall r = 1, 2, \dots$ until the model fit ceases to improve with further addition of regimes. We calculate the CAIC as follows:

$$CAIC = -2 * LL + K * (1 + \ln(N)) \tag{A7}$$

where *LL*, *K*, and *N* stand for 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 latent regimes (Wedel & Kamakura, 2000). We calculate ES (bound to the range 0–1, such that a value closer to 1 indicates a good separation of the regimes) as:

$$ES = 1 - \frac{\sum_{f=1}^F \sum_{r=1}^R -p_{f|r} \ln(p_{f|r})}{N \ln(R)} \tag{A8}$$

where $P_{f|r}$ is the probability of firm *f* belonging to regime *r*, which we calculate using the Bayes rule.

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