Journal of Management
Vol. 39 No. 4, May 2013 985-1015
DOI: 10.1177/0149206311416120

Investor Reactions to New Product Development Failures: The Moderating Role of Product Development Stage

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The authors develop a model of investor reactions to new product development (NPD) failures in high technology firms. They propose that a firm's financial and managerial capabilities, and its strategic focus on R&D, influence investors' perceptions of the firm's market value after NPD failure and that these effects are contingent on the development stage of the failed product. Using data on 148 NPD failures of publicly traded biopharmaceutical firms and an event study methodology the authors find support for their hypotheses. They show that the relationships between a firm's (a) financial capabilities, (b) managerial capabilities, and (c) strategic focus on R&D, respectively, and the decline of firm market value after NPD failure are more negative for products that fail in late development stages than for products that fail in early development stages. The authors' results highlight the importance of a conjoint consideration of product-level and organizational-level effects in explaining investor reactions to NPD outcomes.

Keywords: *project failure; capabilities; biotechnology; product development; event study*

Acknowledgments: This article was accepted under the editorship of Talya N. Bauer. We would like to thank Journal of Management *editor Edward Levitas and two anonymous reviewers for their comments and help with developing this article.*

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Although a substantial body of literature has advanced our understanding why new product development (NPD) projects succeed or fail (Edmondson & Nembhard, 2009; Montoya-Weiss & Calantone, 1994), failure rates in innovation-driven industries remain high. For example, in the pharmaceutical industry only 1 out of 5,000 initial product candidates reaches market launch (Evans & Varaiya, 2003), and even when a potential drug passes the research stage and enters into clinical development, more than 80% of new product candidates fail (Abrantes-Metz, Adams, & Metz, 2005; DiMasi, Hansen, & Grabowski, 2003). High NPD failure rates are also reported in other innovation-driven sectors such as telecommunications (Buganza, Dell'Era, & Verganti, 2009), software (Ethiraj, Kale, Krishnan, & Singh, 2009), and electronics (Terwiesch, Loch, & Niederkofler, 1998).

Only recently have scholars started to investigate why NPD failures affect the performance of some firms more than others (DeCarolis, Yang, Deeds, & Nelling, 2009; Girotra, Terwiesch, & Ulrich, 2007; Sarkar & De Jong, 2006). These studies typically draw on either of two possible theoretical arguments. First, some scholars argue that investor expectations of NPD success determine the decline in firm market value when NPD projects actually fail—the higher investors' expectations of success, the larger the decline (Girotra et al., 2007; Kellogg & Charnes, 2000). For explaining heterogeneity in decline, these studies focus on investors' value associated with a successfully developed product and the likelihood of a successful development process. In contrast, other studies argue that investors' reactions to NPD failures are mainly determined by their perceptions of firms' abilities to recover from failure—the better a firm's recovery potential, the smaller the valuation decline (DeCarolis et al., 2009; Guedj & Scharfstein, 2004). To explain variance in decline across firms, these studies focus on whether firms can avoid potential losses following the failure (e.g., bankruptcy), or recover some of the lost value created by the failing project. Surprisingly, however, existing work has not yet investigated which perspective prevails and under what contingencies. Furthermore, some studies have found empirical results that are in conflict with their theoretical perspective of choice (e.g., DeCarolis et al., 2009). Filling this research gap and addressing the trade-off between both perspectives are important to provide a better understanding of investor reactions to failures of NPD projects.

This article develops a model integrating both perspectives. We consider organization-level characteristics and the development stage of the new product, as well as their interactions, in explaining variance in investors' reactions to NPD failures. We draw on capabilities-based arguments suggesting that firms need the appropriate stock of available assets and the capacity to deploy those assets to achieve a desired end result (Amit & Schoemaker, 1993: 35). We define capabilities as *the set of abilities and resources that go into solving a problem or achieving an outcome* (Zahra, Sapienza, & Davidsson, 2006). Our model proposes that both expectations of NPD success and expectations of firm recovery from NPD failure can explain the impact of organizational capabilities (and their strategic deployment) on investors' reactions to failures but that the development stage of the failed product influences the prevalence of each perspective. We test our model using an event study methodology and data on 148 NPD failures of publicly traded biopharmaceutical firms. In doing so, we make the following contributions to existing literature.

First, the NPD literature demonstrates that prior firm performance (DeCarolis et al., 2009), the availability of cash (Xu, Magnan, & Essec, 2007) and the composition of the product portfolio (Girotra et al., 2007) influence to what extent firm performance declines

after NPD failure. These studies, however, do not investigate how these influences differ for products that fail at different stages of development. This distinction appears important because investors' interpretation of available information about NPD depends on the development stage of a firm's product candidates (Abrantes-Metz et al., 2005). Our model acknowledges variance in the development stage of failed products. Our finding that the impacts of financial and managerial capabilities and a firm's strategic focus on R&D on firm performance after NPD failures are contingent on the product's development stage emphasizes that organizational-level and product-level factors need to be considered conjointly rather than independently to gain a more detailed understanding of the performance consequences of NPD outcomes.

Second, research on the antecedents and outcomes of innovation processes usually focuses on one level of analysis while neglecting heterogeneity at other levels and that those levels may not be independent of the level under investigation (Rothaermel, Agung, & Jiang, 2007). Our study suggests that organizational-level factors can mitigate negative outcomes of innovation processes (NPD failures), but that these effects are not independent of heterogeneity at the level of the product under development. Our data highlight the importance of cross-level effects in the investigation of organizational outcomes of innovation processes.

Finally, our results have important implications for research on market reactions to NPD failure based on the lost value associated with the failed NPD project (e.g., Girotra et al., 2007) and the firm's recovery potential after failure (e.g., DeCarolis et al., 2009). Our findings suggest that heterogeneity in stock price decline depends on organizational characteristics that influence both (a) the value and the probability of successful NPD and (b) the loss associated with a failure including costs that are not directly related to the failed project but follow from it (e.g., bankruptcy). Studies trying to determine the value of NPD projects based on the decrease in stock prices after NPD failure can benefit when they control for firms' recovery potential. Similarly, studies might gain a better understanding of a firm's recovery capabilities after NPD failure when they take into account that (some of these) capabilities might also increase investors' expectations of NPD success.

This article proceeds as follows. First, we develop our model and hypotheses. Second, we describe the research method and results of our study. Finally, we discuss its outcomes and corresponding limitations, highlight its implications, and draw conclusions.

Theory and Hypotheses

Descriptive decision theories such as prospect theory (Tversky & Kahneman, 1992) are an often-used framework for studying investor perceptions of firm values under conditions of uncertainty (De Bondt & Thaler, 1995) as they are typical for NPD (Girotra et al., 2007). Following these theories, in developing our model of investor reactions to NPD failure we make two important assumptions. First, we assume that investor perceptions of a firm's value depend on three elements, the perceived values attached to NPD success and failure as well as the perceived probabilities of these outcomes. These perceptions are based on the set of information available on the firm and NPD (consistent with a medium–strong form of market efficiency).[1] The overall effect of a factor influencing investor judgments is an aggregate of its effects on each of these three elements. This perspective implies that there is the possibility that effects cancel out one another. Our second assumption is that at the

time of NPD failure, only investors' perceived success probability changes (to zero) but not the values associated with success and failure. The latter values are determined prior to failure because investors price in the consequences of success and failure for the firm. After failure the firm value is perceived to be the value associated with failure.

Recent research shows that psychological processes influence how investors weight pieces of information and therefore how stock prices react to NPD failure (cf. De Bondt & Thaler, 1995). For example, investors tend to overreact to newly published information about the firm (De Bondt & Thaler, 1985), underweight information supplied by others (Deaves, Lüders, & Schröder, 2010), and suffer from confirmation biases (Daniel, Hirshleifer, & Subrahmanyam, 1998). Therefore, understanding investor reactions to NPD failures requires going beyond assumptions of market efficiency and its micro foundations such as expected utility maximization, rational expectations, and Bayesian updating (De Bondt, Palm, & Wolff, 2004). A behavioral perspective suggests that investor reactions to market information depend on both the availability of information (as assumed in efficient markets) and the psychological processes that influence how information is interpreted and, as a consequence, acted on (cf. literature on framing and context dependency of judgment under uncertainty; Liberman & Trope, 1998; Tversky & Kahneman, 1992). That is, it is not the purpose of this article to test if stock prices reflect objective firm values and, thus, whether all information available is used by investors in an "objectively correct" way. Rather, the goal of our work is to understand the drivers of investor reactions to NPD failures.

While in some sectors such as software or consumer goods NPD failures may not be obvious to investors and thus have little immediate impact on stock returns, in other sectors such as biopharmaceuticals failures are highly visible. The development of new drugs is a multistep process with the steps being clearly defined by regulatory guidelines (Girotra et al., 2007; Sarkar & De Jong, 2006). After the research phase, new drug candidates must pass the preclinical testing phase and three subsequent clinical phases before entering into the regulatory approval phase that results in either permission or prohibition to market the product. The outcomes of these development steps and the firms' decisions to continue or terminate the development process at each step *have to be publicly announced* because of regular SEC disclosure requirements. Because of their public visibility, often NPD outcomes have a substantial effect on biopharmaceutical firms' market value (DeCarolis et al., 2009; Girotra et al., 2007; Rzakhanov, 2004; Sarkar & De Jong, 2006). Thus, we focus our theorizing below on biopharmaceutical firms and draw special attention to the role of the development stage of the failing product.

Product Development Stage and Investor Perceptions of NPD Failure

The current development stage of a biopharmaceutical product candidate likely influences investor reactions to NPD failure because the more advanced the product candidate, (a) the higher the firm's accumulated investments into that candidate and (b) the more likely the candidate will complete the development process successfully. For example, in the biopharmaceutical industry, average expenditures of early Phase I clinical testing are about $57 million, whereas they amount to $418 million for late Phase III clinical testing

(Girotra et al., 2007). Furthermore, for every 5,000 compounds that emerge from drug discovery, only 5 pass the research stage (Evans & Varaiya, 2003). Even after entering the development stage the accumulated probability of failure for preclinical and clinical development stages is about 80% (DiMasi et al., 2003; Moran, 2003). In contrast, only 20% to 40% of drugs that have already entered into late Phase III clinical development do not reach market launch (Himmelmann & Schiereck, 2009; Kellogg & Charnes, 2000). Therefore, consistent with empirical findings (e.g., Girotra et al., 2007), the (expected) value of the developed product increases with its development stage, leading to more negative investor reactions (disappointments) in case of NPD failure.

In addition to the rather well-established negative relationship between product development stage and firm value change after NPD failure, however, it appears that there is an additional, moderating effect of the product development stage. Although the initial research stage in the biopharmaceutical industry typically takes one year, the following preclinical testing demands, on average, another 3 years. Subsequently, clinical testing in Phases I, II, and III takes about 1, 2, and 3 years, respectively, before the product candidate enters into the FDA approval phase, which can last another 3 years (Kellogg & Charnes, 2000). From initial research to market approval, NPD cycles thus cover about 13 years, and even when the drug candidate has entered the clinical development phase, firms (and their investors) have to wait up to 6 years until the first income is generated. These significant time frames are likely to influence how investors perceive the value of the firm given the development stage of the failed product (Trope & Liberman, 2003).

Summarizing a variety of theoretical and empirical research, such as action identification theory (Vallacher & Wegner, 1987) and work on self-regulation (Carver & Scheier, 1999) and intertemporal choice (Loewenstein, Read, & Baumeister, 2003), Liberman and Trope (1998) and Trope and Liberman (2003: 403) propose that "temporal distance changes people's responses to future events by changing the way people mentally represent those events." They suggest that "distant future situations are construed on a higher level (i.e., using more abstract and central features) than near future situations" (Liberman & Trope, 1998: 5). According to Trope and Liberman (2003) desirability (the value of an action's end state) considerations constitute high-level construals of actions, whereas feasibility (the ease or difficulty of reaching that end state, i.e., the probability of the desired outcome) considerations constitute low-level construals of actions. Therefore, construal level theory (Trope & Liberman, 2003) suggests that feasibility matters more for near-future judgments and preferences, such that the "probability dimension becomes more salient as time passes" (Öncüler, 2010: 113). In near-future decisions people tend to underutilize high-level (desirability) information, whereas in distant-future decisions they tend to underutilize low-level (feasibility) information (Trope & Liberman, 2003). The different weighting extends to the observation that people tend to seek out insufficient information about the odds of uncertain future events, and sometimes even ignore the available information, when these events are distant in time (Öncüler, 2010). Construal level theory therefore suggests that (a) different types of information are weighted differently depending on temporal distance and (b) the acquisition of information is affected by the temporal distance.

Thus, according to construal level theory the different elements contributing to the formation of investors' expectations about future success of NPD projects, that is, values associated with success and failure and perceived probabilities, affect investor judgments of

the firm's value contingent on the temporal distance of the success or failure event. That is, when evaluating the value of a firm pursuing an NPD project in a late development stage, investors are likely to emphasize whether the firm has the abilities to finalize the project successfully. In developing their expectations of NPD outcomes, investors will focus on whether the probability that the product will enter the market is high. On the contrary, for judging NPD projects in early development stages, investors are less likely to focus on the probability of NPD success because the finalization of the development process and the product's market introduction are distant in time.

Furthermore, since failures can happen at each stage in the NPD process, but relevant success materializes only at the future end of the process when the product is marketed, possible failures are closer in time than final success. Therefore, investors are more likely to seek more concrete and less general information about a firm's capability to cope with failure but seek more general and less specific information about a firm's ability to succeed. Thus, the earlier the development stage of a new product candidate, the more investors are likely to insufficiently seek and rely on (or even ignore) information on the firm's ability to successfully complete the NPD process in the future. Instead, they are likely to interpret information about the firm more with respect to their contribution to recovery from a failure that is nearer in time (such as the failure to complete of the next development stage). Since both successful NPD (Lee & Chen, 2009; Montoya-Weiss & Calantone, 1994) and recovery from NPD failure (DeCarolis et al., 2009) depend on the firm's capability stock and both effects could counterbalance one another, we now explore how specific capabilities affect investor reactions to NPD failure for products at different stages of development.

Firm Capabilities, Product Development Stage, and Investor Perceptions of NPD Failure

Financial and managerial capabilities are critical to the performance of firms developing new products (Evans & Varaiya, 2003; R. Henderson & Cockburn, 1994; Rothaermel & Hill, 2005) and are (to a certain extent) observable for investors (DeCarolis et al., 2009; Girotra et al., 2007; Rzakhanov, 2004). Furthermore, in high technology firms, strategic focus on R&D ("intention to innovate") is an important variable reflecting the strategic deployment of capabilities (Levitas & McFadyen, 2009). We focus on these variables below and propose that they influence investors' perceptions that the NPD process will be successful (prevalent for later stage NPD; see above) and, to the extent investors anticipate failure, their expectations that the firm will successfully recover from a failure event (prevalent for early stage NPD). While disappointed expectations of successful NPD enhance investors' negative reactions to NPD failures, expectations of successful recovery from failure decrease these negative reactions.

Financial capabilities refer to the financial slack available that can be used to develop the firm's capability base (George, 2005; Nohria & Gulati, 1996). More specifically, low discretion financial slack denotes the unused borrowing capacity of the firm (Cheng & Kesner, 1997; Hambrick & D'Aveni, 1988). In contrast to high discretion financial slack (cash and cash equivalents) which is highly liquid, low discretion slack allows firms to access finance in the midterm. Since financial returns from a currently developed product

candidate are distant in time and financial requirements of NPD projects are distributed over time (DiMasi et al., 2003), it appears that low discretion financial slack is more sustainable than high discretion slack for ensuring sufficient finance over the time course of NPD projects and compensating for the loss of expected future revenues when these projects fail.

For products in late development stages, the availability of low discretion slack can trigger investors' perceptions that the NPD process will be completed successfully (a feasibility consideration) and that the firm will appropriate the rents from this successful NPD. First, firms can use debt to acquire the capabilities needed for successful NPD even if unforeseen difficulties arise. For example, firms can draw on their unused borrowing capacity to buffer temporary increases in raw material prices, and they can use debt to buy new devices that facilitate the NPD process in later stages (Rothaermel & Deeds, 2004). Furthermore, using debt financing these firms can maintain control over their late stage product candidates and appropriate the rents generated once this candidate has entered the market. For example, the availability of debt to bridge temporary liquidity constraints can strengthen the firm's negotiation position and help avoid strategic NPD alliances with incumbent firms under unfavorable conditions. Such alliances not only result in a sharing of revenues between the allying firms (Bhaskaran & Krishnan, 2009; Gimeno, 2004) but also entail an increased likelihood that the alliance and thus the NPD project fails (Lerner, Shane, & Tsai, 2003). The availability of debt can also help defend a patent associated with a later stage product candidate, an issue particularly important in highly competitive sectors such as biotechnology where imitation is likely and some patents are of questionable strength (Lerner & Merges, 1998). Thus, the more low discretion slack available to the firm the higher the likelihood of successful NPD and the more investors will be disappointed by NPD failure in late development stages leading to a larger decline of the firm's market value.

For early stage products, feasibility consideration is less important, but low discretion slack can trigger investors' perceptions about coping with failure such that firms effectively recover from NPD failure by increasing the strategic options the firm has available to advance or refill its existing product development pipeline (Guedj & Scharfstein, 2004). For example, firms can use debt to enhance and speed up their in-house development efforts of other projects. Furthermore, firms can draw on their unused borrowing capacity to refill their product development pipeline by in-licensing new early stage products and buying intellectual property from other firms, universities, or research institutes (Kasch & Dowling, 2008). Finally, to compensate for early stage NPD failures, firms can pursue joint NPD projects with other organizations (Badir, Büchel, & Tucci, 2009; Baum, Calabrese, & Silverman, 2000). The availability of debt provides the strategic flexibility to choose between alternative recovery paths (or pursue several of them in parallel) and indicates to investors that the firm can refill its NPD pipeline without raising additional equity capital (Xu, 2009). To the extent investors anticipate failure as a likely outcome of early NPD, these recovery benefits of slack are priced in the value of the firm and can partly (or perhaps fully) compensate the disappointed but underweighted success expectations of investors at an early stage failure event. Thus,

Hypothesis 1: When NPD projects fail, the relationship between a firm's low discretion financial slack and the decline in firm value is more negative when the failed project is in a late development stage than when it is in an early development stage.

Managerial capabilities refer to the abilities and know-how of a firm's top management team (TMT; Jensen & Zajac, 2004; Zhang & Wiersema, 2009). The TMT covers "all executives with title above the rank of vice president or serving on the firm's board of directors" (Cannella, Park, & Lee, 2008: 773). A firm's TMT takes decisions to adapt the firm's strategy to environmental demands and thus influences performance (e.g., Jensen & Zajac, 2004). Since mental models of TMTs and thus the decisions they take depend on the characteristics of the team members (Hambrick & Mason, 1984), the composition of the TMT serves as an important signal for investors regarding a firm's future performance (Cannella et al., 2008; Napshin & DeCarolis, 2007). Industry experience of the TMT appears to be a particularly important indicator of managerial capabilities and is crucial for the performance of firms developing new products (Carpenter, Geletkanycz, & Sanders, 2004). Industry experience "embeds tacit knowledge of opportunities, threats, competitive conditions, technology, and regulations specific to an industry, as well as goodwill, with industry players such as buyers and suppliers" (Kor & Misangyi, 2008: 1346).

For products in late development stages, TMT industry experience raises investor expectations about NPD success because it indicates TMTs' market specific knowledge and their industry specific networks (B. D. Cohen & Dean, 2005; Eisenhardt & Schoonhoven, 1990). The more market knowledge a TMT has, the more likely it will develop products that meet customer demands and are launched successfully. Moreover, more experienced teams can better leverage their extensive industry networks to increase the success probabilities of the late stage products they develop (Dietz & Bozeman, 2005; Patzelt, Shepherd, Deeds, & Bradley, 2008; Westphal & Milton, 2000). For example, these alliances can offer access to specialized knowledge about regulatory guidelines in late development stages (Rothaermel & Deeds, 2006). Furthermore, in late product development stages, biopharmaceutical firms often enter into alliances with incumbent firms to access their production, distribution, and marketing capabilities (Baum et al., 2000; Lerner & Merges, 1998; Rothaermel & Deeds, 2004). More industry experience signals to investors that TMTs have both the sector-specific knowledge and networks to successfully complete the NPD process once the product has reached a later stage, thus enhancing the perceived feasibility and, thus, leading to a decline in investors' perceived firm value when NPD fails.

For early development stage products, TMTs' industry experience can signal to investors that firms can recover from NPD failure because knowledge of, and networks within, an industry facilitate managers to deal with the challenges arising from failure. Knowledge of industry regulations allows managers to select those new opportunities and technologies that comply with regulatory guidelines and patent laws, ensuring that the recovery process will not be delayed or even stopped by legal battles and patent infringements. Industry experience and knowledge also enable managers to successfully reorganize internal assets after early NPD failure (DeCarolis et al., 2009; Himmelmann & Schiereck, 2009). Furthermore, industry-experienced managers can draw on a network of potential alliance partners (Eisenhardt & Schoonhoven, 1996) and leverage their network contacts to identify intellectual property and new product candidates for filling up their development pipeline by in-licensing and collaborative research (Fischer & Pollock, 2004). Knowledge of the industry's players will help to identify those partners with the necessary goodwill for successful collaboration and counteract entering into unsuccessful alliances with opportunistic

partners (Kor & Misangyi, 2008). These benefits of managerial industry experience for recovery from early stage failure suggest that firms with more experienced TMTs experience can (partly or fully) counteract investors' disappointment about NPD failure. Thus,

Hypothesis 2: When NPD projects fail, the relationship between a firm's TMT industry experience and the decline in firm value is more negative when the failed project is in a late development stage than when it is in an early development stage.

A firm's *strategic focus on R&D* denotes the deployment of available capabilities toward the creation of internal knowledge and its use to produce marketable compounds (cf. Rzakhanov, 2004). A strong focus on R&D is also important to take advantage of external knowledge, generate future cash flows, and, in the end, sustain competitive advantage over time (Eisenhardt & Schoonhoven, 1990).

Regarding products in late development stages, a strong strategic focus on R&D signals to investors that a firm has allocated comparatively more of its capabilities to the development of late stage product candidates than firms that are less focused on R&D. That is, high R&D firms' late stage products under development may be higher in quality and more likely to reach market launch than those of firm less focused on R&D (Xu et al., 2007). For example, if a firm invests a substantial part of its capabilities in the development of a prototype, this indicates that the prototype and its compounds have been extensively tested in the laboratory and field studies. In the biopharmaceutical industry, a strong focus on R&D indicates extensive and thoroughly conducted laboratory and animal testing, and only those drug candidates that pass all the tests are moved forward to late stage clinical development. In contrast, less focus on R&D indicates that firms conduct only a necessary minimum of laboratory and preclinical tests, and these firms' late product candidates could have been subject to more sophisticated analysis and selection before further development. In their perceptions of firm value, investors will expect a higher likelihood of success for late stage product candidates of firms that are highly focused on R&D than for product candidates of firms investing less in R&D (Rzakhanov, 2004). That is, for late stage product candidates signaling a strong strategic focus on R&D is likely to enhance the decline in firm value after late stage NPD failure.

For products in early development stages, a strong strategic focus on R&D can signal to investors that the firm is able to recover from NPD failure (DeCarolis et al., 2009) because it enables the firm to generate new, and capitalize on, existing knowledge to quickly develop new product candidates compensating for the loss experienced. For example, firms with strong R&D capabilities can create new knowledge by pursuing several internal research projects in parallel. This increases the probability that at least one of these projects will successfully complete the research stage and yield an early stage prototype that they can move forward into advanced stages (Levitas & McFadyen, 2009; Xu et al., 2007). Furthermore, a strong R&D focus indicates to investors that firms have a substantial stock of existing knowledge. With a growing stock of existing knowledge, the firm's absorptive capacity—its ability to identify and acquire knowledge from partners as well as understand and apply this knowledge for its own use—also increases (W. M. Cohen & Levinthal, 1990; Zahra & George, 2002). Increased absorptive capacity facilitates the use of strategic alliances to fill

the gap in the firm's research pipeline. For example, after early NPD failure firms can enter into strategic alliances with universities (Rothaermel & Deeds, 2006) or other firms (George, Zahra, & Wood, 2002; Rothaermel & Deeds, 2004) to acquire the knowledge they need to develop new product candidates. In contrast, being less focused on R&D indicates to investors that the firm's product pipeline is drying out after early NPD failure and that there are only limited opportunities to establish partnerships that help to refill the product pipeline (Girotra et al., 2007; Levitas & McFadyen, 2009). Therefore, a stronger strategic focus on R&D is associated with enhanced recovery potential from early NPD failure. For early stages, this enhanced recovery potential may (partly or fully) compensate disappointed investor expectations. Thus,

Hypothesis 3: When NPD projects fail, the relationship between a firm's strategic focus on R&D and the decline in firm value is more negative when the failed product is in a late development stage than when it is in an early development stage.

Research Method

Data and Sample

To test our hypotheses we use the U.S. biopharmaceutical industry as a sampling frame and focus on firms commercializing drugs for the treatment of human diseases. This sector is a knowledge- and invention-intensive industry where NPD is essential for success (DeCarolis & Deeds, 1999; DeCarolis et al., 2009; Girotra et al., 2007). Our sample consists of NPD failures announced by biotechnology firms that were traded at the NASDAQ during the period 1994 to 2008. We explicitly focus on NPD failures that occurred during the clinical development stages and the FDA approval phase since (a) announcement of these failures must be published and (b) the impact of these failures on firm value is more substantial than, for example, failures in the research or preclinical development stages. Clinical trial data were collected from the Recombinant Capital Database (ReCap), a database of biotechnology firm press releases that has been widely used for empirical studies in this field before (DeCarolis et al., 2009; Rzakhanov, 2004). In addition, financial data, data on the TMT, and other data were gathered from the *Wall Street Journal*, MarketWatch, LexisNexis, and the companies' annual reports and web pages.

Our initially identified sample consisted of 593 failures at clinical trial stages experienced by 92 biopharmaceutical firms. A total of 307 failures were dropped from the sample because the exact failure date or the failed product's development stage could not be identified. Moreover, 76 failures were excluded because stock market data or other relevant firm data at the time of the failure date were not available, leading to a set of 210 failures. Personal communication with ReCap employees yielded that failures that were listed in the database as having occurred on the first day of a month may indicate failures for which only the month, but not the accurate day, could be correctly identified by ReCap. Therefore, we cross-checked all failure dates with the firms' press releases, SEC filings, and secondary information (e.g., press reports about the firm). To be conservative and ensure high data quality, we

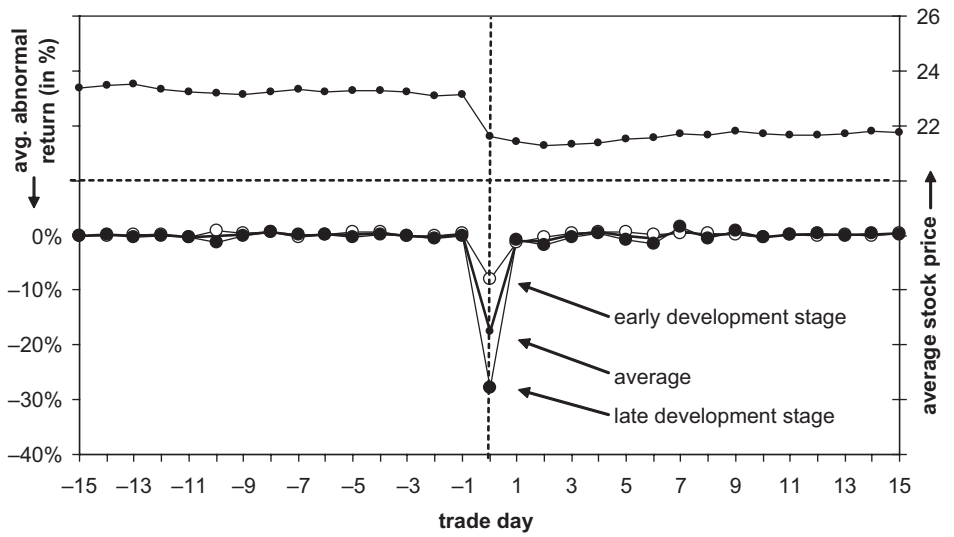
excluded all data points where (a) ReCap lists the first day of a month as the failure date but we were not able to gain further confirmatory information (46 cases), (b) ReCap reports days different from the month's first day but we found conflicting press releases or secondary information (3 cases), and (c) ReCap reported data that could not be validated by any other secondary source (12 cases). Finally, we excluded one data point that was identified as a biasing outlier. When we included this data point, all models reported below this data point had an extreme residual as well as an extreme leverage (cf. outlier analysis in J. Cohen, Cohen, West, & Aiken, 2003). This leads to a final sample of 148 clinical product failures from 66 biotechnology firms, which is slightly larger than those used in similar studies (e.g., DeCarolis et al.'s, 2009, event study on NPD failure in U.S. biotech firms used a sample of 105 failure events).

Our data screen is rather strict and leads to a final sample consisting of only 25.0% of the initially identified failures. Although this screening is not uncommon for event studies because it is difficult to acquire firm data for exact dates back in time (e.g., in their event study, Nixon, Hitt, Lee, & Jeong, 2004, had to narrow down 1,445 initially identified downsizing announcements to a final sample of 346, or 23.9% of the initial sample), we test for sample-selection bias in two ways. First, we use *t* tests to compare events of our sample to those excluded based on several variables we had available for (a varying number) of excluded events. We find no significant differences (*t* test with unequal variances) for firm age ($t = 0.46$, $p = .64$), firm size ($t = 1.42$, $p = .16$), equity-to-debt ratio ($t = 1.21$, $p = .23$), current ratio ($t = 0.71$, $p = .48$), R&D intensity ($t = 1.34$, $p = .17$), TMT industry experience ($t = 1.13$, $p = .26$), TMT tenure ($t = 0.21$, $p = .83$), TMT age ($t = 1.49$, $p = .14$), and products in pipeline ($t = 0.52$, $p = .61$). However, we do find that the selected failures (a) were more often at late development stages (Mann–Whitney test because of the binary nature of the variable; $z = 3.28$, $p = .001$) and (b) tended to be experienced more recently ($t = 3.40$, $p < .001$). This selection bias is not surprising because it is more likely to find data on more recent failures (e.g., we had difficulties finding stock prices further back in time) and on failures with more serious implications for the firm. Second, we perform a robustness check in our analysis (see Model 13 in Table 3 below) where we use all 209 events including those for which data from ReCap could not be validated (see above). Our results are robust for this less strictly screened sample. In sum, the results of these tests suggest that our final sample provides a rather good representation of NPD failures in biopharmaceutical firms.

Variables

Dependent variable. The dependent variable in our study, *cumulative abnormal return* (CAR), captures the financial impact of clinical product failures on valuation of biopharmaceutical firms (Girotra et al., 2007; McWilliams & Siegel, 1997). We define the event day as the day when the event is announced if it is a trading day (defined with respect to the NASDAQ) or the following trading day if the day of announcement is not a trading day. Figure 1 plots the average daily stock price for the event day and 15 days before and after the event day and illustrates the effect on NPD announcements at the event day. Following others (Girotra et al., 2007; Godfrey, Merrill, & Hansen, 2009) we estimate daily abnormal returns (AR)

Figure 1
Average Stock Prices and Average Daily Returns
Around the Failure Announcement



using continuously compounded returns based on a single-index market model with the NASDAQ biotech index as the market index (cf. G. V. Henderson, 1990).[2] The estimation period is from 170 to 20 days before the event day (our results are robust to changes in the length of the estimation period). Because of the formal requirements for disclosing NPD failure in the biopharmaceutical industry and because of our strict data screen and validation procedures reported earlier, we were able to determine the event day with high levels of accuracy. In addition to average stock prices, Figure 1 plots the average daily abnormal return (the percentage changes corresponding to the average abnormal return are assigned to the vertical axis) and shows a substantial abnormal return at the event day and substantially smaller AR across all other days. This observation supports the use of a standard event window of one day before and one day after the event and CAR(–1, +1) calculated as the sum of the AR at the event day plus the day before and the day after (cf. Girotra et al., 2007; McWilliams & Siegel, 1997) as the dependent variable in our model (we also use larger and smaller event windows as robustness checks; see Table 3 below).

Independent variables. To measure the constructs of our model we selected the following variables. First, a firm's (low discretionary) financial slack is measured by the *equity-to-debt ratio* (calculated as equity to debt = [total assets – total liabilities] / total liabilities), which indicates a firm's unused borrowing capacity (Cheng & Kesner, 1997; Hambrick & D'Aveni, 1988). "This measure captures Singh's conception of unabsorbed slack, i.e.,

excess uncommitted resources. The measure tends to signal potential resource availability rather than resources available for instantaneously buffering operations. That is, the higher the firm's equity-to-debt ratio, the more potential it has-when and if needed-to secure more capital. A firm with a very low equity-to-debt ratio would not have access to much more capital" (Hambrick & D'Aveni, 1988: 9). Unlike liquidity ratios, such as current ratio, which reflect the high discretionary financial slack of a firm (DeCarolis et al., 2009), equity-to-debt ratio measures the extent to which the firm is using long-term debt (Ross, Westerfield, & Jaffe, 1998). For our specific sample, we prefer using equity-to-debt ratio instead of debt-to-equity ratio because the latter is negative in 10% of the failure events in our sample, resulting in an essential discontinuity and a non-monotonicity around zero, which makes a monotonic interpretation of the ratio impossible.[3] To control for potentially confounding effects of high and low discretionary slack, we use *current ratio* as a control variable (DeCarolis et al., 2009). Data were taken from the 10-K SEC filings and the annual reports in the reporting period before the NPD failure.

Second, with respect to firms' managerial capabilities, we followed Zhang and Wiersema (2009) and Carpenter et al. (2004) and captured the average years of industry experience of the firms' top managers as reported at the end of the year before the NPD project failed. This variable was labeled *TMT industry experience*. To distinguish industry experience from general knowledge and wisdom that accumulates with age and from knowledge about the own organization, we control for the *TMT's average age* as well as the TMT's *average TMT tenure* (both measured in years). We operationalize the latter as total number of years spent in the current company as a member of the TMT (Carpenter, 2002; Zhang & Wiersema, 2009). All data were validated by cross-checking with the firms' 14-A SEC filings and consolidated balance sheets. Since industry experience and tenure need to be extracted from texts, two research assistants coded these variables. Between-rater correlations of .83 for industry experience and .89 for tenure indicate that the measures are sufficiently reliably extracted from the data sources. Deviations between the coding were discussed among the authors, and corrections made where necessary.

Third, in line with others (DeCarolis et al., 2009; Xu et al., 2007), to measure firms' strategic focus on R&D we use *R&D intensity*, operationalized as a firm's R&D expenses per employee (Baysinger, Kosnik, & Turk, 1991). Importantly, another often used proxy for R&D intensity, R&D per sales revenues (W. M. Cohen & Klepper, 1992), is not defined for zero revenues. Many young biopharmaceutical firms in our sample do not earn any or just marginal revenues because of the long NPD cycles (6.1% out of our 148 cases have either zero sales or spent at least 500 times their sales on R&D). Using this measure would lead to sample selection bias (dropping data points because of division by zero) or extreme values and thus extremely skewed distributions (division by very small numbers). Importantly, although R&D intensity is measured per employee, its correlation with the number of employees in the firm is low (see Table 1 below, $r = -.23$). Thus, an employee-based measure of R&D intensity does not create problems of multicollinearity in our data set even if we use the number of employees as an additional (control) variable (see below).

Since R&D intensity denotes a strategic orientation (an "intention to innovate") rather than an actual R&D outcome, we control for R&D outcomes. In biopharmaceutical firms,

Table 1
Descriptive Statistics and Pearson Correlation Coefficients

	M	*SD*	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
1. CAR(–1, +1)	–0.20	0.37																	
2. CAR(–3, +3)	–0.22	0.39	.97***																
3. CAR(–7, +7)	–0.20	0.40	.93***	.96***															
4. Firm age	15.15	5.42	.10	.09	.10														
5. Firm size (1,000 employees)	1.46	3.32	.21*	.21**	.21*	.41***													
6. Return on assets	–0.31	0.41	.34***	.33***	.36***	.12	.34***												
7. Late stage failure	0.55	0.50	.32***	.34***	.36***	.09	.01	.08											
8. Progress in early stage	0.40	0.72	.20*	.21*	.21**	–.00	–.06	.10	.20*										
9. Progress in late stage	0.24	0.46	.23**	.22**	.20*	–.06	.12	.11	–.15†	–.04									
10. Restructuring announced	0.09	0.29	.02	–.00	–.00	.05	–.10	.06	.15†	.08	–.02								
11. Announced as part of QFR	0.07	0.25	.11	.09	.09	–.03	.04	.09	.08	.19*	.03	–.09							
12. R&D intensity (per employee)	0.25	0.18	–.57***	–.56***	–.56***	–.13	–.23**	–.55***	–.02	–.02	–.15†	.04	–.09						
13. Products in pipeline ($N = 126$)	6.59	6.58	.21*	.23**	.21*	.30***	.85***	.28**	.06	.03	.12	–.14	.11	–.14					
14. Equity-to-debt ratio	3.07	4.23	–.08	–.07	–.08	–.22**	–.10	.09	–.03	.07	–.00	–.11	.09	–.05	–.12				
15. Current ratio	8.23	11.01	.07	.07	.03	–.15†	–.16†	.15†	.19*	.03	–.07	–.06	–.04	–.03	–.10	.30***			
16. TMT industry experience	15.93	3.75	–.12	–.12	–.10	.09	–.13	.03	–.08	–.03	.04	.23**	.04	–.08	–.18*	–.14†	–.14†		
17. TMT tenure	4.79	2.51	.08	.09	.09	.32***	.03	.01	.04	.03	–.04	.03	–.02	–.13	–.02	–.17*	–.00	.37***	
18. TMT age	51.88	4.81	–.10	–.08	–.08	–.02	.00	.01	–.08	–.09	.05	.01	–.00	–.01	–.03	.00	–.04	.51***	.16†

Notes: $N = 148$ (except for products in pipeline, which has 126 cases). QFR = quarterly financial report; TMT = top management team.
†$p < .10$. *$p < .05$. **$p < .01$. ***$p < .001$.

these outcomes are reflected by products in pipeline or patents (e.g., Deeds, DeCarolis, & Coombs, 1999). Because in our sample the number of patents is highly correlated with the number of products in the pipeline ($r = .76$, $p < .001$) and products in pipeline are closer to actual outcomes in terms of a marketable product, we control for a firm's product pipeline (results are stable when using patents as innovation output measure). We operationalize this variable by counting the number of therapeutic indications represented by the products under clinical development or in the FDA approval phase (consistent with Rothaermel & Deeds, 2004). To avoid a further reduction of the data set, missing values (25 data points) were set to the average level. Estimations on the reduced sample led to equivalent estimation results (see Table 3 below).

Fourth, to simplify analysis we consider only two product development stages: Phases I and II as the "early stage" and Phase III and the FDA approval phase as the "late stage." *Stage* is coded with a value of 0 if the failure occurred in early stage and 1 if it occurred in the late stage. Our final sample consists of 67 late stage and 81 early stage failures.

Control variables. Besides the above-mentioned controls that specifically address potential confounds of our independent variable constructs, we include various additional control variables known or expected to influence CAR. First, we control for *firm age* since investors may assess the NPD failure risk of younger ventures higher because of their capability constraints (Zheng, Liu, & George, 2010). Firm age is operationalized as the number of years from firm inception to the NPD failure (DeCarolis et al., 2009). Second, we control for firm size by including the total numbers of *employees*. Guedj and Scharfstein (2004) argue that larger firm size signals better opportunities to access new, and control existing, capabilities. Third, following DeCarolis et al. (2009), we control for firm performance measured by return on assets (ROA) defined as the ratio of income to total assets, which we obtained from the annual reports for the fiscal year prior to the NPD failure announcement. Firm performance is also reflected in our earlier reported control variables patents and products in pipeline (Deeds et al., 1999; Rothaermel & Deeds, 2004).

Finally, we use additional controls that account for characteristics specific to a failure announcement. First, we control for whether or not the failure announcement was made part of a quarterly report of company results (dummy variable labeled *quarterly report*). The simultaneous publication of other information might influence the salience of the failure communication. Furthermore, we control for announcements of overlapping events that we identified as being announced simultaneously with the failure in our sample. We use dummies to control for (a) whether or not an organizational restructuring was announced at the time of the failure (*restructuring*) and (b) the number of projects that the firm announced to have made progress in early stages (*progress in early stage*) or late stages (*progress in late stage*) within the event window. We acknowledge that a further possibility to deal with overlapping events is to eliminate the respective data points. However, since this procedure might introduce a sample selection bias, we favor controlling for overlapping events. Specifically, excluding these events reduces our sample size by 45%. Even with this reduced sample, however, our results reported below remain robust.

Results

Descriptive Statistics and Correlations

Descriptive statistics and correlations for the variables are reported in Table 1. There are a few correlations with coefficients above .4. Larger firms seem to be older and have more products in the pipeline, which is an intuitive observation. Furthermore, R&D intensive firms have larger returns on assets, which is consistent with others' findings (DeCarolis et al., 2009). To ensure that these moderate correlations are no problem in our data set, we calculated variance inflation factors (VIFs) for a test of multicollinearity. All VIFs were below 5, which does not justify concerns about multicollinearity.

Average Stock Returns to NPD Failure

We first establish that NPD failure causes negative stock returns for investors. We calculate a Patell z of –5.79 based on standardized AR for the 3-day event window (G. V. Henderson, 1990; Patell, 1976) which indicates that the stock market shows substantial negative reactions to these announcements (consistent with Figure 1). Also, the sign test is significant at $p < .001$ with 109 negative and 39 positive CAR(–1, +1). We further calculate Patell z as well as a nonparametric sign test for each individual trade day between 15 trading days before and 15 trading days after the event day. No trade day outside the event window consistently shows significantly negative deviations. For exploratory reasons, Figure 1 also splits the data into failure occurring in early and occurring in late product development stages. The visual inspection as well as corresponding statistical tests provide evidence that the abnormal return substantially depends on the development stage of the failed project (t test on difference between daily AR with unequal variances: $t = –3.94$, $p < .001$, rank sum test: $z = –3.030$, $p = .002$). These tests demonstrate that NPD failure does negatively affect firm valuation across the range of our data in a statistically significant manner.

Test of Hypotheses

Since in event studies residuals of ordinary least squares (OLS) regression are often non-normally distributed (G. V. Henderson, 1990), we first tested skewness and kurtosis for the residuals geared when estimating a full OLS model covering all control variables, independent variables, and interactions embedded in our hypotheses (Model 9 in Table 2). We find that residuals are leptokurtic (kurtosis = 4.97, $p = .001$), not skewed (skewness = –0.15, $p = .431$), and therefore non-normal ($\chi^2 = 9.49$, $p = .009$). To account for this non-normality, we estimate two robust regression models based on robust estimations of the abnormal return (Model 1) and a robust estimation of both our basic model and market models (Model 2). The robust estimation procedure based on weighted least squares and using Huber weights and biweights (as provided by Stata 11.1) iteratively reweights least squares to reduce the influence of outliers.

Table 2
Regression Analyses

Model	1, CAR(–1, +1)[a]	2, CAR(–1, +1)[b]	3, CAR(–1, +1)	4, CAR(–1, +1)	5, CAR(–1, +1)	6, CAR(–1, +1)	7, CAR(–1, +1)	8, CAR(–1, +1)	9, CAR(–1, +1)
Firm age	0.00 (0.020)	0.00 (0.018)	0.01 (0.03)	–0.00 (0.03)	–0.01 (0.02)	–0.00 (0.02)	–0.00 (0.02)	–0.01 (0.02)	0.00 (0.02)
Employees (EM)	–0.01 (0.028)	–0.02 (0.030)	0.02 (0.03)	0.03 (0.04)	0.00 (0.03)	–0.00 (0.03)	0.00 (0.03)	–0.00 (0.03)	–0.01 (0.03)
Return on assets (ROA)	0.03 (0.034)	–0.01 (0.021)	0.09 (0.04)*	0.09 (0.03)**	–0.00 (0.03)	–0.00 (0.03)	–0.01 (0.03)	0.02 (0.03)	0.03 (0.03)
Prod. in pipeline (PIP)	0.03 (0.030)	0.04 (0.028)	0.03 (0.04)	0.01 (0.04)	0.02 (0.04)	0.02 (0.03)	0.02 (0.04)	0.02 (0.03)	0.03 (0.03)
Top management team age (TAG)	–0.02 (0.023)	–0.03 (0.019)	–0.05 (0.03)[†]	–0.04 (0.03)	–0.00 (0.02)	–0.01 (0.02)	0.00 (0.02)	–0.02 (0.02)	–0.02 (0.02)
Top management team tenure (TTE)	0.01 (0.025)	0.00 (0.018)	0.04 (0.03)	0.04 (0.03)	0.02 (0.03)	0.02 (0.03)	0.02 (0.03)	0.02 (0.03)	0.01 (0.02)
Current ratio (CUR)	0.01 (0.011)	0.02 (0.017)	0.02 (0.02)	–0.00 (0.01)	0.01 (0.02)	0.01 (0.02)	0.02 (0.02)	0.01 (0.01)	0.01 (0.01)
Quarterly report (QFR)	–0.00 (0.07)	–0.02 (0.08)	0.06 (0.06)	0.02 (0.08)	0.04 (0.07)	0.05 (0.06)	0.03 (0.05)	0.04 (0.06)	0.06 (0.06)
Restructuring (RST)	0.00 (0.06)	–0.04 (0.04)	0.01 (0.08)	–0.06 (0.09)	0.03 (0.08)	0.03 (0.08)	0.05 (0.08)	0.03 (0.07)	0.04 (0.08)
Progress in early st. (PES)	0.06 (0.03)*	0.06 (0.03)*	0.08 (0.03)**	0.05 (0.03)*	0.07 (0.03)*	0.05 (0.03)[†]	0.04 (0.03)	0.05 (0.03)*	0.05 (0.03)[†]
Progress in late st. (PLS)	0.13 (0.05)**	0.12 (0.05)*	0.16 (0.04)***	0.19 (0.05)***	0.15 (0.05)**	0.14 (0.04)**	0.12 (0.05)*	0.14 (0.04)**	0.13 (0.04)**
Late stage (LST)	–0.22 (0.05)***	–0.27 (0.05)***		–0.23 (0.06)***	–0.21 (0.05)***	–0.20 (0.04)***	–0.19 (0.05)***	–0.20 (0.04)***	–0.20 (0.05)***
Equity to debt (ETD)	0.01 (0.02)	0.02 (0.02)			–0.05 (0.03)[†]	–0.00 (0.02)	0.00 (0.02)	0.00 (0.02)	0.00 (0.01)

(continued)

Table 2 (continued)

Model	1, CAR(–1, +1)[a]	2, CAR(–1, +1)[b]	3, CAR(–1, +1)	4, CAR(–1, +1)	5, CAR(–1, +1)	6, CAR(–1, +1)	7, CAR(–1, +1)	8, CAR(–1, +1)	9, CAR(–1, +1)
Top management team industry exp. (TIE)	0.01 (0.02)	0.02 (0.03)			–0.06 (0.03)†	–0.00 (0.02)	0.01 (0.03)	–0.00 (0.02)	–0.00 (0.02)
R&D intensity (RDI)	–0.10 (0.03)**	–0.09 (0.03)**			–0.20 (0.03)***	–0.09 (0.04)*	–0.09 (0.04)*	–0.08 (0.03)*	–0.05 (0.03)
LST × ETD	–0.11 (0.051)*	–0.16 (0.031)***				–0.08 (0.05)			–0.11 (0.05)*
LST × TIE	–0.12 (0.045)**	–0.07 (0.032)*					–0.10 (0.05)*		–0.12 (0.04)**
LST × RDI	–0.17 (0.037)***	–0.16 (0.034)***						–0.15 (0.04)***	–0.17 (0.04)***
Constant	–0.17 (0.030)***	–0.12 (0.026)***	–0.28 (0.04)***	–0.17 (0.03)***	–0.18 (0.03)***	–0.18 (0.03)***	–0.18 (0.03)***	–0.18 (0.03)***	–0.17 (0.03)***
Observation (clusters)	148 (66)	148 (66)	148 (66)	148 (66)	148 (66)	148 (66)	148 (66)	148 (66)	148 (66)
R^2 (F value)	.58 (16.51)***	.53 (17.81)***	.22 (4.24)***	.30 (4.14)***	.51 (24.58)***	.52 (11.55)***	.53 (9.87)***	.55 (17.47)***	.59 (17.21)***
Delta R^2 (F value)	—	—	—	.08 (13.73)***	.21 (14.72)***	.01 (2.26)	.02 (4.36)*	.03 (16.89)***	.07 (7.92)***

Note: Cluster-robust standard errors in parentheses.

[a]Market model estimated based on robust regression; standard errors in parentheses.

[b]Market model and final model estimated based on robust regression; standard errors in parentheses.

†$p < .10$. *$p < .05$. **$p < .01$. ***$p < .001$.

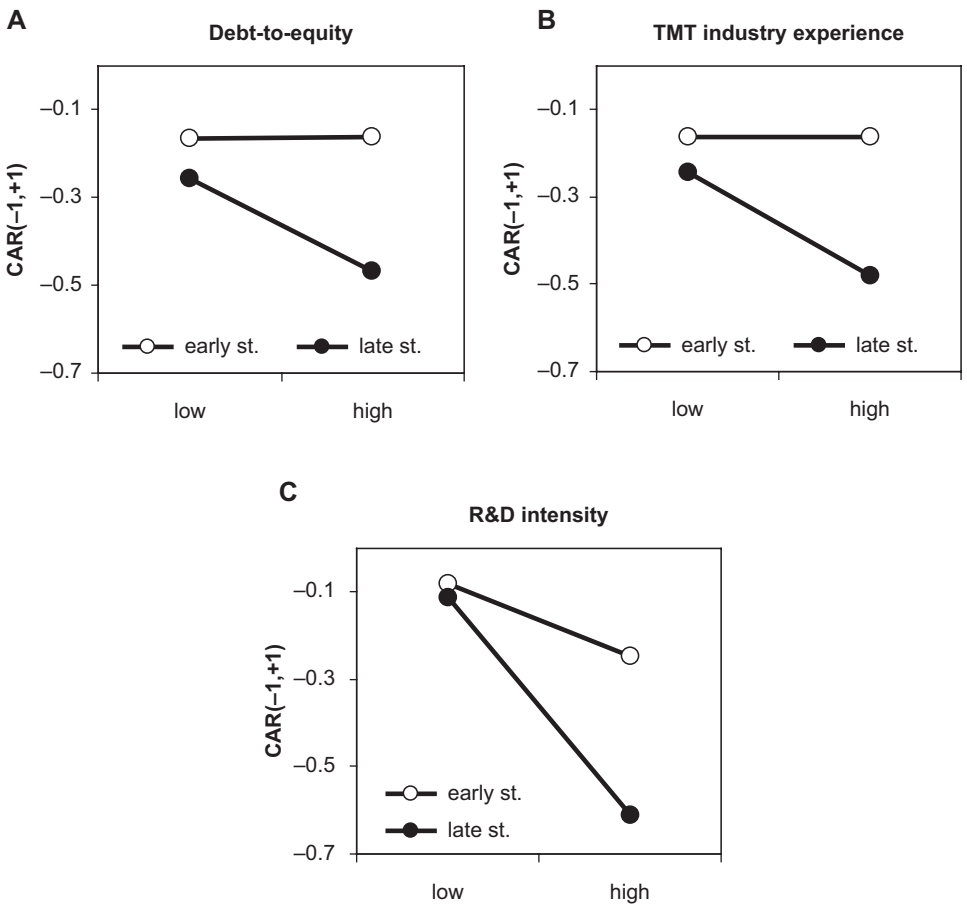
While robust regression handles issues of non-normality well, however, two important disadvantages are associated with this statistical procedure as compared to OLS regressions. First, robust regression does not address the clustered nature of our data (more than one NPD failure nested within one firm) appropriately. Second, because of endogenously generated weights, robust regression does not allow a straightforward comparison between models and, thus, building on the benefits of hierarchical moderated regression analyses to quantify the contribution of an interaction effect over and above the related main effects. On the other hand, some statisticians argue that OLS regressions are relatively robust to violations of normality (J. Cohen et al., 2003) and that "in the interest of conservatism—that is, in controlling the probability of a type I error—one should generally use the critical value from the t-distribution even in the absence of normality" (Greene, 2008: 94). Therefore, following many related studies (DeCarolis & Deeds, 1999; DeCarolis et al., 2009; Girotra et al., 2007), in addition to robust regression we use OLS regression to analyze our data (Models 3 to 9 in Table 2). This yields the additional advantage that our results can be compared to those of other important studies in the field.

In the OLS models we calculate heteroscedasticity- and cluster-robust standard errors based on the Huber–White sandwich estimation. This procedure is especially appropriate if there are, as in our data, few observations per cluster compared to the sample size (Wooldridge, 2002). To compare nested models and test whether the increase in explained variance (R^2) from one model over the other is statistically significant, we use Wald-like tests. Table 2 reports the results of the robust regressions (Models 1 and 2) and then the results of the OLS regressions (Models 3 to 9).

The results of the robust regression analysis, which are represented in Models 1 and 2 in Table 2, reveal that there are significant, negative interaction effects between financial slack (equity to debt) and product development stage, TMT industry experience and product development stage, and the firm's strategic focus on R&D (R&D intensity) and product development stage, respectively. To corroborate these findings, we use OLS regression.

We first estimate an OLS model with our basic control variables only (Model 3). Adding the distinction of early and late stage (Model 4) leads to a substantial increase in delta R^2 ($\Delta R^2 = .083$, $F = 13.73$, $df = 65$, $p < .001$). Adding our independent variables equity-to-debt ratio, TMT industry experience, and R&D intensity (Model 5) substantially increases the explained variance ($\Delta R^2 = .208$, $F = 14.72$, $df = 65$, $p < .001$). To test our interaction hypotheses we add the interaction terms of these three variables with the failed project's development stage, first individually (Models 6 to 8) and then all interaction terms together (Model 9). While adding the interactions between development stage and TMT industry experience (Model 7) and between development stage and R&D intensity (Model 8) significantly improves the model, the interaction with equity-to-debt ratio does not significantly increase the model's explanatory power. Since including the interaction terms separately, however, does not control for relevant interactions of the development stage variable (and may thus cause omitted variable bias), in Model 9 all interaction terms are included. In this model, the interaction between debt to equity and development stage is—consistent with the robust regressions—negative and significant, as is the interaction between TMT industry experience and development stage and the interaction between R&D intensity

Figure 2
Interaction Effects of Project Development Stage With Equity-to-Debt Ratio, Top Management Team (TMT) Industry Experience, and R&D Intensity



Note: Interaction plots are based on Model 9 in Table 2.

and development stage. Furthermore, the increase in explained variance over and above the main effects model is significant ($\Delta R^2 = .072$, $F = 7.92$, $df = 65$, $p < .001$). These results are consistent with those of the robust regressions (cf. Models 1 and 2 to Model 9).

To better understand the nature of the significant interaction effects, we plot them in Figure 2. On the y-axes we plot CAR(–1, +1), on the x-axes we plot the independent variables, and we plot separate lines for early stage and late stage failures. Figure 2A shows that the relationship between equity-to-debt ratio and CAR(–1, +1) is more negative for late stage failures than for early stage failures. The nature of this significant interaction supports

Hypothesis 1. Figure 2B shows that the relationship between TMT industry experience and CAR(–1, +1) is more negative for late stage failures than for early stage failures. The nature of this significant interaction supports Hypothesis 2. Figure 2C shows that the relationship between R&D intensity and CAR(–1, +1) is more negative for late stage failures than for early stage failures. The nature of this significant interaction supports Hypothesis 3.

Figures 2A to 2C also suggest that CAR(–1, +1) is generally more negative for late stage failures than for early stage failures (lines do not cross in all figures). Exploring this effect in more detail and calculating the effects of firm characteristics for specific development stages separately, we find that there is only a significant effect for early stage failures for R&D intensity ($\beta_{RDI} = -.08$, $t = -2.44$, $p < .018$), while for late stage failures the influence is significantly negative for all three focal variables ($\beta_{RDI} + \beta_{LST\times RDI} = -.25$, $t = -10.04$, $p < .001$; $\beta_{TIE} + \beta_{LST\times TIE} = -.12$, $t = -2.74$, $p = .008$; $\beta_{ETD} + \beta_{LST\times ETD} = -.11$, $t = -2.32$, $p = .024$). Furthermore, calculating the effects of the development stage for specific levels of firm capabilities, we find that for low values of firms' financial capabilities, managerial capabilities, and strategic focus on R&D (left side in figures) none of the differences between early and late stage failures are significant ($\beta_{LST} - \beta_{LST\times RDI} = -.03$, $t = -0.58$, $p = .57$; $\beta_{LST} - \beta_{LST\times TIE} = -.08$, $t = -1.36$, $p = .18$; $\beta_{LST} - \beta_{LST\times ETD} = -.09$, $t = -1.39$, $p = .17$). For high values of the firm capabilities, this difference is significant for all three cases ($\beta_{LST} + \beta_{LST\times RDI} = -.36$, $t = +5.70$, $p < .001$; $\beta_{LST} + \beta_{LST\times TIE} = -.32$, $t = -4.67$, $p < .001$; $\beta_{LST} + \beta_{LST\times ETD} = -.30$, $t = -4.37$, $p < .001$). Thus, while late stage failures on average (i.e., averaged over all values of firm capabilities; cf. J. Cohen et al., 2003) are associated with more negative investor reactions than early stage failures (see also Model 4), this effect diminishes for firms with lower levels of financial and managerial capabilities (and less so for firms that are less focused on R&D).

Robustness Checks

To test the robustness of our results we performed a number of additional tests, which we report in Table 3. These tests further support our previous findings. First, our results hold for multiple event windows (see Models 10, 11, and 12), that is, a single day window (only the daily abnormal return AR at the event day), 3 days before and 3 days after the event day, CAR(–3, + 3), and 7 days before and after the event day, CAR(–7, + 7). The results also remain robust when we include all data points where we could not sufficiently validate the event date (Model 13). Second, therapeutic indications addressed by the failed drug candidate may have an effect on its development costs and success probability (DiMasi, 1995) and may therefore influence investor expectations reflected by CAR. Controlling for these effects significantly increases the explanatory power (see Model 14) but does not alter the conclusions. Third, to test whether there are differences between failed products in Phases I and II (which we pooled for the above analysis to represent "early stage"), we define a contrast code variable with –1 representing Phase I, +1 representing Phase II, and 0 for all other phases. When including this variable and its interactions with the three firm characteristics into our analysis (Model 15), all corresponding coefficients are negative (the interaction with R&D intensity is significant at the .1 level), indicating that CAR(–1, +1) is more negative for Phase II than for Phase I (consistent with our theory). While we find that there are only weak differences between Phase I and Phase II failures, our more general

Table 3
Robustness Checks

Model	10, AR	11, CAR(–3, + 3)	12, CAR(–7, + 7)	13, CAR(–1, +1)[a]	14, CAR(–1, +1)	15, CAR(–1, +1)	16, CAR(–1, +1)[b]	17, CAR(–1, +1)[c]
Firm age	0.01 (0.02)	–0.00 (0.02)	–0.00 (0.02)	–0.01 (0.02)	–0.01 (0.02)	0.00 (0.02)	0.01 (0.02)	0.00 (0.02)
Employees (EM)	–0.01 (0.03)	–0.02 (0.03)	–0.02 (0.03)	–0.00 (0.02)	–0.00 (0.03)	–0.01 (0.03)	–0.02 (0.03)	–0.01 (0.03)
Return on assets (ROA)	0.04 (0.03)	0.02 (0.03)	0.05 (0.03)	0.04 (0.03)	0.02 (0.04)	0.03 (0.04)	0.04 (0.04)	0.03 (0.03)
Prod. in pipeline (PIP)	0.02 (0.03)	0.05 (0.03)	0.04 (0.04)	0.02 (0.02)	0.04 (0.03)	0.03 (0.03)	0.04 (0.03)	0.03 (0.03)
Top management team age (TAG)	–0.01 (0.03)	–0.01 (0.03)	–0.02 (0.02)	–0.02 (0.02)	–0.03 (0.02)	–0.02 (0.03)	–0.00 (0.02)	–0.02 (0.02)
Top management team tenure (TTE)	0.01 (0.03)	0.02 (0.03)	0.02 (0.03)	–0.00 (0.02)	0.02 (0.02)	0.01 (0.02)	0.01 (0.03)	0.01 (0.02)
Current ratio (CUR)	0.01 (0.01)	0.01 (0.01)	–0.01 (0.01)	0.00 (0.01)	0.02 (0.01)*	0.01 (0.01)	0.02 (0.01)†	0.01 (0.01)
Quarterly report (QFR)	0.04 (0.08)	0.01 (0.06)	–0.03 (0.04)	–0.01 (0.07)	0.04 (0.05)	0.06 (0.06)	0.03 (0.08)	0.05 (0.06)
Restructuring (RST)	0.07 (0.06)	0.01 (0.07)	–0.01 (0.08)	0.03 (0.05)	0.05 (0.08)	0.03 (0.08)	0.02 (0.10)	0.03 (0.08)
Progress in early st. (PES)	0.05 (0.03)†	0.06 (0.03)*	0.06 (0.03)*	0.03 (0.03)	0.04 (0.03)†	0.06 (0.03)*	0.07 (0.03)*	0.06 (0.03)*
Progress in late st. (PLS)	0.13 (0.04)**	0.13 (0.05)**	0.13 (0.05)*	0.10 (0.04)**	0.12 (0.05)*	0.14 (0.04)**	0.15 (0.05)**	0.14 (0.04)**
Late stage (LST)	–0.20 (0.05)***	–0.22 (0.05)***	–0.27 (0.05)***	–0.21 (0.04)***	–0.18 (0.05)***	–0.20 (0.04)***	–0.17 (0.05)**	–0.19 (0.04)***
Equity to debt (ETD)	0.00 (0.01)	0.01 (0.02)	0.02 (0.02)	0.01 (0.01)	0.00 (0.02)	–0.00 (0.02)	–0.00 (0.02)	0.00 (0.02)
Top management team industry exp. (TIE)	0.00 (0.02)	0.01 (0.03)	0.02 (0.03)	0.01 (0.02)	0.01 (0.03)	0.01 (0.03)	0.00 (0.04)	0.00 (0.02)
R&D intensity (RDI)	–0.06 (0.03)	–0.10 (0.03)**	–0.09 (0.03)**	–0.04 (0.03)	–0.09 (0.04)*	–0.06 (0.03)†	–0.08 (0.04)*	–0.09 (0.03)*
LST × ETD	–0.08 (0.04)†	–0.12 (0.06)*	–0.14 (0.05)*	–0.18 (0.07)**	–0.11 (0.06)†	–0.10 (0.05)*	–0.11 (0.05)*	–0.11 (0.05)*
LST × TIE	–0.14 (0.06)*	–0.15 (0.06)**	–0.15 (0.05)**	–0.12 (0.04)**	–0.10 (0.05)*	–0.13 (0.05)*	–0.14 (0.06)*	–0.12 (0.04)**
LST × RDI	–0.19 (0.04)***	–0.17 (0.04)***	–0.17 (0.04)***	–0.22 (0.05)***	–0.16 (0.04)***	–0.19 (0.04)***	–0.17 (0.04)***	–0.17 (0.04)***
Indication A[d]					–0.06 (0.07)			
Indication B[d]					0.07 (0.06)			
Indication C[d]					0.02 (0.07)			
Indication D[d]					–0.01 (0.06)			
Indication E[d]					–0.08 (0.06)			
Indication G[d]					–0.10 (0.08)			
Indication H[d]					–0.15 (0.09)			
First vs. second stage (S12)						–0.01 (0.02)		
S12 × ETD						0.02 (0.01)		
S12 × TIE						–0.03 (0.03)		
S12 × RDI						–0.04 (0.02)†		
Constant	–0.15 (0.03)***	–0.16 (0.03)***	–0.12 (0.03)***	–0.10 (0.02)***	–0.11 (0.04)**	–0.17 (0.03)***	–0.19 (0.04)***	–0.17 (0.03)***
Observation (clusters)	148 (66)	148 (66)	148 (66)	209 (71)[a]	148 (66)	148 (66)	126 (57)[b]	148 (66)
R^2 (F value)	.57 (15.09)***	.59 (17.91)***	.60 (22.75)***	.53 (9.54)***	.61 (14.08)***	.59 (14.65)***	.61 (15.67)***	.59 (18.95)***
Delta R^2 (F value)	—	—	—	—	.02 (2.06)†	.01 (2.67)*	—	—

Note: Cluster-robust standard errors in parentheses.

[a]Includes also those data points where the event day could not be perfectly validated.

[b]Excludes observations with missing values for products in pipeline.

[c]Dependent variable CAR(–1, +1) based on the abnormal return as the difference between the firm's returns and the market index.

[d]Similar to DiMasi, Hansen, and Grabowski (2003), we use the following classes of indications: CNS and psychiatric (Type A: 16 cases), cardiovascular (Type B: 6 cases), respiratory (Type C: 3 cases), viral infection (Type D: 13 cases), arthritis, dermatologic, endocrinological, and gastrointestinal (Type E: 20 cases), cancer (Type F: 44 cases), others (Type G: 22 cases), and not reported (Type H: 24 cases), with dummies taking cancer as the baseline.

†$p < .10$. *$p < .05$. **$p < .01$. ***$p < .001$.

conclusions regarding early versus late stage effects remain robust. Fourth, there are 22 events in our sample for which we could not reliably identify the number of products in pipeline, but we kept these events (setting the missing values the average of our sample) to maintain high statistical power and avoid additional selection biases. Estimating a model where we exclude those with missing data for products in pipeline (Model 16) does not alter our conclusions. Last, instead of estimating the abnormal return based on market models, we estimate the abnormal return as the difference between the firm's returns and the market index (using the NASDAQ Biotechnology Index as the benchmark; Model 17). Although both approaches differ in their theoretical foundation, G. V. Henderson (1990) reports that they yield very similar results in many cases. Our findings corroborate Henderson's description; the observed effects are very similar for both approaches.

Discussion

NPD failure is a frequent phenomenon among high technology firms, yet how investors react to these failures is still poorly understood. In this study, we integrate two sets of theoretical arguments to develop a model of investor reactions to NPD failures. Our data support this combined perspective and suggest that the development stage of the failed project determines, partly, the extent to which investors emphasize either perspective. These results have various implications.

Theoretical and Empirical Implications

The NPD literature is surprisingly silent on the effect of NPD failure at different stages of development. For example, many existing studies focus on only firm-specific factors that influence investor reactions to NPD failure (DeCarolis et al., 2009; Napshin & DeCarolis, 2007; Xu et al., 2007) but neglect the fact that products can fail at different development stages. Indeed, to the best of our knowledge, only three studies on NPD failure explicitly acknowledge heterogeneity in the development stages of new product candidates. First, Girotra et al. (2007) investigate NPD failures of Phase III clinical trials of drug candidates and explain variance in project valuation based on interactions of the failed product with other product candidates at different development stages in the firm's product pipeline. Second, Guedj and Scharfstein (2004) find that when clinical Phase II drug candidates advance to clinical Phase III often agency problems between managers and investors arise. More recently, Himmelmann and Schiereck (2009) showed that stock movements are more substantial when firms announce late stage NPD outcomes than when they announce early stage NPD outcomes. Our finding that product development stages are important to consider when explaining the impact of firm capabilities (and their deployment) on organizational consequences of NPD failure complements these studies and suggests that future NPD theory should more explicitly acknowledge heterogeneity in NPD stages and the impact of this heterogeneity on organizational outcomes of (successful or unsuccessful) NPD processes.

Moreover, this study finds that for both early and late stage development failures firms with a stronger focus on R&D suffer more from NPD failures than those less focused on R&D (although this effect is significantly stronger for late failures; see Table 2). While this finding is consistent with previous work on investor reactions to NPD outcomes (Guedj & Scharfstein, 2004), it challenges the argument that R&D facilitates a quick recovery from failure in the eyes of investors (DeCarolis et al., 2009). At least in our data, this latter effect seems to be small enough to be overcompensated by the signal that a strong R&D focus provides with respect to enhancing success expectation of investors. One explanation of this finding might be rooted in the long product development cycles of the biopharmaceutical industry. Since today's R&D expenditures lead to marketable products (or product candidates in late development stages) only in the distant future, a strong focus on R&D may insufficiently signal the firm's recovery potential on the short and medium term, which might be more relevant for investors' ad hoc reactions to NPD failures. In industries with shorter NPD cycles, a firm's actual R&D focus may therefore contribute more to investors' assessments of its recovery potential. Future research can test this assumption by focusing on sectors like software and electronics.

Our study also informs upper echelon research by investigating the role of the TMT in the context of adverse events (NPD failures). While many upper echelon studies have focused on how TMTs impact the financial performance of firms over an extended time frame (Boeker, 1997; Jensen & Zajac, 2004), much less is known about TMTs' role in case of adverse events. Recently, Napshin and DeCarolis (2007) suggested that investors judge more experience (as indicated by age) as facilitating recovery from failures. Other studies (e.g., Certo, 2003) propose that more industry experienced top management boards signal toward investors the knowledge and ability to change the firm's strategic direction in critical situations. Importantly, however, these authors do not investigate if (and how) this effect is contingent on the nature of the adverse event. Our approach suggests that in some cases (particularly late stage failures; see Figure 2) investor expectations that industry experienced TMTs conduct successful NPD are more important than their judgment of the TMT's ability to recover from NPD failures. It appears that a contingency perspective is necessary to understand in detail how TMTs impact firm performance in the case of adverse events contingent on specificities of the NPD process and the product's development stage.

Existing research on the antecedents and outcomes of innovation processes generally focuses on only one level of analysis while neglecting heterogeneity at other levels of analysis (Rothaermel & Hess, 2007). Focusing on one level of analysis implicitly assumes that most of the existing heterogeneity can be found at the chosen level. Moreover, concentrating on this one level of analysis implies that the focal level of analysis seems to be more or less independent from interactions with other levels. In line with Rothaermel and Hess (2007) we thus advocate a multilevel theoretical approach combining product-level and organizational-level effects. Our finding that organizational-level factors can mitigate the negative outcomes of NPD failure depending on the stage of the product under development highlights the need to consider cross-level effects in the analysis of organizational outcomes of innovation processes. This is also consistent with the capabilities-based view of the firm (Eisenhardt & Martin, 2000; Teece, Pisano, & Shuen, 1997) suggesting that firms are heterogeneous with respect to their idiosyncratic "bundles" of capabilities influencing

performance. Our findings emphasize this "bundle" effect, that is, interdependencies of capabilities (financial and management) are valued by investors when one particular capability (a product under development) is lost.

Our findings can also be interpreted in the light of emerging literature demonstrating that more capabilities are not necessarily better for the firm under all circumstances. For example, scholars have shown that there is a curvilinear relationship between an organization's financial slack and performance because managers tend to deploy too much money available inefficiently (Leonard-Barton, 1992). Our findings indicate that although sufficient and appropriate capabilities are doubtlessly needed to successfully completing NPD processes (Arikan & McGahan, 2009; Evans & Varaiya, 2003), high levels of capabilities can enhance investors' expectations about positive NPD outcomes and thus increase their negative reactions to NPD failures. It appears that succeeding in NPD and not suffering too much from NPD failures are two sides of the same performance coin.

Since our study shares a number of characteristics with DeCarolis et al. (2009), including parts of the sample and variables, a more detailed comparison of findings with this particular study is warranted. However, because we also deviate from this study design in some important aspects, this comparison needs to be done carefully. For example, DeCarolis et al. and the main-effect-only model of this study (Model 5) are consistent in not finding an average main effect of low discretion financial slack on CAR, even though DeCarolis et al. (2009) use debt-to-equity ratio and we use equity-to-debt ratio (the effect in our study is significant at only the 10% level). Importantly, however, our finding that there is a significant interaction between product development stage and low discretion slack suggests that this type of slack does explain a significant amount of variance in CAR and emphasizes the benefits of a contingency approach. Regarding high discretion slack (a control in this study), while DeCarolis et al. find a significant and negative effect of current ratio in two of four models, we find no significant effect. Finally, DeCarolis et al. find a significant positive main effect for R&D intensity, but we find a significant negative main effect and, in addition, a significant interaction with product development stage. Importantly, however, for the reasons reported earlier, we use an employee-based measure while DeCarolis et al. use a revenue-based measure. An exploratory analysis using DeCarolis et al.'s revenue-based measure of R&D and the debt-to-equity measure for slack yields results that are more similar to DeCarolis et al. For instance, ROA becomes significant and in the same direction as reported by DeCarolis et al., and R&D intensity becomes significantly positive for early stage failures. Nevertheless, also in this specification we find a significant negative interaction between R&D intensity and development stage, leading to a significant negative effect for late development stages. Perhaps DeCarolis et al.'s sample contains more early stage failures than our sample. Finally, products in pipeline is a control in our study and an independent variable in DeCarolis et al. While we find a positive but insignificant effect on CAR, DeCarolis et al. find a significant positive relationship. Thus, while some results reported here mirror those of DeCarolis et al., others expand or are different to those reported by these authors. Explanations for diverging findings might be that both studies use different control variables (e.g., DeCarolis et al., 2009, do not control for product development stage, which this study identifies to be an important [moderating] variable), that only this study includes interaction variables, and that there are differences in the operationalization of

constructs and differences in the composition of the sample. Future research explaining and exploring the differences between both studies can make an important contribution.

Practical Implications

Our findings have implications for practice, especially for managers of high technology firms since they allow them to better anticipate and understand the financial consequences of potential NPD failures. Our results highlight the influence that investors' perceptions of the financial and managerial capabilities of the firm, and its strategic focus on R&D, have on value destruction after NPD failures, and how this influence is dependent on the development stage of the failed product. Based on the success probabilities managers attribute to their product candidates, they might align development stages of product candidates with signaling their firm's capabilities in terms of financial slack, managerial experience, and R&D focus. Managers should be aware that signaling firm-specific capabilities and their deployment strategy to investors can influence investor expectations and preserve shareholder value in case of NPD failures, contingent on the development stage of the firm's product portfolio. Specifically, when products with a considerable likelihood of failure enter into later development stages, signaling less strong financial and managerial capabilities, and a weaker focus of R&D, appear to be a means to preserve firm value in case the failure materializes. For example, perhaps managers can delay the extension of the management team until the NPD process is finalized, or they can delay the initiation of new R&D projects (thus diminishing their focus on R&D). Importantly, however, managers must consider whether such measures to protect firm value in the short term might affect the long-term success perspectives of their firms.

Limitations, Future Research, and Conclusion

As all studies, this one has limitations that in turn provide opportunities for future research. The first limitation refers to potential issues of endogeneity reflecting a correlation between our independent variables and error terms. To perform a rigorous test of endogeneity, we attempted to use an instrumental variable approach and the related Hausman test for endogeneity (Wooldridge, 2002). The identification of valid instrumental variables, however, is a difficult task (Murray, 2006), and it is particularly difficult in our case because it would require four instrumental variables (one for each of the four potentially endogenous independent variables). We were unable to identify four exogenous variables that could serve as sufficiently valid and sufficiently strong instruments in our data set. Therefore, we attempted to minimize potential sources of endogeneity covering (a) measurement errors, (b) sample selection errors, (c) omitted variables, and (d) simultaneous measurement of independent and dependent variables (Wooldridge, 2002). Since most of our variables are objective numbers and established in the literature it appears that measurement errors are not a major source of endogeneity in our work (at least not more than in most other studies). However, since we apply a strict data screen for ensuring high validity of the failure

announcement date, our sample may be vulnerable to sample selection errors. As reported earlier, we test for these errors in various ways, and find that most of these tests suggest that our selected sample mirrors the overall population well. Furthermore, to minimize omitted variable bias, we use a substantial number of control variables (including interactions) that might be expected to correlate with our variables of interest and at the same time may influence the dependent variable. The variety and number of controls included exceeds that of similar studies (DeCarolis et al., 2009). Finally, all independent and control variables in our data set are measured before the failure date (because they were taken from reports published before) except for those indicating announcements of simultaneous events (restructuring, publication in quarterly reports, early and late stage NPD progress). Our results remain robust even if we eliminate these events from our sample. However, although these tests and our methodological design suggest that we can address potential sources of endogeneity to some extent, we want to emphasize that we cannot rule out endogeneity concerns completely. We hope that future studies on NPD failure can address this important issue by using a more rigorous test such as an instrumental variable approach.

Second, we focus only on biopharmaceutical companies, and thus on a single high technology industry. While this sampling technique rules out methodological threats such as potential confounding effects (Zheng et al., 2010), it raises the question of generalizability to a larger population. Caution must be exercised when transferring findings from a single industry to others, for example to an industry with shorter NPD cycles (as outlined in the discussion). We hope that future research will test whether our findings are robust in settings other than the biopharmaceutical industry.

Finally, this study provides only a snapshot of investors' reactions to failure events, but it does not investigate which firms over time actually recover from the failure event and which ones do not. While we show that the availability of capabilities at the time of NPD failure impacts investors' judgment of the firm's future perspectives (as reflected in its stock price), an effective use of these capabilities in the time period following the failure is important for recovery. For example, on a midterm horizon (e.g., several months) financial and managerial capabilities might have different effects on investor judgments than at the immediate time of failure announcement. Future studies can investigate the recovery paths of firms after the failure of a new product candidate has been announced.

In conclusion, our study investigates how investors react to NPD failures and the role of firm-specific capabilities, a firm's strategic focus on R&D, and the development stage of the failed product in these reactions. Our findings extend existing NPD literature by demonstrating that the impact of firm-specific capabilities on investor reactions to NPD outcomes depends on the development stage of the project. The results emphasize the complexity of investor reactions to NPD failures and the interdependencies between product-level and organizational-level factors in explaining these reactions.

Notes

1. Dependent on the nature of the information integrated into the stock price, Fama (1970) distinguishes among a weak form (stock-price-relevant information reflects only historical firm values), a medium–strong form

(stock-price-relevant information also includes public firm announcement of annual earnings, stock splits, etc.), and a strong form of market efficiency (stock-price-relevant information also includes investors' monopolistic access to some pieces of information).

2. This index has a closer relation to the firms in our sample than other indices. Specifically, "The NASDAQ Biotechnology Index includes securities of NASDAQ-listed companies classified according to the Industry Classification Benchmark as either Biotechnology or Pharmaceuticals which also meet other eligibility criteria" (dynamic.nasdaq.com/dynamic/nasdaqbiotech_activity.stm, accessed on July 7, 2011). An alternative to this index would be to construct our own index based on only firms that develop pharmaceuticals based on biotechnological methods. This, however, requires the identification and collection of stock data on all these firms over the time range of our data (15 years). Furthermore, during the 15-year time period of our study, new firms enter and some firms exit or merge. Thus, a meaningful index has to be dynamic. To avoid these potential problems, we decided to use the NASDAQ Biotechnology Index as a well-established index that is commonly used in a professional context and that has been adapted and changed over time to reflect the stock price dynamics appropriately. In addition, the index covers stock market cycles and industry-wide turbulences.

3. An example illustrates the case. Imagine four firms, which each have assets of 100, but they differ in debt, that is, 150, 120, 80, and 50. The corresponding debt-to-equity ratios are –3, –6, 4, and 1. This suggests that for positive and independently for negative ratios, more debt is associated with higher scores (–3 is larger than –6 and 4 is larger than 1). However, those firms with more debt than assets have generally a smaller score than firms with less debt than assets, that is, –3 and –6 are smaller than 4 and 1. A monotonic interpretation over the whole range of scores, that is, negative and positive scores, is therefore impossible.

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