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R&D Learning from Failure and Success: Evidence from Biotech Industry

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Abstract

While we increasingly understand that organizations learn more effectively from failure experience than from success experience when doing repetitive work, we know less about how organizations process failures and successes when radically different products are innovated during the R&D process. This study addresses the question that whether improved organizational performance is driven by learning from innovation failure or innovation success using attention theory. Instead of aggregating data and using time-firm panel analysis, I deploy survival model to test project-level drug development data from 37 biotechnology companies, and find that organizations may not learn from either successes or failures. To uncover the unlearning mechanism, I conduct 12 semi-structured interviews with several senior biotech scientists, and find three possible explanations. Furthermore, I also explore potential factors which change the learning boundary and propose two task context factors– the novelty of innovation and the inventorship–enhance learning from failure experience but deteriorate learning from success experience. Together, these findings offer both theoretical and practical insights into how R&D organizations learn from successes and failures.

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Exploratory Learning from Failure and Success: Evidence from Biotech Industry

Introduction

Learning from experience and making changes to improve performance is a central idea in organizational learning theory (Cyert& March, 1963; Levitt&March, 1988; Argote et al., 1990). The ongoing debate about the performance implications of learning variation points to fundamental questions as to whether and under what conditions organizations learn from past experience (Argote, 2013).

One perspective is experiential learning is conditional on prior outcomes. Success leads to local search and refinement of previous actions to improve performance, whereas failure benefits learning by stimulating search for novel strategy (Haunschild&Sullivan, 2002; Baum&Dahlin, 2007). However, the relative effect between these two is under investigated. Traditionally, the majority of studies of learning in organizations either do not distinguish between success and failure, or simply focus on one of them (Madsen&Desai, 2010). Some research demonstrate that failure is central to organizational learning by adapting new knowledge and change status quo (e.g. Baum&Dahlin, 2007), whereas others hold the view that success experience is indispensable since it may change the willingness and ability to recognize failures (e.g. Diwas et al, 2013). When some scholars allege that failure is more important than success for organizational learning, the evidence is anecdote (Tax&Brown, 1998; Cannon&Edmondson, 2001).

Indeed, very few empirical examinations of the relative efficacy of learning from failure and learning from success exist in the organizational learning literature and often provide contradictory conclusions. Madsen and Desai (2010) find that orbit launch vehicle companies learn more effectively from failure experience but not from success experience, and the magnitude of failure influences the learning process. Muehlfeld and his colleagues (2012) find that newspaper producing firms could learn from both previous failure and success acquisition experience but this learning process depends on two context factors—the degree of structural variance and the level of stimulation of deliberate learning.

In addition to their disparate results, these two studies focus primarily on first-order learning which is a routine and incremental process and the increasing efficiency is a result of practice and exercise of ingenuity and increased dexterity in repetitive activities (McKee, 1992; Lant&Mezias, 1992). However, with the growing recognition of the importance of organizational learning in strategy literature, learning is not limited to repetitive task situations anymore and organizations also can learn during innovation, which is often regarded as second-order learning (Nooteboom, 1999). This second-order learning is the increasing effectiveness of the innovation efforts as a result of searching for and exploring of alternative routines to practice and the refinement of innovation-related skills. But unlike first-order learning, complex, unstructured task environments impede reinforcement second-order learning and exacerbate the identification of links between current actions and observed outcomes (Denrell et al, 2004). These two types of learning require different skills and have distinct learning process (McKee, 1992; Lant&Mezias, 1992; Nooteboom, 1999).

Although both types of learning faces uncertainty due to competition and business cycles, second-order learning faces increasing dynamics by producing radically different products over a certain number of time periods. Second-order learning helps upgrade models dramatically as well as to simultaneously produce several variants at the same time and change quickly to accommodate the competitive environment (Benkard, 1999). During this process, failure is not only common but also necessary. Organization needs to trial and error among variants to get to the optimal solution, thus failure is no longer blameworthy (Tucker&Edmondson, 2003). Regardless of the fact that failure still challenges organizational knowledge and provides an indication of where the gap is, the attention and willingness

to explore the knowledge behind failure is reduced. In addition, the ambiguous causal relationship and the difficulty of interpreting the composition and interrelationship of competencies of exploratory innovation failure render learning from these failed experiments less straightforward (Eggers, 2012).

On the other hand, success becomes scarce, more surprising and more salient comparing with failure during the innovation process. They can compensate the huge R&D investment of failure projects so decision makers tend to allocate more attention. Therefore, learning from success experience is not only possible but also unequivocal by promoting the refinement of existing routines and economizing on scarce resources (Cyert&March, 1963).

The purpose of the present study is to disaggregate failure and success experience and address their relative learning effect on organizational performance during second-order learning process. Unlike first-order learning in which failures are uncommon, second-order learning process is swamped with failures which are an integral part. So this study investigates whether organizations could still learn more effectively from failure experience comparing with success experience if the incidence of failure overwhelms that of success building on attention theory (Ocasio, 1997). Furthermore, this study also demonstrates that two task context factors—the innovation intensity and the inventorship-- also determine the knowledge transferring efficiency and learning outcomes. These two factors serve as boundary conditions of second-order learning.

In addition to the theoretical gap in learning literature, this study also wishes to address a methodology issue in analyzing the effects of experience on learning and performance. Generally speaking, to account for the learning outcomes, researchers tend to aggregate data to form firm-year panel and calculate the influence of previous experience on yearly failure outcome. Comparing to cross-section data, this capture the complexity of firm behavior by controlling the impact of omitted variables and reduce measurement errors by observing individual firm multi times. However, this method also ignores individual outcomes and micro foundation of learning.

If individual projects are similar conditional on certain variables, firm-year panel data provide the possibility of learning an individual's behavior by observing the behavior of others (Hsiao et al, 1993). However, if there is enormous variations among projects, which is common under innovation context, acknowledging the heterogeneity instead of aggregating data and supplementing observation with data on others is more sensible.

Aggregate data analysis often invokes the "representative agent" assumption. However, if micro units are heterogeneous, not only can the time series properties of aggregate data be very different, but result evaluation based on the data may be grossly misleading (Hsiao, 2005). Furthermore, the prediction of aggregate outcomes using aggregate data can be less accurate than the prediction based on micro-project data. Therefore, unlike previous literature, this study deploy project level analysis and use duration model to investigate learning effect.

THEORY AND HYPOTHESES

Learning from Success and Failure Experiences

The key insight of learning models, no matter first-order learning or second-order learning, is that change is triggered by performance below aspirations: satisfactory or superior outcomes tend to result in the reinforcement of lessons drawn from earlier experience, while unsatisfactory outcomes call existing practices and strategies into question (Levitt&March, 1988; Cyert&March, 1992). Success innovative experience reinforces that the existing knowledge is up to date and development of new knowledge is unnecessary. The status quo will be maintained and justified, resulting "local search" (Cyert&March, 1963; March, 1982).

On the contrary, failed innovation endeavors upset the status quo, call existing routines and practices into question, draw attention to potential problems, and stimulate a search for possible solutions. As a result, organizations are more likely to undertake major changes, initiate exploration of new practices, strategies, and courses of action to raise performance above the aspiration level. In other words, failed innovation leads to organizational change, while satisfactory and superior performance does not (March&Shapira, 1992; Chuang&Baum, 2003).

Although aspiration acts the same in first-order learning and second-order learning, providing a moving target to be adapted to performance, the attention allocation differs. Organizations are problem-solving entities with limited attentional capacity (Cyert&March, 1963) and allocate attention based on selective stimuli or responses (Ocasio, 2011). A principal mechanism by which attention structures govern and distribute the attentional focus of decision-makers is through the valuation and legitimization of issues (Ocasio, 1997). And the attentional perspectives of organizational decision makers are embedded in environment and organizational change (Ocasio, 2011). Second-order learning normally happens in a volatile environment, so the aspiration levels mediate the allocation of attention to interpret failure and success differs from first-order learning.

Comparing to operational failures in manufacturing or service industries (Haunschild&Sullivan, 2002; Baum&Dahlin, 2007), where it is desirable to minimize the instance of failures, innovation failures in experimentation are often the only way to learn about causal relationships when a complete understanding of the underlying mechanism is unavailable (Sitkin, 1992). However, organizational decision makers may not attend to failures because they do not recognize the cues as indicators of potential problems (Weick, 1995; Rerup, 2009) under innovation context. During the innovation process, failure is no longer considered as a disaster for organizations, but a necessary experimental step. Innovation failures arising in the natural course of experimentation are distinct from those studied in the prior literature, because innovation failure is generally accepted as a likely, albeit unwelcome, outcome of the experimentation process. During drug development process, 5000 to 10000 chemical compounds are included initially, and about ten of them qualify for clinical trial (Kola&Landis, 2004). This high attrition rate is common in the pharmaceutical industry and organizations never treat these failures as disasters. They do not intend or have enough attention to investigate every failure throughout.

Even if organizations intent to learn from these failures, the process is not without peril. Although biotechnology has advanced the drug development process enormously, most gene functions are still unknown and signal transduction is mystery. In other words, basic scientific advancement could not meet the needs of drug discovery. Without clear knowledge, unveil the failure mechanism is simply out of question. Therefore, decision makers may face inertia of existing technology and limiting effective knowledge creation in the new technology (Eggers, 2012). Innovation process is also path dependent and new knowledge generating ability may be constrained by previous failures (Liebowitz&Margos, 1995).

On the other hand, success will elicit clearer knowledge and more desirable learning outcomes than failure. Given that managerial attention is scarce and selective, it is likely to be allocated to more prominent issues (Hoffman&Ocasio, 2001). Organizational decision makers may fail to attend the weak cues created by failures (Eggers, 2012; Rerup, 2009), neglect to acknowledge failures due to the large quantity and attend to successful projects instead (Cannon&Edmondson, 2005; Madsen&Desai, 2010). Failures of projects are not likely to attract decision makers' attention and challenge their core beliefs (Baumard&Starbuck, 2005). But successes, as the rare events with increasing attentions, trigger learning because they audit existing response repertoires, strengthen organizing routines and redirect organizational identity (Christianson et al, 2009).

In addition, behavior theory of the firm suggests that experiential learning processes differ for success and failure experiences because of limitations on organizational resource-both financial and cognitive (Cyert&March, 1963; March, 1991). Success experience promotes refinement of existing routines without too much variation (Sitkin, 1992), which economizes on resources (Cyert&March, 1963). Such learning has a routine in place that predisposes to complete a local search and convey new information to improve performance. On the other hand, failure experience induces non-local 'problemistic search' for superior solutions (Cyert&March, 1963). This search process is systematically more uncertain (March, 1991), and learning from failure is particularly difficult in complex tasks characterized by causal ambiguity, especially under inadequate attention situation. Given the complexity and causal ambiguity of innovation processes, and the under-attention of search efforts, it is therefore unlikely that responses to failure will immediately result in correct identification of the flawed routine and improvement methods.

Performance feedback has been identified as an important contributor to organizational learning (Greve, 2003). Delays in feedback and unclear feedback have been found to hinder learning from experience (Gibson, 2000). The mechanisms of failure experience are usually ambiguous comparing with those of success experience, therefore, learning is always impaired with failure experience.

Overall, this suggests that innovative organizations learn more effectively from success experience than failure experience.

Hypothesis 1: *Prior organizational success experience reduces the incidence of future organizational failure more than does prior organizational failure experience.*

Innovation Novelty and Learning

Based on innovation novelty, innovative tasks can be dichotomized into incremental innovation tasks and radical innovation tasks (Tushman&Anderson, 1986). A variety of empirical studies have shown that the level of innovation novelty strongly influences the factors that shape the innovative performance, notably learning (e.g. Garcia&Calantone, 2002).

Incremental innovation uses the same technology, introduces relatively minor changes to the existing product and reinforces the current competence (Schumpeter, 1942; Tushman&Anderson, 1986; Henderson&Clark, 1990). During incremental process, firms focus on 'fine tuning' products by means of incremental improvements which are inspired by other sources of innovation use existing technology continuity and previous knowledge(Abernathy&Utterback, 1975), and conducts local search to recombine knowledge. Incremental innovation often needs less investment and effort, and the

performance implications appear to be more modest (Marsili&Salter, 2005). Accordingly, incremental innovation is a routinized behavior and requires less attention and mindfulness.

Therefore, organizations have adequate attentional resources to response to other stimuli and change behavior to adapt the stimuli (Simon, 1947; Ocasio, 1997). Although learning from innovation failure is not straight forward, but it is necessary since only by doing this organizations could uncover the causal relationship (Sitkin, 1992). Spotting big, painful, expensive failures is easy, but the hidden failures or regular failures which are unlikely to cause immediate or obvious harm are hard to detect. Increasing cognitive resources could help to detect failure, which is the first step to learn from failure. Many institutional systems, such as Total Quality Management and soliciting feedback from customers by the United Stated Navy and Color Code System by Boeing respectively, have been implanted to set additional attentions and other resources to surface failures alongside the routine operations (Edmondson, 2011). In addition, the spare attention also facilitates organizations to conduct non-local 'problemistic search' to discover the underlying mechanism of failures and generate novel knowledge for superior solutions.

Success experience, as a strong clue in innovation, already has enough attention and the extra cognitive resource from incremental innovation will be useless and wasted. In addition, learning from success experience only conducts local search, which generate similar knowledge and short-term competence, leading organizations into a sub-optimal position and competence trap (Levinthal&March, 1993; Gavetti, 2005). Only new knowledge from failure experience and novel opportunity could create new routines (Nelson&Winter, 1982) and change the underlying institution, leading to escape the potential competency traps.

On the other hand, radical innovation incorporates new changes and departing from existing technology, destroys competence for incumbents and opens up a wholly new market (Tusheman&Anderson, 1986; Henderson&Clark, 1990; Stringer, 2000). Radical innovation is not only necessary but also essential for sustainable performance improvement in organizations (Levitt&March, 1988). Organizational evolution scholars propose that radical innovation could abduct knowledge from "adjacent possible projects" and put that into a similar context for prediction while it is sufficiently different to yield novel experience and indications (Nooteboom, 1999).

Nonetheless, achieving radical innovation is not without trade-off and cost. According to evolutionary economic theory, organizations need to adapt to novel opportunities to maximize the chance of survival in the changing environment (Nelson&Winter, 1982). And during this process, organizations face the trade-off between the need to adapt and the costs involved in uncertainty of the outcome (March, 1991), and need to prepare for the external pressure of the shortfall of performance below aspiration (Baum&Dahlin, 2007; Nooteboom, 1999). This dilemma is conceived as involving attentiveness and can respond to different context flexibly. In addition, radical innovation is highly uncertain, which involves more cognitive processes and relies less on the past routine (Shiffrin&Schneider, 1977). It is highly likely that radical innovation will drain cognitive resource and unable to attend other stimuli. Radical innovation also constrains attention and reduces knowledge embeddedness when organization members tend to engage in problemistic search for new knowledge in response to failure (Laursen&Salter, 2006).

To sum up, working on incremental innovation makes organizations learn more effectively from failure experience than success experience.

Hypothesis 2a: *Working on incremental innovation enhances learning from failure comparing with working on radical innovation.*
Hypothesis 2b: *Working on incremental innovation diminishes learning from success comparing with working on radical innovation.*

Co-development and Learning

Collaborative task facilitates both the search for information and its interpretation and co-developed products are conductive to developing new knowledge (Powell et al, 1996). R&D intensity or level of technological sophistication of industries is positively correlated with the intensity of co-development. When there is a regime of rapid technological development, research breakthroughs are so broadly distributed that no single firm has all the internal capabilities necessary for success. Sources of innovation do not reside exclusively inside firms and they are commonly found in the interstices between firms, universities, research laboratories, suppliers and customers (Powell, 1990). Thus co-development task could reduce uncertainty by sharing complementary knowledge and enhance organizational learning (Hamel, 1991).

In addition, co-development with external members complement firm's internal capacity (Cohen&Levinthal, 1990; Arora&Gambardella, 1994). Internal capacity evaluates the progress and external collaboration provides knowledge and resources (Nelson, 1982). External collaboration also develops and strengthens internal competences, enhancing learning experience (Powell et al, 1996).

Although failure experience is no longer regarded as an important source of second-order learning as discussed above, co-development may facilitate learning from failure. According to behavior theory of the firm, collaboration is a response to transaction costs that emerge under conditions of bounded rationality. This argument locates inter-firm collaboration within the broader justification for institutions, which build on Coase's (1988) transaction cost explanation for the firm. A key feature of collaboration is high level of mindfulness, a condition where new product decisions and participants' actions reflect an integrated understanding of the agenda and constraint (Jassawalla&Sashittal, 1998). Co-development processes are characterized not only by participant's who think globally, act locally, and achieve high levels of openness about each other's' motive and mindset, but also by participants who understand, accept, and internalize differences that exist and agree to focus on common objectives (Dougherty, 1992). Accordingly, collaborative partners tend to focus on weak clues which are ignored by self-development, and uncover the causal relationship of failure experience. The uncertainty of this non-local search is largely reduced and the chance of conveying new information is enhanced due to the high level of mindfulness.

In addition, decision makers tend to ignore their own failure and learn from others' failure because they attribute their own failure to external reasons and others' failure to their efforts and actions (KC et al, 2013). In this sense, collaboration facilitates vicarious learning, especially from failure experience, and provides new routines and novel knowledge which could reduce the ambiguity of self-failure. Collaboration also helps organizations to learn on how to prioritize failure and allocate more attentions to seemingly weak clues (Baum&Dahlin, 2007).

Furthermore, R&D collaboration in the biotechnology industry facilitates knowledge sharing and knowledge transfer (Rothaermel&Deeds, 2004). This process combines different knowledge together,

enhance the knowledge repository and promote the understanding of the underlying mechanism for exploratory innovation failure and solve causal ambiguity problem.

On the other hand, co-development may diminish learning from success due to knowledge sharing dilemma (Gulati, 1998). Organizational decision makers interpret success experience as evidence that existing internal knowledge is perfect and further development of knowledge is unnecessary (Lant, 1992; March&Shapira, 1992). As a result, they tend to ignore external knowledge. At the same time, although success experience is normally casual unambiguous, decision makers may be over-confident about their existing knowledge and co-development task may direct attention to other issues. This may seem appropriate under first-order learning process. But second-order learning faces increasing dynamics, so simple refine existing assumptions and approaches are not sufficient.

In sum, collaboration makes that innovative organizations learn more effectively from failure experience than success experience.

Hypothesis 3a: *Working with other partners enhances learning from failure comparing with working alone.*
Hypothesis 3b: *Working with other partners diminishes learning from success comparing with working alone.*

Inventorship and Learning

Due to bigger portion of time and resources invested, the inventors, no matter sole inventor or co-inventors, take the leader position in the innovation process and are responsible for the innovation. Traditionally, the inventors receive a bigger portion of the profit due to the intellectual property right if the drug is launched in the end. Even if the drug does not succeed in the clinical trial process, the inventors could also generate revenue by charging the license fee along the development. But to keep the leader position and enjoy financial return subsequently, these inventors also need to have more resource and attention comparing to others to ensure that every effort has been made to commercial their products. The increasing resource and attention help to attend to weak cues and trigger non local search of potential problems to learn from failure (Cyert&March, 1963; Weick, 1995; Rerup, 2009).

As the inventors, they also possess a monopoly of knowledge in the field and have the right to reject outside new ideas (Katz&Allen, 1982). This monopoly of knowledge in the field has the potential to disentangle failure causal relationship to understand the cause and effect relationships of previous failures and help to replace existing routines and knowledge with more useful and accurate ones for failure experience (Hauschild&Sullivan, 2002; Henderson&Stern, 2004). With diversified knowledge, they could easily detect earlier error to prevent subsequent expensive failure (Edmondson, 2011).

In addition, inventors may not be willing to share all information with other partners even under alliance agreements (Zaheer et al, 2000) to avoid leaking crucial information. In R&D intensive industries, most knowledge is tacit and only the inventors have the ability to interpret the related failures and change the scope and direction of the search activities (Lam, 2000). Therefore, only the inventors have the resource and ability to trigger problemistic search and look for solutions or alternatives that can address the problems.

However, excess attention which inventors possess has no privilege in interpreting success experience. Information of successful products are more transparent and easy to access to anyone. Both inventors and followers feel confident about the adequacy of their knowledge since the knowledge generated during success is akin to the existing knowledge (Madsen&Desai, 2010). The redundant searching activities reduce learning from success experience (Wildavsky, 1988) and the extra attention is wasted. Furthermore, success may also induce all partners to prematurely adopt suboptimal world-views and to ignore valuable environmental feedback and imperil learning (March, 1991).

Therefore, inventor may suffer the experience with success and learn more effectively from failure experience.

Hypothesis 4a: *Working as an inventor enhances learning from failure comparing with working as followers*
Hypothesis 4b: *Working as an inventor diminishes learning from success comparing with working as followers.*

METHODS

Quantitative Analysis

Setting

Drug development R&D process is a lengthy process and most experimentations end up in failure. The innovation of new drugs is fueled by innovative technologies, including combinatorial chemistry, robotics, cell therapy, genomics, proteomics and personal genome sequencing. It is widely believed that most chemicals do not reach potential drug status are considered as failure (Henderson&Cockburn, 1994) and no formal innovation process has a higher failure rate than new drug development. Cannon and Edmondson(2005) reports that 90% of newly developed drugs fail in the clinical trial stage and Kola and Landis(2004)gets similar result that the average success rate for all therapeutic areas is approximately 11%. Although this figure may vary from year to year and among different therapeutics areas, the overall situation is not optimistic. In sum, most drug developments do not become a commercial product in the end and the outcomes of R&D are highly skewed like in many innovative industries (Scherer&Ross, 1990).

Therefore, in the context of drug development, failures are the natural course of innovation and perceived at the aspiration level, running the risk of going unnoticed or deliberately ignored. Whereas successes, which are treated as rare events and considered important to the firm in generating an incredible amount of revenues, normally millions of dollars per year, trigger more extensive search for the causes and a more careful reallocation of R&D resources, improving the firm's subsequent innovation outcomes.

Data and Sample

The sample for this study consists of 37 top US biotechnology companies. To select the sample, I compile the top 100 biotechnology companies list ranked by revenue from Compustat and exclude companies either not US based or with incomplete data. Among these top 100 companies, 38 companies have their headquarters outside the US, 12 of them do not develop drugs for human, and 13 of them have incomplete data.

Another concern of my sample is the selection problem which argues that my sample is too small and will not represent the industry. Admittedly, since 1970s, over 1600 new biotechnology companies have emerged but many of them disappeared due to failure or acquisition. Most of these firms are small start-up from universities or research institute, the majority market share is controlled by only a few big companies and most of them are located in America. Even at the bottom part of the top 100 biotechnology companies, most of them have less than ten drugs under development. So the unbalanced market share makes my sample more representative of this industry and conclusion convincing.

To investigate my hypothesis, I compile a unique dataset by combining data from several sources. I collected drug development data from Pharmaproject, clinical trials data from clinicaltrial.gov website, ventures' alliances data from Deloitte Recap and financial data from Thomson One. The sample consists of all drug development projects carried out by these 37 top US Biotechnology firms in the period beginning from 1987 to 2012. Altogether there are 2237 projects, including 491 successes and 1746 failures.

Dependent Variable

The dependent variable tracks the hazard rate of product development failure. Project failures are frequently used in empirical studies on organizational learning as a proxy for improved performance (Baum and Ingram, 1998; Haunschild and Suilivan, 2002; Haunschild and Rhee, 2004; Madsen and Desai, 2010). Moreover, in drug development context, failures are a convenient proxy for performance for several reasons. First, project failures are a common occurrence in therapeutic product development (Henderson, 1994; Cannon and Edmonson, 2005). Second, given the significant resources involved in therapeutic product development projects (typically, firms spend in excess of US$ 500 Million to commercialize a new therapeutic product), failure incidences represent a financially meaningful measure of a firm's R&D performance (Pisano, 2006). Third, although defining learning by fixed outcome could lead to an overly narrow representation of organizational learning (Kim and Miner,2007), it is well capture the knowledge from the product development process that operates to produce survival-enhancing learning in the biotech industry.

Admittedly, using failure as a proxy for innovation performance is widely accepted in learning literatures and captures the dynamics of learning, but it ignores failure heterogeneity. Not all failures contribute equally to future performance and previous research shows that big failures grant more knowledge than small failures (Madsen&Desai, 2010). In addition, innovative products are dissimilar from each other and failure mechanisms and knowledge embedded in each failure are divergent. Simply aggregate all failures may generate unreliable results by neglecting complexity. To alleviate these issues, I use project level data and use the duration model and failure incidence to compare learning from failure and learning from success.

Independent Variables

Success and failure experience: The independent variable measuring success experience is the cumulative time an organization spending on developing a successful drug. The independent variables measuring failure experience is the cumulative time spending by an organization on prior failure drug development. Drug development is a long process and normally takes more than ten years and varies

dramatically across products. So just including the count of a firm's prior success or failure like other literatures would not fully capture the variation of experience. Therefore, the cumulative prior R&D failure or success duration would be more appropriate and justifiable to proxy experience.

Incremental innovation: According to the US Food and Drug Administration (FDA), a drug that contains an active moiety which has not been approved by the FDA in other drugs is considered as a new chemical entity. Developing NCEs as potential drugs is considered as conducting radical innovation since NCEs are different from existing molecular and all of them must be reviewed by an advisory committee before approved by the FDA. On the other hand, non-NCE equals to incremental innovation, which is the modification of existing chemicals and drugs. This process includes new dosage of existing drugs, combination of existing chemicals, new indication and formula changes of existing drugs. I code non-NCE, which is incremental innovation, as 1, and NCE as 0.

Co-development: Strategic alliance is rather common in the biotech industry to alleviate uncertainty and prior research shows that alliance affects organizational learning and performance (e.g. Powell et al, 1996). However, how collaboration affects learning from success and failure separately is ignored to a great extent. Therefore, I include collaboration as a dummy variable. If the product is developed under collaboration with other organizations, the variable is coded as 1. Otherwise it is coded as 0.

Inventorship: As discussed above, many innovations in biotechnology industry are co-developed by several partners and these partners share the knowledge and risk. However, the benefits and risk are not distributed equally among all partners and inventors take more responsibility. First, the inventors of the innovation normally have a monopoly of knowledge in the field (Katz&Allen, 1982). Second, they faces more uncertainty than other partners since they invest more capital and time. Third, they could capitalize more financial reward by charging licensing fees or getting a larger portion of revenue. Therefore, inventorship affects the willingness and ability to learn from experience. If the product is solely developed or invented by the focal company, the variable is coded as 1. Otherwise it is coded as 0.

Control Variables

Several control variables are also included to account for factors other than organizational experience that might impact failure hazard rate.

Vicarious learning experience: Organizational learning theory suggests that organizations develop knowledge not only from their own experience, but also through observation of other companies' experience (Ingram&Baum, 1997; Madsen&Desai, 2010; Argote, 2012). To control for the vicarious learning, I measure industry experience by including R&D experience from other pharmaceutical companies, universities and research institutes.

In practice, since there are thousands of biotechnology and pharmaceutical firms developing new drugs and many universities and research institute contributing during the drug development process, many of their R&D activities are not publicly available and it is impossible to calculate total R&D duration. So I include the cumulative number of FDA approved drugs as the proxy of industry experience.

Firm size: Annual drug development is included because larger firms tend to have more products under development and it could also be a factor to reflect the size of the firm (Haunschild&Rhee, 2004; Stan&Vermeulen, 2013). Total assets is also included to control for the firm size.

R&D expenditure: R&D expenditure may affect the investment in equipment, human capital, and management, which may have an effect on knowledge creation and retention, so I include annual R&D expense (indexed to 1980 dollars) in my model following the suggestion of others (Haunschild&Sullivan, 2002; Haunschild&Rhee, 2004; Stan&Vermeulen, 2013).

Firm age: Previous research has examined the effect of ageing on the organizational performance (e.g. Tushman&Anderson 1986; Henderson&Cockburn, 1994). So besides the control variable discussed above, I also include the age of the firm since it not only related to the technology advancement, but also can indicate the knowledge endowment of an organization (Argote, 2012).

All independent variables and control variables are also illustrated in Table 2.

Model

For the purpose of understanding whether success or failure experience could reduce the incidence of failure, I estimate a series of Cox proportion hazard models in which the hazard of failure is a function of both success and failure experience.

Hence, I estimate the following equation:

$$h(t|x_i) = h_0(t)\exp(x_i\beta_x)$$

where $h(t|x_i)$ is the hazard of project failure, $h_0(t)$ is the baseline hazard (i.e. the hazard when all covariates are equal to zero), and xi is a matrix of covariates, including independent variables, control variables as well as company and therapeutic class dummy.

When developing a new drug, it is important to consider the therapeutic class in which the drug belongs to. The drug development failure incidence varies greatly among different therapeutic classes due to the innate molecular mechanisms (Kola&Landis, 2004). To account for therapeutic classes, I include 31 indicator variables, corresponding to the therapeutic class guideline given by FDA. In addition, I also include a set of company dummy to capture variation in failure incidence trends across companies. Since some of the dates are missing in the original data and other resources, I estimate those missing data using different assumptions(see appendix table 1 for more detail).

Qualitative Analysis

To understanding the quantitative result, I also conduct some semi-structured interviews with senior scientists in biotechnology firms. Unlike data for the regression analysis, the qualitative data are collected from biotechnology companies in China instead of in the US. The reason for this mismatch is most of the scientists in the private sectors do not willing to talk about their drug development projects in any sense and the management team also forbid them to discuss these with others due to the confidentiality issue in the field mentioned above and the author could only get in-depth information with them in China because of previous connections with some of them.

To minimize the influence of this mismatch, I only choose firms are founded by people with US educational background and US pharmaceutical development experience. Also since Chinese Biotech industry starts ten years later than the US one and many state programs encourage returnees from

America to come back to China to set up new biotechnology companies, Chinese biotech industry is a close replica of the US biotech industry (Frew, et al, 2008). And all the interviewees have been worked either in the US biotechnology companies or US universities and research institutes.

A total of 12 semi-structured interviews from five firms were conducted and all the interviewees are senior scientists with at least five years drug development industry experience. The interview consists of three sections. The first covers interviewee's background, education, work history. The second consists of a detail narrative of the relationship among the projects the company has been worked without technique detail. This section of the interview focuses on the specific problems the firm face during the R&D process, as well as actions the person takes respect to these issues. The goal is to understand how the scientist sees the connections among projects and what the sharing activities inside firm are. In this section, I also explore their opinion on the sky-high attrition rate and whether they can learning-by-doing. Each interview lasts between 30 minutes to one hour.

RESULTS

Table 1 presents descriptive statistics and correlations for the study variables. As can be seen from the table, some very high correlations exist among certain variables. For example, the correlations between total assets and R&D expense (r =0.937), as well as between these two and annual drug development (r= 0.698 and 0.689 respectively). To avoid multicollinearity, I run analyses adding the variables sequentially and checked the fitness of each regression. These analyses show that multicollinearity is not affecting my main conclusion.

In addition, the correlation between success experience and failure experience is also high. One reason for the fairly high correlation could be that success and failure experience both increase as organization gains overall experience (Madsen&Desai, 2010). To determine whether success and failure experience contributes information to the models independent of general experience, I conduct preliminary tests to estimate the impact of an organization's general experience. Although total experience has a significant effect on performance improvement, models separating general experience into success experience and failure experience yielded significantly better model fit. This finding suggests that success experience and failure experience contribute independent information to the models despite their fairly high correlations. Therefore, only failure experience and success experience are included in the models and the general experience is omitted.

Table 2 reports hazard models of drug development. Model 1 contains only control variables and provides a baseline model against which models containing experience variables are compared. In model 1, the coefficients for co-development and incremental innovation are highly significant and smaller than one, indicating that co-development and incremental innovation reduce the failure incidence dramatically.

The coefficients for annual drug development and inventorship are significant and above 1 in model 1, suggesting that failures increase with the number of projects under-development and inventors take more responsibility and experience higher risk of failure. It is worth noting that the former point only considers absolute number of failure and the failure ratio might decrease. Interestingly, however, the coefficients of R&D expense and total assets are not significant, showing that R&D intensity and firm size do not play an important role in reducing failure. This might because larger firm has a more complex structure, which reduces efficiency.

The coefficient of firm age is not significant, which means that old firms are not more sophisticated in innovation than younger firms. This is in accordance with innovation literature since many radical innovations are brought by new entrants and these new entrants are normally more innovative and productive (e.g. Schumpteter, 1942; Acemoglu&Cao, 2010).

The coefficient of industry experience is also not significant, indicating that vicarious learning is absent which contradicts previous literature (Ingram&Baum, 1997; Madsen&Desai, 2010). There might be two reasons: First, intellectual property protection is highly efficient in biomedical research and some of the information is not publicly available, rendering knowledge sharing among biotechnology companies. Second, drug development knowledge is strictly confidential and tacit, therefore inter-organizational knowledge transfer would be much more difficult than intra-organizational knowledge transfer.

Learning from Success and Failure

Model 2 shows the comparing of learning from success and failure. Model 2a and model 2b include only failure experience and success experience respectively and model 2 includes both. Neither the coefficient of failure nor the coefficient of success is significant, indicating that both of them are less likely to reduce future failure incidence. The coefficient of failure experience is above 1 and the coefficient of success experience is below 1, showing that failure experience has the tendency to induce future failure whereas success experience is more likely to improve performance. Further Wald's test confirm that organization has the tendency to learn more effectively from success experience than from failure experience. These results are in contradiction to Madsen and Desai's (2010) study.

Boundary Condition of Learning from Success and Failure

Model 3 to 5 explore the boundary condition of learning from failure and learning from success. Model 3a includes the interaction term between failure experience and incremental innovation. The coefficient of this interaction term is significant and below 1, indicating that doing incremental innovation project helps organization learning from failure experience and proving hypothesis 2a. Model 3b includes the interaction term between success experience and incremental innovation. The non-significant coefficient indicates that learning from success experience is not affected by the innovation intensity. Therefore, hypothesis 2b is not supported. Model 3 combines these two interaction terms and the results are similar to when they enter regression separately.

Model 4a includes the interaction term between failure experience and co-development. The coefficient of the interaction term is not significant and below 1, demonstrating that co-development with other organizations does not increase the chance of learning from failure. Model 4b contains the interaction term between success experience and collaboration. The non-significant coefficient indicates that learning from success experience is not affected by collaborations. Model 4 aggregates these two interaction terms and the coefficient of both failure and success experience are not significant, indicating that co-development is not a strong moderator of either learning from failure or learning from success. Thus, both hypothesis 3a and 3b are not proved empirically in this study.

Model 5a includes the interaction term between failure experience and inventorship. The coefficient of this interaction term is highly significant and below 1, which proves hypothesis 4a and indicates that inventors take more responsibility and have a higher tendency to learn from failure experience. Model 5b includes the interaction term between success experience and inventorship. The highly significant

and above 1 coefficient indicates that being the inventor not only unlearn from success experience but learn negatively, disapproving hypothesis 4b. When these two interaction terms enter model 5 together, the results stay unchanged.

Model 6 combines all three interaction terms mentioned above and the results stay unchanged.

Disentangling Mechanisms

Why could not organization learn from either successes or failures during the innovation process? To answer this question, I conduct several semi-structured interviews with senior scientist in biotechnology firms in China. A first potential explanation arises from the interview is that the direct information from previous drug development is the disease mechanisms and it takes long time for the information to translate into new drug development. One chief scientist from one of the biggest biotechnology company in China said:

> Although pharmaceutical development is aimed at producing new drugs, the most valuable product of translation efforts is information about disease and drug mechanisms. This information is valuable because it informs drug development and it guides clinical practice. However, unlike other fields, the translational process in pharmaceutical development could not be accomplished overnight and there is a huge lag.

Other interviewers also mention similar points which provide further support for this argument. One scientist recalls that some oncogenes which promote tumor growth have been discovered more than thirty years ago from clinical research, however, our understanding of cancer causation is still limited and the drugs targeting these oncogenes are still far-fetched. My analysis only covers 25 years data and this short time span is potentially an issue to find real learning effect in the baseline model. This also indicates a possibility that the context factors I find in this study moderate learning from failures and successes through accelerating the learning process. As discussed in the theory section, increasing attention does spur learning process.

The second reason for the unlearn effect is that efficient methods for generating information may not be effective. To reduce cost and promote speed, many drug development activities, especially early stage investigations, are conducted on small sample sizes and surrogate endpoints. This benefit also comes at a cost, since small and less rigorous studies tend to produce more false positives and the information may not useful as it seems to be for other drug developments. Several scientists mention in the interview that to explore a vast, multidimensional landscape of agents, doses, disease indications and treatment schedules in a tight budget and limited time frame, they have to look for other intermediate indicators or use the minimal sample size. One of the researchers becomes really upset when discuss this issue, he tells me:

> These managers only care about cash and profit and they do not have any sympathy for the suffering victims. Science could not be measured by money, especially medical science. Money is only a number and it is useless in front of life. They are the real causes of unethical behaviors in medical research.

Some neuroscientists also mention that many spurious clinical promise is caused by bias or random variation in their review article (Button et al, 2013). Some signs or knowledge generated from former drug development may not be vindicated in the later drug development due to this reason.

The third possible explanation part of the information and knowledge generated from drug development is not well-captured. My interviews also support this argument. For example, several

researchers note that the reporting and publication scheme is inadequate in pharmaceutical research. In one case, a senior scientist who works in a top US university complains that only limited patho-physiological data and theories are shared among peers in the same company. If he wishes to publish the clinical result, he has to withhold some part of methods or data.

Another issue is individuals tend not to record or share negative or inconclusive studies because they are afraid of admitting failures. One of the interviewee also mentions that positive and conclusive results could diminish off-label use of a licensed drug and be used to compile a clean narrative for investors.

The three reasons presented above help explain why biotechnology firms could not learn from failures nor successes and build a circumstantial case in favor of interpreting the learning process during innovation. However, they do not enable me to reject some potentially relevant versions of theory-such as mindfulness of researchers in interpretation information-nor do they allow me to learn about the degree of each effect.

Robustness Checks

In addition to the main analyses reported above, I also conduct several supplemental analyses to assess whether the patterns of results are robust to alternative specifications and samples. First, I test different estimation methods of missing data. It is possible that the estimation might distort the data, thus generating significant results as reported above, but which would not be reflected in the real situation. To rule out this possibility, I use different assumptions to calculate the missing data (see appendix table 1 for more detail).
Minimum: Assume the missing stage date is one day later than previous stage date
Maximum: Assume the missing stage date is one day earlier than later stage date
Random: Assume the missing stage date is a random date between previous stage and later stage
All those estimation assumptions give similar results.

Second, given the concern of the distortion of results by missing data, it is also possible that these missing data are not random but relate to innovation or performance. One possibility is the decision makers pay less attention to some projects and choose not to record them if they think these projects are less likely to succeed. Or these missing data could also be caused by losing key scientists or important achievement records. The missing data could also represent missing relative knowledge. To rule out these possibilities, I test the models including projects with non-missing data only. This subsample contains 1919 products with 1579 failures and 340 successes. The main results do not change qualitatively.

Third, the duration of drug development varies drastically from less than a year to over ten years in my dataset. If the duration is less than a year, it is less likely to enter the clinical trial stage and these data are sometimes considered as no-reliable (Kola&Landis, 2004). In addition, limited attention is unlikely to be distributed to these projects due to the short longevity of their life. So to further test whether my findings are deceived by this, I drop 51 projects which have less than one year lifespan. The results are similar to the main findings and suggest that these short duration projects do not twist my results.

Fourth, many researchers have found that the value of prior experience depreciates over time in such a way that recent experience is more valuable than the older experience (e.g. Ingram&Baum, 1997,

Madsen&Desai, 2010; Argote, 2012). This is caused by organization members exit (Argote et al, 1990) or changes of organizational processes or structures (De Holan&Phillips, 2004). Several methods have been developed to model knowledge depreciation (e.g. Baum&Ingram, 1998; Haunschild&Sullivan, 2003).

Typical values assigned to the discount factor include 1 (assuming that knowledge is non-depreciating), the age of experience (assuming that knowledge depreciate linearly), the age of experience squared (assuming that knowledge depreciate rapidly), the square root of age of experience (assuming that knowledge depreciate slowly). To examine whether knowledge depreciation reduces learning effect and changes my results, I replicate my analyses using the same sample but including different discount factors. All three commonly used discount factors do not change my main findings.

Furthermore, the hazard model used in this study could also cause bias. As mentioned above, I estimate the hazard of failure as a function of both success and failure experience. In this sense, drug development failure is the event and the hazard rate is the probability that the project will fail at time t while it is at risk for having a failure. However, the final outcome is not a dummy and non-failure does not mean success. Non-failure can mean both success and still under development. In this sense, failure rate is underestimated due to the potential failures in the under development products. To ameliorate this problem, I use success as the event and test all the hypotheses in the new context. The results show that success experience increases future success incidences but failure experience has no effect. And innovation intensity and inventorship still enhance organizations' ability to learn from failure experience.

Last but not least, to further examine whether the finding of inventorship is susceptible to the self-development products, I also estimate the effect of inventorship in a partial data set including only collaborative drug development. The results are similar to the main models and suggest that the difference between organizational learning from success experience and failure experience can be driven by innovation inventorship.

DISCUSSION AND CONCLUSION

Previous study using orbital launch vehicle data (Madsen&Desai, 2010) disaggregates learning from failure and learning from success and alleges that organizations learn more effectively from failures than successes. However, this study suggests that this learning difference does not hold under second-order learning context. By investigating drug development, this paper demonstrates that organization tends to learn more effectively from success experience than from failure experience even though none of the learning is statistically significant. This study not only yields strong evidence that organizations do not learn by observing their own successes as reported previously, but also fails to uncover evidence of significant learning from observation of their own failures. Coefficients estimating the effect of failure experience on future performance are indistinguishable from zero. It should not be interpreted as evidence that organizations cannot learn from failures or successes to improve performance. But the fact that biotechnology companies do not experience demonstrable learning from failures or successes suggests that learning from innovation success and innovation failure separately is far from an automatic process.

This unlearning situation may be explained by the high causal ambiguity of innovation. Although the development of biotechnology has transformed drug development from blind screening to aim-specific genetic manipulation and targeting (Pisano, 2006), the underlying mechanism of molecular interaction

and signal transduction is still largely unknown. Experiences cannot be interpreted within the current belief system (Argyris&Schon, 1978) or organizational paradigm (Pfeffer, 1981), and the process of experimentation need new ways of assembling responses and the new construct to integrate into existing cognitive structures (March, 1988; Lant&Mezias, 1992). Therefore, learning from either success or failure experience seems difficult even though not impossible. Additional tests show that organizations could learn from aggregated experience, suggesting that the aggregation of failure and success could alleviate causal ambiguity and enhance learning. Since innovation failures in experimentation are often the only way to learn about causal relationships when a complete understanding of the underlying mechanism is unavailable (Sitkin, 1992) and successes elicit surprise and are recognized more easily to changes behavior, the interaction of success and failure may illustrate underling causal relations. Additional research of how this interaction promotes learning may uncover the unlearning mechanism.

What is also worth mentioning in this study is that collaboration does not enhance learning from failure nor learning from success. This does not discord or reject others' study on alliance and learning. This study only takes intra-organizational learning into consideration whereas most studies of alliance and learning focus on inter-organizational learning (e.g. Powell et al, 1996). So it is highly likely that collaboration contributes to inter-organizational learning but could not moderate intra-organizational learning. Limited resources, both cognitive and financial, may limit organizations' ability to balance between inside knowledge and outside knowledge.

Theoretical Contribution

This study contributes to existing learning theory in several ways. First, it extends the current literature on first-order learning and second-order learning, especially comparing the efficacy of second-order learning from failure experience and success experience. Although previous studies (e.g. Lant&Mezias, 1992; Edmondson, 2002) have shown that second learning and first-order learning are conceptually different, whether failure or success promotes improvement in second-order learning is still mysterious.

This study constitutes the first direct comparison of the effects of learning from innovation failure and learning from innovation success. It confirms the suggestion that studies from first-order learning may be of little value to uncover the effects of second-order learning (Miner&Mezias, 1996) since they are under different contexts and require different capabilities. In manufacturing industry, where first-order learning is dominated, organizations learn more effectively from failures than successes since failures are rare and disastrous (Madsen&Desai, 2010). But in knowledge intensive industries, where R&D innovation determines the fate of organizations and second-order learning takes charge, failures are common and generally accepted as a likely outcome of the experimentation process, and the desire to minimize the instance of failure is largely reduced. In this sense, learning from failure may seem less urgent and even impossible due to the causal ambiguity.

Second, this work extends literature on intelligent failures (Sitkin, 1992). Intelligent failures are those in which expectations are not met but something useful for the future is learned (McGrath, 1997). Intelligent failures are necessary experimental steps for innovative outcomes but learning from them is not straight forward. Organizations need special schema to take advantage of these failures. For example, Eli Lilly's "failure parties" since 1990, which honor intelligent experiments that fail to achieve the desired results, redeploys valuable resources for new projects and kickstarts many new discoveries

(Edmondson, 2011). This study tries to uncover that some contextual factors can enhance learning from intelligent failure.

Third, this study introduces three new task characteristics as the boundary conditions of learning from innovation failures and innovation successes. Previous research show that the task sequence and routines deposit knowledge and enhance knowledge transfer (Dar et al, 1995), but how other aspects of task facilitate knowledge search between different performance outcomes is under studied. This paper argues and proves that conducting incremental innovation or acting as an inventor enhances learning from innovation failures. These factors not only alleviate the problem of unable to learn from failure, but also lead to negatively learning from success. It suggests the trade-off between learning from failure and learning from success and also confirms that the aggregated experience may not represent the real learning result. This raises the caution of interpreting previous results in terms of learning from aggregated experience (Madsen&Desai, 2010; KC et al, 2013).

Limitations, Directions for Future Work, and Conclusion

The implication of the findings in this study is that there are crucial differences between first-order learning and second-order learning, especially when failure experience and success experience are considered separately. However, the current study only focus on second-order learning and compares with previous first-order learning literatures. Indeed, I could not directly compare first-order learning and second-order learning in this study. Future work could attempt to choose organizations with both routine process production and exploration of alternative routines production to compare the learning effects between them. This would not only contribute to the finding of factors which lead to the variation of learning rate (Argote, 2012), but also provide practical implications for firms' to choose ideal learning path.

While I am able to figure out some of the boundary conditions of second-order learning, this should be interpreted with cautious. Although incremental innovation could enhance learning from failure experience, organizations only focus on incremental innovation will fall into the competence trap by just developing current and short-term competence. They will lose out the chance to move to new and useful competence (Levitt&March, 1988). In this sense, radical innovation is necessary for organizations in the long run although learning from failure is compromised. Therefore, the balance between radical innovation and incremental innovation need to be reached and only by doing this, organizations could have a sustainable competitive advantage.

Similar condition applies to inventorship. Although being an inventor is beneficial to learn from failure, it is impossible to invent everything due to limited resource and attention. Co-invent or co-development could be a compromise and organizations could benefit from vicarious learning. In addition, co-development also reduce uncertainty and cost and diversify organizations' portfolio, increasing survival (Nelson&Winter, 1982; Powell, 2003).

In addition, not all failures have the same contribution to learning since the magnitude of failure varies and future work could include the financial data of each drug development process to weigh for the magnitude of failure and see whether it will have the same result. This would not only control the magnitude of failure, but also test the learning curve framework in innovation learning using the most acceptable outcome (Argote&Epple, 1990).

This study demonstrates that neither success nor failure experience primarily drives organizational improvement in innovative industries, at least in the biotechnology industry. But innovation intensity and inventorship moderate learning from failure and learning from success. Collectively, the study's findings suggest the need to further explore organizational learning practices associated with failure under second-order learning and to determine how organizations may be able to reap the benefits of failure without exposing themselves to its cost.

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Table 1 Descriptive Statistics

	mean	sd	failexp	succexp	rdexpense	firmage	annualdrug	totalasset	industryexp	alliance	inventor	nonNCE
failexp	10.15292	2.283415	1									
succexp	7.905438	3.777791	0.3253881	1								
rdexpense	10.83201	1.627324	0.6245555	0.514981	1							
firmage	20.68158	16.11696	0.2418938	0.412014	0.4821285	1						
annualdrug	34.91101	28.7279	0.5883752	0.490356	0.6892539	0.2111848	1					
totalasset	12.52689	2.201073	0.5903594	0.555788	0.9371417	0.5634086	0.6980949	1				
industryexp	11334.25	550.8164	0.591986	0.124761	0.4101664	0.2241505	0.2193848	0.3512934	1			
alliance	0.5857971	0.4926022	-0.0135755	0.011273	-0.0829637	-0.1871787	-0.0272831	-0.091622	0.018438	1		
inventor	0.7814944	0.4132476	0.1304303	-0.14661	-0.0384154	-0.1394446	0.0530763	-0.0832661	0.038002	-0.3160997	1	
nonNCE	0.5172337	0.4997215	0.0238183	-0.02058	0.0421956	0.0628168	-0.0209389	0.0639113	-0.13491	0.0452965	0.0165361	1

Table 2 Variable Construction

	Variables	Description	Measurement
IV	Success experience	Firms learn from their successes (Ingram&Baum,1997; Madsen&Desai, 2010)	Cumulative time in developing launched drugs
	Failure experience	Firms learn from their failures (Madsen&Desai, 2010)	Cumulative time in developing failure drugs
	Incremental Innovation	Innovation intensity strongly influences the factors that shape innovation performance (Garcia&Calantone, 2002)	Non-new chemical entity as 1, new chemical entity as 0
	Collaboration	Strategic alliance could alleviate uncertainty and promote learning (Powell et al, 1996)	Co-development as 1, self-development as 0
	Inventorship	Inventor has monopoly of knowledge and face increasing uncertainty (Katz&Allen, 1982)	Sole developed or invented by focal company coded as 1, otherwise 0
Control	Industry experience	Organizations develop knowledge not only from their own experience, but also through observation of others experience (Ingram&Baum, 1997; Madasen&Desai, 2010; Argote, 2013).	Cumulative number of FDA approved drugs
	Annual drug development	Control for the firm size(Haunschild&Sullivan, 2002; Haunschild&Rhee, 2004)	Annual number of drug development
	Total assets	Control for the firm size	Company total assets
	R&D expenditure	Control for the firm size and knowledge creation and retention(Haunschild&Sullivan, 2002; Haunschild&Rhee,2004)	R&D expense each year(Indexed to 1980 dollar)
	Firm age	Ageing has effect on organizational performance(Tushman and Anderson 1986; Henderson 1994)	Company Age

Table 3 Regression Result

	Model 1	Model 2a	Model 2b	Model 2	Model 3a	Model 3b	Model 3	Model 4a	Model 4b	Model 4	Model 5a	Model 5b	Model 5	Model 6
Failure experience		1.09		1.09	1.175*	1.091	1.195*	1.109	1.092	1.101	1.191	1.083	1.288*	1.210*
		(0.07)		(0.07)	(0.09)	(0.07)	(0.09)	(0.08)	(0.07)	(0.08)	(0.11)	(0.07)	(0.13)	(0.09)
Success experience			0.998	0.998	1.005	1.006	0.99	0.996	1.002	1	1.002	0.936	0.912*	0.98
			(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
R&D expense	0.939	0.936	0.94	0.936	0.933	0.935	0.935	0.938	0.934	0.936	0.936	0.937	0.936	0.936
	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)
Firm age	1.096	1.051	1.096	1.05	1.051	1.049	1.054	1.051	1.049	1.05	1.051	1.038	1.037	1.042
	(0.16)	(0.15)	(0.16)	(0.15)	(0.15)	(0.15)	(0.15)	(0.15)	(0.15)	(0.15)	(0.15)	(0.15)	(0.15)	(0.15)
Annual drug development	1.010***	1.009***	1.010***	1.009***	1.010***	1.009***	1.010***	1.009***	1.009***	1.009***	1.009***	1.009***	1.009***	1.009***
	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Total Assets	1.041	1.034	1.04	1.033	1.035	1.034	1.033	1.029	1.034	1.032	1.033	1.034	1.036	1.035
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.06)	(0.05)
NDA Approved	0.999	0.999	0.999	0.999	0.999	0.999	0.999	0.999	0.999	0.999	0.999	0.999	0.999	0.999
	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Collaboration	0.587***	0.587***	0.587***	0.587***	0.589***	0.586***	0.590***	1.075	0.682**	0.921	0.586***	0.586***	0.584***	0.590***
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.53)	(0.08)	(0.48)	(0.03)	(0.03)	(0.03)	(0.03)
Inventor	2.032***	2.014***	2.032***	2.014***	1.988***	2.013***	1.985***	2.012***	1.990***	1.994***	8.623**	1.158	11.206**	2.223**
	(0.18)	(0.18)	(0.18)	(0.18)	(0.18)	(0.18)	(0.18)	(0.18)	(0.18)	(0.18)	(6.88)	(0.28)	(9.69)	(0.29)
Incremental innovation	0.762***	0.759***	0.762***	0.759***	3.766*	0.833	4.213**	0.760***	0.758***	0.759***	0.756***	0.760***	0.755***	0.760***
	(0.05)	(0.05)	(0.05)	(0.05)	(2.00)	(0.14)	(2.29)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
Failure * Incremental					0.864**		0.841**							0.855**
					(0.04)		(0.05)							(0.05)
Success * Incremental						0.989	1.021							1.01
						(0.02)	(0.02)							(0.02)
Failure * Collaboration								0.946		0.97				0.96
								(0.04)		(0.05)				(0.05)
Success * Collaboration									0.981	0.986				0.99
									(0.01)	(0.02)				(0.02)
Failure * Inventor											0.875		0.792**	0.781**
											(0.06)		(0.07)	(0.07)
Success * Inventor												1.064*	1.097***	1.089***
												(0.03)	(0.03)	(0.03)
Loglikelihood	-2594.28	-2593.352	-2594.279	-2593.349	-2588.707	-2593.178	-2588.197	-2592.596	-2592.339	-2592.166	-2591.544	-2590.649	-2586.37	-2580.25
Chi-squared	512	513	512	513	523	514	524	515	516	516	517	519	527	536.00
N	2237	2237	2237	2237	2237	2237	2237	2237	2237	2237	2237	2237	2237	2237

***p < 0.001; **p < 0.01; *p < 0.05

Appendix

Table 1 Missing Value Calculation

	Missing Data	Additional Conditions	Remedy
Middle Point	Dc	$Mc \neq Mp$ or $Mc \neq Mn$	$Dc = 15$
	Dc	$Yc = Yp$ and $Mc = Mp$	$Dc = (Dp + Dldm)/2$
	Dc	$Yc = Yn$ and $Mc = Mn$	$Dc = Dn/2$
	Mc, Dc	$Yc \neq Yp$ or $Yc \neq Yn$	$Mc = 6, Dc = 30$
	Mc, Dc	$Yc = Yp$	Mc Dc = (Mp Dp + Dldy)/2
	Mc, Dc	$Yc = Yn$	Mc Dc = Mn Dn /2
	Yc, Mc, Dc		YcMcDc = (YpMpDp - YnMnDn) * ratio
Minimum	Dc	$Mc \neq Mp$ or $Mc \neq Mn$	$Dc = 1$
	Dc	$Yc = Yp$ and $Mc = Mp$	$Dc = Dp + 1$
	Dc	$Yc = Yn$ and $Mc = Mn$	$Dc = 1$
	Mc, Dc	$Yc \neq Yp$ or $Yc \neq Yn$	$Mc = 1, Dc = 1$
	Mc, Dc	$Yc = Yp$	$Mc = Mp, Dc = Dp + 1$
	Mc, Dc	$Yc = Yn$	$Mc = 1, Dc = 1$
	Yc, Mc, Dc		YcMcDc = (YpMpDp - YnMnDn) * ratiomin
Maximum	Dc	$Mc \neq Mp$ or $Mc \neq Mn$	$Dc = 30$
	Dc	$Yc = Yp$ and $Mc = Mp$	$Dc = Dn - 1$
	Dc	$Yc = Yn$ and $Mc = Mn$	$Dc = 30$
	Mc, Dc	$Yc \neq Yp$ or $Yc \neq Yn$	$Mc = 12, Dc = 31$
	Mc, Dc	$Yc = Yp$	$Mc = 12, Dc = 31$
	Mc, Dc	$Yc = Yn$	$Mc = Mn, Dc = Dn -1$
	Yc, Mc, Dc		YcMcDc = (YpMpDp - YnMnDn) * ratiomax

Notations: Current stage year: Yc; Current stage month: Mc; Current stage day: Dc;
Previous stage year: Yp; Previous stage month: Pc; Previous stage day: Pc;
Next stage year: Yn; Next stage month: Mn; Next stage day: Dn;
Last day of the year: Dldy Last day of the month: Dldm
Stage duration ratio: ratio (this ratio is calculated based on existing data by using previous stage duration divided by the previous stage duration plus next stage duration)