



When opportunity meets ability: The moderating effects of prolific inventors on novel drug innovation following product development failure in biotechnology

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Abstract

Research Summary: Through a longitudinal study of the product development portfolios of 457 US-based firms in the biotechnology industry, we investigate how prolific inventors shape a firm's innovative direction following product development failure. Contrary to received wisdom, we argue and demonstrate that an increase in the number of prolific inventors is associated with a *decrease* in firm propensity to pursue novel product innovation following such failure. We further find that the presence of prolific inventors with greater collaborative strength and longer tenure negatively moderate the positive relationship between failure and the pursuit of novel product development. We discuss the implications of our results for research on learning from failure and strategic human capital.

Managerial Summary: In case of adverse events such as product development failure, managers often rely on the firm's prolific inventors to help the firm learn from failure. Our study shows that there are limits to this approach. While prolific inventors increase firm propensity for novel product development, such propensity is significantly decreased following product failure. We further establish that the presence of prolific inventors with greater collaborative strength and long tenures is



especially likely to reduce firms' pursuit of novel products, while the presence of those with low collaborative strength and tenure tend to increase this propensity.

KEY WORDS

biotechnology, learning from failure, product development failure, prolific inventors, strategic human-capital

1 | INTRODUCTION

A central determinant of a firm's competitive advantage is its ability to create novel products for the marketplace (Eggers & Kaul, 2018). In technology-intensive industries, however, the development of new products is often fraught with technological and market uncertainty (Brown & Eisenhardt, 1995; Toh & Kim, 2013). Such projects often result in failure (Urbig, Bürger, Patzelt, & Schweizer, 2013). Research examining learning from failure has focused primarily on the effect of prior organizational experience with failure on the ability to recover from it (e.g., Eggers & Suh, 2019; Khanna, Guler, & Nerkar, 2016). These studies have typically examined reductions in failure rates (e.g., Baum & Dahlin, 2007; Desai, 2015; Haunschild & Sullivan, 2002) or the nature of subsequent innovation activities (Haunschild, Polidoro, & Chandler, 2015; Maslach, 2016; Polidoro, 2016) as indications of learning from failure.

While this literature has generated rich insights regarding the importance of learning from failure for organizations, organizational learning scholars have noted that relatively little is known about the effect that key organizational members have on learning from failure and the impact of this learning on post-failure product innovation (Desai, 2015; Zahra, Neubaum, & Hayton, 2020). More specifically, even though organizational learning is led and directed by key organization members, there is a dearth of information about how organizational actors facilitate learning from significant organizational setbacks. Prolific inventors, for example, identified as "individuals who have demonstrated disproportionately high levels of performance and superior visibility in the external market" (Kehoe & Tzabbar, 2015, p. 711), are regarded as the locus of knowledge creation and the conduit of learning (Grant, 1996; March, 1991; Zucker & Darby, 1996). These inventors command power and social status within and outside the firm based on their exceptional performance and unique expertise (Lahiri, Pahnke, Howard, & Boeker, 2019; Zucker, Darby, & Armstrong, 1998). In times of adversity, organizations turn to their experts, such as prolific inventors, to identify new solutions (Almandoz & Tilcsik, 2016). Despite the critical role prolific inventors play in a firm's knowledge search (Jekunen, 2014), much remains to be understood regarding the ways they facilitate post-failure learning. Hence, we investigate how prolific inventors (also referred to as "star scientists") shape a firm's innovative efforts following product development failure. This focus on the role of prolific inventors is particularly important because it gets us closer to the level at which learning occurs in organizations and enables us to clarify the links between a firm's human capital and its learning after failure (Dahlin, Chuang, & Roulet, 2018; Desai, 2015).

We explore this role of prolific inventors in the context of novel drug innovation (NDI). Following Cardinal (2001), we conceptualize NDI as the creation of knowledge that is new to the world (i.e., knowledge that was previously undiscovered) (Grant, 2013; Kneeland,



Schilling, & Aharonson, 2020), as reflected in new chemical entities (NCEs).¹ Previous studies have described them as radical innovations because they require a great deal of experimentation with new knowledge rather than a reliance on incremental modifications or combinations of existing knowledge (Cardinal, 2001). The novelty of the molecule is therefore representative of both the technological and scientific knowledge created by the firm, which relies on new sources of knowledge and the development of new expertise (Abernathy & Clark, 1985; Cardinal, 2001). Novel drug development typically follows organizations' search and experimentation with new knowledge (i.e., exploration). Given the strong influence of prolific inventors in driving breakthrough innovations as demonstrated in prior research (Chen & Garg, 2018; Conti, Gambardella, & Mariani, 2014), understanding how failure influences the pursuit of novel drug development in firms with prolific inventors can yield rich insights on the underlying mechanisms through which organizations learn from failure.

Organizational learning scholars commonly agree that product development failures increase search and novel knowledge creation (Eggers & Suh, 2019; Levinthal & March, 1993). In times of adversity, such as the period following product development failure, organizations typically turn to their experts, such as prolific inventors, to identify new solutions (Almundoz & Tilcsik, 2016). Firms with no prolific inventors, however, are forced to rely on a broader range of expertise (Chen & Garg, 2018; Tzabbar & Kehoe, 2014). Our research provides an opportunity to compare the responses to product development failure by firms endowed with different levels of human capital resources. We argue that in the aftermath of product development failure, a greater number of prolific inventors in a firm result in more pressure to link learning to familiar knowledge. We suggest that this pressure limits the firm's motivation to create new and unfamiliar knowledge (Audia & Goncalo, 2007; Conti et al., 2014), resulting in a reduction in the firm's likelihood of NDI following product failure.

We further argue that the effect of failure on novel drug development will vary based on the degree of influence and control that the prolific investors exert on the firm's innovation. An individual's influence, power, and control have been associated with their degree of collaboration (Tzabbar & Kehoe, 2014) and tenure (Perretti & Negro, 2006). Therefore, we also examine the moderating role of prolific inventors' collaboration and tenure on the relationship between product development failure and novel drug development.

To test our hypotheses, we conducted a longitudinal study of the product development portfolios of 457 U.S.-based biotechnology firms from 1973 to 2010. By examining how prolific inventors moderate the relationship between product development failure and novel drug development, we make several contributions. First, we extend the research on learning from failure (e.g., Madsen & Desai, 2010; Maslach, 2016), delving deeper into the level at which learning occurs and the behavioral mechanisms that drive the process of post-failure learning and new knowledge development. In doing so, we shed light on the micromechanisms of learning from failure.

Second, our results help explain an apparent contradiction in the effect of prolific inventors on innovation. As experts in their fields, prolific inventors have been shown to be the individuals who are most likely to initiate breakthrough innovations (Chen & Garg, 2018; Conti et al., 2014). However, they also heighten a firm's tendency to exploit existing knowledge in

¹The Food and Drug Administration (FDA) defines a NCE as "a drug that contains no active moiety that has been approved by FDA in any other application submitted under section 505(b) of the act" (FDA, 2014, p. 4). Cool (1985) presents a similar definition: "NCEs are totally new drugs which, in most cases, represent significant therapeutic advances" (p. 250).



their areas of expertise, thus limiting the firm's ability to modify or transform its knowledge base (Conti et al., 2014; Tzabbar, 2009). Our results contribute to a resolution of this contradiction by demonstrating that prolific inventor's likelihood to initiate breakthrough innovation is reduced in the context of failure. Hence, organizational context, as reflected in product failure and number of prolific inventors, needs to be considered when determining the influence of prolific inventors.

Our results also advance our understanding of the conditions under which prolific inventors affect a firm's innovative direction following product development failure, providing a novel understanding of the effect of strategic human capital on learning from failure. We find that the presence of prolific inventors with greater collaborative strength and longer tenure negatively moderates the positive relationship between failure and novel product development. Conversely, prolific inventors with low collaborative strength and tenure increase the firm's propensity to pursue novel products.

2 | THEORY AND HYPOTHESES

2.1 | Product development failure and the moderating role of prolific inventors on NDI

In the biopharmaceutical industry, products in development are tested in a sequentially staged process of increasing intensity of rigor and scale, as reflected in the investment of tangible and intangible resources (Deeds, 2001). The goal of this testing is to establish that the product is both safe and effective for treatment on human subjects, ultimately culminating in FDA approval. Product development failure results when concerns regarding the safety and/or efficacy of the drug, based on the previous phase of testing, prevent its progress to the next phase of development (cf. De Carolis, Yang, Deeds, & Nelling, 2009; Hoang & Rothaermel, 2005, 2010). While failures are a common outcome of product development efforts in the industry (Schilling, 2015), firms strive hard to avert such outcomes since they may involve millions of dollars of investment and losses in time and resources (DiMasi, Grabowski, & Hansen, 2016; Strovel et al., 2016). Furthermore, these failures can lead the firm to question its earlier assumptions regarding how to develop products successfully (Brown & Eisenhardt, 1995; Shepherd, Wiklund, & Haynie, 2009).

Product failure in the development stage exposes firm members to novel and unexpected information, and it may generate new causal links between actions and outcomes (Baum & Dahlin, 2007; Madsen & Desai, 2010; McGrath, 1999). As such, failure may guard against overconfidence and encourage more seeking, learning, and incorporation of new knowledge (Rerup, 2005). It may prompt organization members to take action to find a solution, which typically involves the search for and acquisition of new and unfamiliar knowledge to determine the reasons for the product's failure (Argyris & Schön, 1996; Cyert & March, 1963) and to investigate new technological trajectories that may lead to success (Khanna et al., 2016; Levitt & March, 1988; Posen, Keil, Kim, & Meissner, 2018).

This position is consistent with March and Shapira's (1987) argument that "fewer risks should, and would, be taken when things are going well" (p. 1409). They expect organizations to make riskier choices when they are "failing" and are more likely to experiment with solutions that go beyond their existing knowledge base (Levinthal & March, 1981; Wildavsky, 1988). Product development failures, then, may lead firms to take more risks as they test different



approaches (Argote & Ophir, 2002; Levinthal & March, 1993). These new solutions tend to involve inventions associated with new and novel knowledge creation (Argote & Ophir, 2002).

Although we have argued so far that failure increases risk-taking and novel knowledge creation, we posit that the presence of experts in the firm is likely to limit this firm-level propensity. Organizations tend to rely on experts, such as prolific inventors, to identify the path forward in times of adversity (Almundoz & Tilcsik, 2016). As a conduit of a firm's knowledge and capabilities, prolific inventors have a strong influence on the direction of its product development. Zucker et al. (1998), for example, found that the top 0.75% of contributors to the genetic sequence database GenBank qualified as star inventors and accounted for almost 17% of the contributions to the database. Given their expertise and access to internal and external sources of knowledge, prolific inventors are often associated with novel innovation (Chen & Garg, 2018; Conti et al., 2014). As experts, prolific inventors are believed to be in the best position to understand the causes and effects of product development failure (Gephart, Steier, & Lawrence, 1990; Hardy & Maguire, 2016). Indeed, given their expertise and status in the organization, prolific inventors' opinions matter more in times of adversity (Tzabbar, 2009). And in companies with more prolific inventors, these inventors' influence on firm decisions is increasingly dominant (Groysberg, Polzer, & Elfenbein, 2011). As they assume responsibility for arriving at solutions following failure, prolific inventors may become more risk-averse, searching for solutions within their areas of expertise and avoiding solutions associated with more novel ideas and approaches (Audia & Goncalo, 2007; Kehoe & Tzabbar, 2015). Furthermore, because of prolific inventors' relative dominance, the contribution and ideas of less prominent employees may be discounted, limiting creativity, information flows, and the sharing of innovative ideas among members (Chen & Garg, 2018; Janis, 1991; Vaughan, 1990). This constraint upon input from others following product development failure may result in a narrower set of ideas and a more limited set of beliefs (Cummings, 2004).

Research in behavioral theory suggests that individuals with more expertise and experience may discount negative news (Staats, Diwas, & Gino, 2018). They are also more likely than less experienced individuals to continue using existing solutions (Sleesman, Conlon, McNamara, & Miles, 2012; Staats et al., 2018). When experts receive negative feedback such as product development failure, they tend to express "excessive certainty regarding the accuracy of one's[their] beliefs" (Moore & Healy, 2008, p. 502). Experts are more inflexible (Dane, 2010) and more resistant to incorporating new information and altering their perspectives in the face of negative news (Furr, Cavarretta, & Garg, 2012; Staats et al., 2018). Research also suggests that experts are more likely than nonexperts to recognize and value information that enhances their firm's existing competencies and disregard conflicting evidence (Christensen & Bower, 1996; Tripsas & Gavetti, 2000). Staats et al. (2018) suggest that experts tend to exhibit self-confirmation bias, as they believe their logical processes are superior to those of others. Therefore, they give greater weight to their opinions and view their own opinions more favorably. As a result, in times of trouble when firms turn to their prolific inventors for solutions, there may be a greater discounting of negative news and more commitment to the firm's current direction, leading to greater status quo bias (Staats et al., 2018; Tripsas & Gavetti, 2000). Furthermore, much of the firm's research budget is likely to be tied to the prolific inventors' innovative activities, exacerbating the firm's reluctance to engage in novel knowledge creation following product development failure. Given a somewhat fixed and established research budget, a greater number of more prolific inventors in the firm would generally denote a greater investment in their areas of research, in turn limiting opportunities to experiment with new solutions that go beyond the research agendas of these prolific inventors (Groysberg et al., 2011).



In comparison, firms without prolific inventors are likely to rely on the knowledge and experience of a greater number of more diverse inventors (Chen & Garg, 2018) who jointly bear responsibility for solutions that are proposed following product development failure. Reliance on a broader range of expertise enables the firm to avoid framing solutions within any specialization and leads to a greater openness to search more broadly (Chen & Garg, 2018; Tzabbar & Kehoe, 2014). In addition, this openness to a broader set of ideas and inputs following product development failure may enhance a firm's learning, its consideration of a wider range of options (Gibson & Vermeulen, 2003; Van Der Vegt & Bunderson, 2005), and its creative potential (Reagans & Zuckerman, 2001). The involvement and input of more inventors in the firm, then, is associated with improved creative problem solving, creating a cross-fertilization of ideas that motivates firm members to identify and create novel knowledge (Sutton & Hargadon, 1996). Building on these arguments, we expect:

Hypothesis (H1). An increase in the number of prolific inventors in a firm is likely to weaken the positive effect of product development failure on novel drug innovation.

2.2 | Product development failure and the role of prolific inventors' collaborative strength and tenure on NDI

Although prolific inventors generally have more authority over and influence on the innovation process, there may be variation in the degree of power and influence these inventors exert on a firm's technological direction. Research has demonstrated that two characteristics which increase an individual's power and influence on decision-making in firms are collaborative strength (Tzabbar & Kehoe, 2014) and tenure (Azoulay, Graff Zivin, & Wang, 2010; Perretti & Negro, 2006; Simsek, 2007). Accordingly, we expect prolific inventors' collaborative strength and tenure to moderate the positive effect of product development failure on NDI.

2.2.1 | Prolific inventors' collaborative strength

Prolific inventors with a great deal of collaborative strength, reflected in extensive and repeated intrafirm research collaborations, gain broader recognition as innovative leaders in the firm, particularly in periods of greater internal adversity that follow product development failure (Almundoz & Tilcsik, 2016). They are more visible and central to research activities (Paruchuri, 2010), and their colleagues are likely more familiar with them and committed to their research agendas, enhancing their influence in the organization.

Behaviorally, collaborative strength breeds familiarity among firm members. Familiarity is likely to strengthen reciprocity between prolific inventors and their colleagues (Tzabbar & Kehoe, 2014), benefiting both parties and increasing the willingness of others in the firm to support prolific inventors' initiatives (McEvily, Perrone, & Zaheer, 2003). Repeated collaboration facilitates the development of a shared identity and understanding, as well as more common mental models (Kogut & Zander, 1992). These factors, in turn, increase the likelihood of mutual support and reduce the interpersonal conflict that may result from the tension created by product development failure (Reagans & McEvily, 2003). Such broad support for prolific inventors' research agendas may also reduce the emergence of alternative and competing internal factions



that could pursue innovative new products following product development failure. Prolific inventors with a strong coalition of collaborators are thus likely to engender a greater commitment to familiar technologies that are already within their areas of expertise (Cummings, 2004). Such strong support among collaborators can be expected to increase prolific inventors' tendency and motivation to persevere rather than diverge from their areas of expertise in the face of negative news (Furr et al., 2012; Staats et al., 2018). In contrast, prolific inventors who collaborate less frequently with their colleagues are likely to have less impact, exposure, and influence on subsequent product development decisions. As a result, they are likely to have a more limited influence on the firm's direction following product development failure. Accordingly, we expect:

Hypothesis (H2). An increase in the level of prolific inventors' collaborative strength in the firm is likely to weaken the positive effect of product development failure on novel drug innovation.

2.2.2 | Prolific inventors' tenure

Prolific inventors' tenure in the firm may also reduce the firm's tendency to create new knowledge after product development failure. Prolific inventors who have been with the firm longer are likely to exert greater influence on both the firm's research agenda and the opinions of their colleagues (March, 1991). Extensive research on firm tenure has demonstrated that individuals with longer tenure have a stronger commitment to the firm's existing research agenda, policies, procedures, history, and strategies (Hambrick, Geletkanycz, & Fredrickson, 1993), as well as a preference for the status quo (Finkelstein & Hambrick, 1990; Staw & Ross, 1980). The pursuit of novel knowledge can be a "clear, risky departure from existing practice" (Ettlie, Bridges, & O'Keefe, 1984, p. 683), which individuals with higher tenure are likely to avoid, preferring to focus on refinements or extensions of existing ideas or technologies (Dane, 2010). Overall, individuals with longer tenure are likely to be more cognitively rigid, favor established routines, and avoid change (Miller & Shamsie, 2001). This affinity for the exploitation of existing knowledge and risk-avoidance may be rooted in their early success and domain-specific knowledge and training (Ericsson, 1999; Ericsson & Charness, 1994). Employees with longer tenures are often building on their early achievements and relying on their previous successes (Hambrick & Fukutomi, 1991; Miller, 1991). As such, tenure exacerbates the tendency of prolific inventors to recognize and value information that enhances their firm's existing competencies while discounting conflicting evidence (March & Shapira, 1987). This propensity to discount negative news, coupled with an inclination to perpetuate approaches that have been tried and tested, leads to greater status quo bias and self-confirmation bias (Staats et al., 2018; Tripsas & Gavetti, 2000).

Prolific inventors' social influence also tends to increase with their tenure. Those who have worked longer in the organization are likely to have a stronger commitment to their work and their colleagues (Nahapiet & Ghoshal, 1998; Slaughter, Archerd, & Campbell, 2004). Prolific inventors with longer tenure are also likely to play a more central role in the firm's strategic direction and are likely to have greater authority and control over important resources, increasing their colleagues' dependence on their expertise (Paruchuri, 2010). As a result, their position allows them to exert greater influence on the search for answers following failure. Conversely, key employees who have been with the organization for less time are likely to be more open to

experimentation (Hambrick & Fukutomi, 1991), demonstrate a greater willingness to change their organization's strategic direction (Finkelstein & Hambrick, 1990; Gabarro, 1987; Wiersema & Bantel, 1992), and pursue more innovative ideas (Bantel & Jackson, 1989; Thomas, Litschert, & Ramaswamy, 1991). Thus, we posit that:

Hypothesis (H3). An increase in the level of prolific inventors' tenure in the firm is likely to weaken the positive effect of product development failure on novel drug innovation.

3 | METHODS

3.1 | Research context: Product development failures in the biotech industry

We test our hypotheses in the biotech industry. The process of developing a drug is long and uncertain, with the path to market for a single drug requiring at least a decade and a major financial investment (Bains, 2004; DiMasi & Grabowski, 2007). The highly regulated nature of this industry, which requires companies to provide fine-grained information about their product portfolios and the path to their products' successes and failures during the development process (Hoang & Rothaermel, 2005), makes this industry well-suited for our study.

The drug development process includes a series of sequential stages, including identifying new compounds, filing patents, pre-clinical trials, and clinical trials (Deeds, 2001). Studies have shown that the most common reason for failure in drug development is the inability to demonstrate its efficacy (Fogel, 2018). Other reasons for failure include safety concerns (e.g., serious adverse side effects), trial design issues such as the inability to recruit a suitable patient population, excessive patient dropout, improper dose selection, nonoptimal assessment schedules, inappropriate efficacy metrics/markers, and issues with the data analyses (Fogel, 2018; Jekunen, 2014).

Despite the prevalence of failures during the drug development process, they represent a serious setback to firms with losses ranging from tens of millions of dollars for early-stage failures to hundreds of millions of dollars for late-stage failures (DiMasi et al., 2016; Girotra, Terwiesch, & Ulrich, 2007). Given that failure in the drug development process is common and costly, it underscores the crucial role of learning from failure in determining a firm's competitive advantage (Casper, 2007). One means by which a firm learns is through developing and integrating NCEs into its drug development. NCEs, which are brand new-to-the-world chemical entities whose medical effects are unknown, reflect the creation of novel knowledge. Given that their medical effects are unknown, these NCEs are considered high risk-high return innovations.

As experts, inventors play a critical role in shaping the ultimate success of the drug through the product development process (Jekunen, 2014). In this context, inventors have a great deal of influence over the firm's knowledge search and response to failure. The development of Pfizer's Viagra is a good example of such influence. In the mid-1980s, Pfizer discovered a new NCE, Sildenafil (UK-92,480), involving nitric oxide—a short-lived chemical released by many cells in our bodies and associated with relaxing the smooth muscle linings of blood vessels. This discovery was instrumental in reducing blood pressure and hence, was thought to have the potential for treating angina, chest pain due to reduced blood flow to the heart. The drug failed in clinical



trials on both safety and efficacy grounds, which led Pfizer's executives to consider terminating the angina program (Anderson, 2019). However, Pfizer researchers noted that the effects of Sildenafil might be useful in treating impotence (Anderson, 2019). Despite management's skepticism about pursuing a new direction for a problem that was not even established as a clinical target (Tozzi & Hopkins, 2017), some key inventors were instrumental in championing the project. New trials started in 1993. This drug was eventually commercialized as the blockbuster drug, Viagra. This example illustrates how some firms are more successful than others in learning from failures and transforming them into eventual successes.

3.2 | Sample

Using the Bioscan and Pharmaproject databases, we compiled the life histories of all US-based biotechnology firms operating in the human therapeutic sector between 1973 and 2010.² We began construction of our dataset with the Bioscan database, which provided a comprehensive historical record of firms in the biotech industry (e.g., Rothaermel & Deeds, 2004). We then identified those firms in the Bioscan database that were also listed in the Pharmaprojects database. Pharmaprojects is a premier database for information on the biopharmaceutical R&D pipeline. It contains fine-grained data on firms' drug portfolios and history based on company questionnaires, annual reports, SEC and FDA filings, journals, investment reports, press releases, and industry conferences (e.g., Hoang & Rothaermel, 2005; Kapoor & Klueter, 2015).

From the initial list, we manually inspected and eliminated service firms (e.g., labs and consulting services) that were unlikely to develop a drug or patent, resulting in a total of 679 firms. We augmented these two data sets with the Harvard Patent Dataverse (Li et al., 2014). We identified 457 matches (i.e., firms with products and patents), representing our final sample. Excluding firms with no products throughout their existence was important because, by definition, such firms cannot experience a product development failure or incorporate new knowledge into future products. Including them would introduce unnecessary heterogeneity (Berk, 1983; Foragues, 2012; Short, Ketchen, & Palmer, 2002). Employing this strategy also enabled us to control for and eliminate unobserved heterogeneity in terms of the firms' strategic focus and capabilities. In an unreported analysis of variance test,³ we found that firms with patents, but no products were significantly younger than the firms in our sample (i.e., firms with product and patents, and firms with products but no patents). As reported below, we also employed a two-stage instrumental variable regression using the "ivreg2" command in Stata, as well as Heckman's correction to deal with unobserved heterogeneity and potential selection bias.

For firms that were subsequently acquired by another firm and hence became a subsidiary, we tracked those firms as independent entities until the time of acquisition, after which their drugs were subsumed under the acquirer's drug portfolio. We also followed this procedure for firms that changed their name. To ensure that we did not inadvertently exclude firms that had name changes and hence were listed with different names in the two databases, we supplemented our database matching process with extensive web searches to ensure that such firms were recorded and tracked accurately.

²We ended our observation period in 2010 because in this industry the drug development process is long and uncertain, with the path to market for a single drug often requiring a decade (Bains, 2004; DiMasi & Grabowski, 2007).

³Results are available upon request.

This process enabled us to build a longitudinal, firm-level record of the firms' products and patents over time. Furthermore, consistent with prior research, we created complete inventor patenting and firm histories (Paruchuri, 2010). Overall, the firms in our sample were involved with 6,197 products; 21,731 unique patents; and 18,041 inventors between 1973 and 2010. We use firm-year level for our analysis. We built a dataset that included the entire portfolio of products and patents for these firms, and identified the prolific inventors associated with these firms based on their patenting history.

3.3 | Dependent variable

3.3.1 | Novel drug innovation

Consistent with prior research in the context of biotechnology industry (e.g., Rothaermel & Deeds, 2004) and learning from failure literature (Bennett & Snyder, 2017), we operationalized *NDI* as the number of new drugs with NCEs that appeared in the firm's current drug portfolio, using a 3-year moving average($t, t + 1, t + 2$), as reported in the Pharmaprojects database. Using moving averages as opposed to annual counts enabled us to smooth out annual fluctuations (Mc Namara & Baden-Fuller, 2007; Rothaermel & Deeds, 2004). In an unreported robustness check, we also tested our model using a five-year window for calculating the moving average, with similar results. An NCE is a completely NCE whose medical effects were previously unknown. Finding an NCE requires a search beyond the known libraries of active ingredients (Suzuki, 2018). As such, NCE-based pharmaceutical products represent the exploration of novel knowledge (Bierly & Chakrabarti, 1996; Cardinal, 2001; Dunlap-Hinkler, Kotabe, & Mudambi, 2010).

3.4 | Independent variables

3.4.1 | Failure

We recognized a drug as a failure if its final recorded status in the Pharmaprojects database indicated that the firm permanently discontinued the drug development. We were able to determine the reason for the failure of specific drugs in Pharmaprojects and its sister database Trialtrove to ensure we were not inadvertently counting drugs that were strategically discontinued by the firm as failures. We operationalized failures as the number of drug discontinuations during the development stage (comprising preclinical, Phase 1, Phase 2, and Phase 3 testing of drugs) for the focal firm using a 3-year moving average ($t - 3, t - 2, t - 1$) to smooth out annual fluctuations (Mc Namara & Baden-Fuller, 2007; Rothaermel & Deeds, 2004).

3.4.2 | Number of prolific inventors

In the context of biotechnology, scientists are evaluated by their patent productivity. To count the number of prolific inventors, we first identified prolific inventors in accordance with existing conventions (Kehoe & Tzabbar, 2015; Tzabbar & Kehoe, 2014). First, we used this function to measure the patent productivity of all inventors in our dataset:



$$\text{InvProductivity} = \left[\left(\frac{\text{InvPat}_{it}}{\text{IndTenure}_{it}} \right) \times \text{AveForwardCite}_{it} \right]$$

where InvPat_{it} represents the number of patents for which scientist i applied by year t . IndTenure_{it} refers to inventor i 's tenure in the industry as defined by the total number of years since inventor i 's first patent application in our sample. $\text{AveForwardCite}_{it}$ refers to the average forward citations of scientist i 's patents received by year t . Assessing inventor productivity with forward citations is important because forward citations in patents provide the best proxy for a patent's impact and quality. After calculating the productivity of all of the inventors in our sample, we categorized certain inventors as prolific inventors if their individual productivity was greater than two SDs above the mean (Kehoe & Tzabbar, 2015). As a result of this process, we identified a total of 294 prolific inventors out of 18,041 inventors in our sample (prolific inventors accounted for about 2% of the inventors in our sample) who were employed by 96 firms (out of 457 firms) through our study period (21% of our sample).

3.4.3 | Prolific inventors' collaborative strength

Using co-invention patent data, we operationalized a prolific inventor's collaborative strength as the level of co-invention frequency between a prolific inventor and his or her colleagues in the firm in a prior 5-year window to account for changes in the size of the firm over time. Consistent with previous work (Reagans & Zuckerman, 2001; Uzzi, 1996), we computed collaborative strength as the average level of co-invention frequency between prolific inventors and their colleagues in firm s ,

$$\text{collaboration}_s = \sum_{i=1}^{N_s} \sum_{j=1}^{N_s} Z_{ijs}, j \neq i,$$

where Z_{ijs} ($\{0,1,2,3,4\}$) is the frequency with which prolific inventor i co-invents with inventor j .

We aggregated a prolific inventor's collaborative strength to the firm level by averaging collaborative strength of all prolific inventors at a focal firm in a specific year t . For a robustness check, we also used the highest value of collaborative strength among prolific inventors active in the firm in year t (Tzabbar & Kehoe, 2014).

3.4.4 | Prolific inventors' tenure

We operationalized a prolific inventor's tenure as inventor i 's organizational tenure in the firm, as defined by the total number of years since inventor i 's first patent application in the firm. We computed the prolific inventor's tenure at the firm level as the average tenure of all prolific inventors at a focal firm in a specific year t . As a robustness check, we also used the highest value of tenure among prolific inventors active in the firm in year t .

3.5 | Control variables

To account for heterogeneity among the firms in our sample and eliminate alternative explanations, we included several control variables, using a 1-year lag in our analyses. As past failures and the ongoing process of product development can affect a firm's likelihood of new product development failure (McGrath, 2001), we controlled for the number of *prior product development failures*⁴ and, due to skewness, we included the natural logarithm of *unique therapeutics*, *new chemical structures*, *drugs in preclinical stage*, and *drugs in clinical stage*. Given that a firm's knowledge base, innovative capabilities, and quality can affect product development failure (Moorman & Miner, 1997), we also included the natural logarithm of the cumulative number of products introduced by the firm (*prior products*) and the cumulative number of patents (*prior patents*), as well as the average *patent forward citations*. To account for the potential effect of decision makers, we also controlled for the number of members on the top management team (*number of TMT*), their average tenure (*TMT tenure*), the *CEO's power* as reflected in the number of titles the CEO held, and the *number of TMT inventors* (TMT members registered as assigned inventors), reflecting the number of executives who had at least one patent. To account for changes in the firm's human capital, we controlled for the natural logarithm of *number of new recruits*. Given that an alternative explanation of our results could be the hierarchical structure of innovation, we controlled for the natural logarithm of the *firm's innovative centrality*, as reflected in a Gini coefficient, to capture the distribution of innovative productivity among firm members. Since firms with a broader technological span have more absorptive capacity, we used a Herfindahl index to account for the *firm's technological breadth*, as reflected in the number of patent classes included in its patents (Tzabbar, 2009).

Given that a firm's age reflects not only its cumulative learning and experience in dealing with organizational failure but also its obsolescence, we controlled for the *firm's age*, operationalized as the number of years since the firm's founding year as reported in Bioscan and web searches. In a handful of cases, we detected a discrepancy in the data such that the focal firm had patent applications recorded with the USPTO prior to its founding date. In these cases, we considered the year of the firm's patent application as its founding date. We also included the natural logarithm of the *firm's size*, measured by the number of its employees. Finally, to account for potential variance in technological opportunity, that is, differences across the primary technological and clinical domain of the firm, we control for the primary (most frequent) therapeutic area that underpinned a focal firm's products (Hoang & Rothaermel, 2010). These therapeutic area fixed effects accounted for five broad therapeutic area dummies and one reference category and were implemented at the firm level.

3.6 | Correcting for endogeneity

3.6.1 | Instrumental variable

While our sampling strategy and controls may account for some degree of heterogeneity among the firms in our sample, the relationship between the number of prolific inventors in the firm and the firm's novel drug novel innovation following failure may involve unobservable factors, that is, omitted variables which are correlated with the error term, that could be driving the

⁴To avoid any overlap with our independent variable, "failure," this variable was lagged for the year $t - 4$.



results. We address this potential endogeneity by conducting a two-stage instrumental variable regression using the ivreg2 (2SLS) command in Stata 14.2 (Hamilton & Nickerson, 2003). We followed Certo, Busenbark, Woo, and Semadeni's (2016) steps for incorporating an endogenous variable into the estimation. We used the natural logarithm of the number of biotechnology firms in a geographic region as the instrumental variable. Conceptually, we expect that the number of biotechnology firms in a geographic region should be positively correlated with the firm's number of prolific inventors since it represents the intensity of competition over knowledge and resources within the geographic region (Carroll & Hannan, 1989). However, we expect that the number of biotechnology firms in a geographic region is unlikely to influence a specific firm's innovation strategy in the aftermath of product development failure. We followed Thompson and Fox-Kean's (2005) procedure to identify a geographic region, assigning a firm's geographic region based on the location associated with a majority of its patents (each patent was assigned a location based on the location of the first listed inventor on the patent). Accounting for the number of biotechnology firms in a geographic region allows us to identify an instrument that varies by firm-year. To examine the appropriateness of our instrument, we used the three tests (under-identification, weak identification, overidentification) provided by the ivreg2 command in Stata. The Cragg–Donald Wald F -statistic is above 10, suggesting that this instrumental variable passes a weak-identification test. This indicates that the instrument is not only conceptually relevant but also technically suitable.

3.6.2 | Heckman's two-stage correction

Another possible source of endogeneity could arise from our sample selection. To study product development failure, we had to select firms that had at least one product during the period of our research. In addition, a firm's number of prolific inventors is an outcome of self-selected hiring decision by the firm and is hence nonrandom. To address these two sources of endogeneity, we employed Lee's (1982) variation of the Heckman model (Hamilton & Nickerson, 2003). Heckman models mitigate endogeneity from self-selection by incorporating exclusion restrictions to compute an adjustment rate (i.e., IMR) that is included in the second-stage estimation.

We developed two Mills ratios. The first is to account for the likelihood of having a prolific inventor, and the second accounts for a firm's likelihood of developing a new product (see Table 2). To predict both likelihoods, we examined the natural logarithm of *prior products*, *prior patents*, and *firm size* as well as *firm age*, all of which represent access to the resources critical for new products. We then generated the Mills ratios using the predict function in Stata 14. Our approach is consistent with several others who have used a similar procedure (e.g., Lacetera, Cockburn, & Henderson, 2004; Rao & Drazin, 2002). In the second stage, we included the Mills ratios as coefficients.

4 | RESULTS

4.1 | Descriptive statistics

In Table 1, we present the means, *SDs*, and correlations among the independent and control variables. We derived the variance inflation factors (VIFs) from an ordinary least square

TABLE 1 Summary statistics and pairwise correlations

Variables	Mean	SD	1	2	3	4	5	6	7	8	9	10	11	12
1 Drug innovation	0.32	0.95												
2 Failure	0.15	0.47	0.38											
3 Num. of prolific inventors*	2.33	2.12	0.18	0.21										
4 Prolific inventor's collab. strength*	12.63	41.23	0.08	0.15	0.41									
5 Prolific inventor's tenures*	6.77	4.66	0.17	0.22	0.60	0.26								
6 Num. of prior failures	0.39	1.34	0.35	0.68	0.16	0.10	0.20							
7 Num. of unique therapeutics (log)	0.24	0.55	0.38	0.12	0.17	0.07	0.13	0.09						
8 Num. of new chemical structures (log)	0.04	0.23	0.37	0.29	0.07	0.06	0.12	0.30	0.14					
9 Num. of drugs in preclinical stage (log)	0.04	0.20	0.24	0.28	0.15	0.04	0.11	0.20	0.12	0.09				
10 Num. of drugs in clinical stage (log)	0.16	0.39	0.43	0.43	0.28	0.12	0.26	0.40	0.31	0.33	0.24			
11 Prior products (log)	0.12	0.38	0.34	0.49	0.18	0.11	0.24	0.49	0.14	0.32	0.17	0.42		
12 Prior patents (log)	2.12	1.54	0.23	0.36	0.32	0.15	0.35	0.35	0.15	0.21	0.16	0.36	0.39	
13 Average forward citation (log)	0.67	1.33	0.18	0.18	0.32	0.13	0.36	0.15	0.16	0.07	0.16	0.23	0.16	0.43
14 Num. of TMT	6.81	2.37	0.17	0.12	0.16	0.06	0.14	0.10	0.16	0.10	0.07	0.21	0.18	0.20
15 TMT tenure	5.91	2.30	0.01	0.10	-0.01	-0.00	0.01	0.13	-0.06	0.04	-0.00	0.04	0.12	0.09
16 CEO power	0.55	0.16	-0.01	-0.03	0.02	0.00	-0.01	-0.04	-0.00	-0.02	0.00	-0.03	-0.10	0.00
17 Num. of TMT inventors	0.55	0.67	-0.02	-0.10	-0.02	-0.02	-0.05	-0.09	-0.00	-0.02	-0.04	-0.08	-0.09	-0.08
18 Num. of new recruits (log)	0.52	0.89	0.28	0.20	0.38	0.18	0.29	0.15	0.23	0.10	0.19	0.27	0.16	0.43
19 Firm's innovative centrality (Gini)	0.05	0.10	0.19	0.18	0.44	0.29	0.38	0.13	0.17	0.08	0.16	0.23	0.15	0.47
20 Firm's technology breadth	3.08	4.06	0.24	0.24	0.26	0.11	0.23	0.22	0.13	0.15	0.12	0.25	0.26	0.69
21 Firm age	12.25	8.47	0.05	0.20	0.01	0.02	0.06	0.23	-0.01	0.12	0.03	0.15	0.31	0.55
22 Firm size (log)	1.25	1.50	0.23	0.19	0.29	0.12	0.30	0.15	0.23	0.09	0.17	0.26	0.14	0.50
Variables	13	14	15	16	17	18	19	20	21					
13 Average forward citation (log)														
14 Num. of TMT														

TABLE 1 (Continued)

Variables	13	14	15	16	17	18	19	20	21
15 TMT tenure	-0.02	0.02							
16 CEO power	-0.01	-0.09	-0.11						
17 Num. of TMT inventors	-0.03	0.07	-0.04	-0.00					
18 Num. of new recruits (\log)	0.54	0.21	-0.04	0.01	-0.01				
19 Firm's innovative centrality (Gini)	0.39	0.13	-0.05	0.03	-0.03	0.51			
20 Firm's technology breadth	0.40	0.16	0.06	0.02	-0.00	0.54	0.38		
21 Firm age	0.04	-0.04	0.18	-0.06	-0.04	-0.01	0.05	0.29	
22 Firm size (\log)	0.58	0.21	-0.07	0.00	-0.01	0.69	0.43	0.47	-0.03

Note: N = 8,892. All correlations with absolute values greater than 0.2 are significant at $p < .05$. N = 8,892 (* = 732). All correlations with absolute values greater than 0.2 are significant at $p < .05$.

at $p < .05$.

TABLE 2 Heckman probit first stage model

	Presence of prolific inventor (Mills1)	Likelihood for new product (Mills2)
Prior products (log)	0.304 (0.135)	0.557 (0.079)
Prior patents (log)	0.497 (0.078)	0.070 (0.033)
Firm age	-0.096 (0.019)	-0.012 (0.005)
Firm size (log)	0.264 (0.050)	0.213 (0.025)
Constant	-2.274 (0.133)	-1.066 (0.050)

Note: $N = 8,892$. Robust SEs are in parentheses (clustered by firm).

regression. The modest correlations between the independent variables suggested that multicollinearity problems were unlikely (mean VIF = 1.77; highest VIF = 4.38). In Table 2, we present the results of the first stage analysis to account for the endogeneity associated with the likelihood of having a prolific inventor (Mills ratio 1) and new product (Mills ratio 2). As indicated, prior products ($p = .024$), prior patents ($p = .000$) and firm size ($p = .000$) increase the likelihood to have a prolific inventor while firm age decreases such likelihood ($p = .000$). Similarly, prior products ($p = .000$), prior patents ($p = .037$) and firm size ($p = .000$) increases the likelihood for new product while firm age decreases such likelihood ($p = .000$). In Table 3 (column 6), we employed a stepwise analysis which allowed us to further assess potential model estimation issues. Both indicate that there is no issue of multicollinearity. Our measures are also not highly correlated, which further reduces the risk of multicollinearity.

4.2 | The effects of failure and prolific inventors on NDI

Table 3 reports the results of the two-stage correction and the 2SLS regression, each using robust SEs. Model 1 provides the first stage instrumental variable analysis of the *number of prolific inventors*. Models 3–5 report the second-stage model for the full sample, while Models 6–9 test our hypotheses using a prolific inventor sample (i.e., only firms with at least one prolific inventor).

The instrument (Model 1), number of biotechnology firms in a region, is positive in predicting the number of prolific inventors ($p = .001$). Model 2 introduces the main effect and control variables for the full sample. As shown, number of prolific inventors increase NDI ($p = .003$), while prolific inventor collaborative strength ($p = .011$) and tenure reduces such likelihood ($p = .003$). Consistent with our theory, failure increases the propensity for new product development. An examination of the control variables in Model 2 reveals several findings. First, for the main effect, prior failure, number of unique therapeutics, new chemical structures, drugs in clinical stage, prior products, firm technology breadth and firm size are associated with a positive effect on drug innovation, while prior patents, TMT tenure, and CEO power are associated with a negative effect.

The results reported in both Models 3 (full sample) and 7 (prolific inventor sample) provide strong support for Hypothesis (H1), suggesting that the number of prolific inventors are associated with a weakening of the positive effect of product development failure on NDI. Our results indicate that the interaction is negative ($p = .015$ for Model 3, $p = .000$ for Model 7), consistent with our expectation. To further investigate the moderating role of the number of prolific inventors on the relationship between failure and NDI, we plotted the results of the interaction in

TABLE 3 Instrumental variable 2SLS: The moderating effect of prolific inventors on novel drug innovation

	Second-stage DV: Drug innovation _(t + 1, t + 2)								
	First-stage DV: Num. of prolific inventors		Full sample			Prolific inventor sample			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Number of biotech in the region (log)	0.023 (0.004)								
H1: Failure × num. of prolific inventors			-0.355 (0.146)			-0.404 (0.102)			
H2: Failure × prolific inventor collaborative strength (average)				0.002 (0.002)			-0.002 (0.000)		
H3: Failure × prolific inventor tenure (average)					-0.023 (0.019)			-0.144 (0.029)	
Num. of prolific inventors	0.917 (0.309)	1.344 (0.511)	0.906 (0.304)	0.897 (0.311)	0.444 (0.118)	0.971 (0.275)	0.457 (0.121)	0.502 (0.127)	
Prolific inventor collaborative strength (average)		-0.014 (0.005)	-0.010 (0.005)	-0.020 (0.010)	-0.013 (0.005)	-0.004 (0.001)	-0.001 (0.002)	0.001 (0.003)	-0.003 (0.001)
Prolific inventor tenure (average)			-0.129 (0.043)	-0.158 (0.060)	-0.124 (0.042)	-0.112 (0.040)	-0.057 (0.020)	-0.018 (0.024)	-0.054 (0.020)
Failure	0.186 (0.088)	0.568 (0.151)	0.167 (0.089)	0.250 (0.074)	0.508 (0.197)	2.036 (0.446)	0.581 (0.212)	1.515 (0.295)	
Number of prior failures	0.002 (0.015)	0.089 (0.025)	0.069 (0.024)	0.091 (0.025)	0.090 (0.025)	0.202 (0.052)	0.119 (0.049)	0.195 (0.055)	0.238 (0.053)
Num. of unique therapeutics (log)	0.056 (0.021)	0.169 (0.037)	0.145 (0.046)	0.170 (0.037)	0.163 (0.036)	0.179 (0.108)	0.179 (0.103)	0.176 (0.108)	0.143 (0.106)
	-0.234 (0.061)	0.900 (0.130)	0.832 (0.124)	0.903 (0.130)	0.891 (0.129)	1.466 (0.293)	1.089 (0.283)	1.445 (0.294)	1.309 (0.274)

TABLE 3 (Continued)

Second-stage DV: Drug innovation _(t, t + 1, t + 2)								
First-stage DV:			Prolific inventor sample					
Num. of prolific inventors	Full sample	Full sample	(6)	(7)	(8)	(9)		
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Num. of new chemical structures (log)								
Num. of drugs in preclinical stage (log)	0.061 (0.096)	0.139 (0.133)	0.156 (0.127)	0.146 (0.132)	0.273 (0.130)	0.047 (0.343)	0.152 (0.323)	0.014 (0.347) 0.153 (0.284)
Num. of drugs in clinical stage (log)	0.272 (0.047)	0.174 (0.074)	0.162 (0.086)	0.176 (0.073)	0.167 (0.073)	0.318 (0.149)	0.273 (0.171)	0.318 (0.150) 0.180 (0.155)
Prior products (log)	0.048 (0.074)	0.364 (0.098)	0.567 (0.157)	0.356 (0.096)	0.378 (0.100)	-0.102 (0.046)	0.647 (0.451)	-0.105 (0.409) -0.029 (0.418)
Prior patents (log)	0.064 (0.011)	-0.139 (0.016)	-0.157 (0.021)	-0.136 (0.015)	-0.140 (0.016)	-0.578 (0.168)	-1.066 (0.287)	-0.633 (0.176) -0.659 (0.170)
Average forward citations (log)	0.016 (0.009)	-0.008 (0.014)	-0.004 (0.017)	-0.008 (0.014)	-0.010 (0.014)	-0.043 (0.037)	-0.028 (0.045)	-0.043 (0.037) -0.045 (0.038)
Number of TMT	0.017 (0.006)	0.005 (0.008)	-0.007 (0.014)	0.006 (0.008)	0.004 (0.008)	0.034 (0.022)	0.030 (0.034)	0.036 (0.023) 0.029 (0.022)
TMT tenure	0.002 (0.004)	-0.008 (0.004)	-0.009 (0.005)	-0.008 (0.004)	-0.007 (0.004)	0.005 (0.024)	-0.018 (0.033)	0.005 (0.024) -0.005 (0.024)
CEO power	0.136 (0.052)	-0.172 (0.076)	-0.229 (0.102)	-0.165 (0.075)	-0.169 (0.075)	-0.900 (0.374)	-0.993 (0.462)	-0.902 (0.374) -0.510 (0.365)
Number of TMT inventors	0.012 (0.012)	-0.013 (0.016)	-0.001 (0.019)	-0.013 (0.016)	-0.010 (0.016)	0.041 (0.062)	-0.003 (0.079)	0.038 (0.062) 0.024 (0.062)
Number of new recruits (log)	0.157 (0.022)	-0.049 (0.055)	-0.053 (0.064)	-0.045 (0.054)	-0.043 (0.054)	-0.096 (0.106)	-0.253 (0.146)	-0.117 (0.108) -0.152 (0.106)
Firm's innovative centrality (Gini)	2.106 (0.200)	-0.463 (0.351)	-0.947 (0.559)	-0.387 (0.338)	-0.474 (0.357)	0.021 (0.582)	0.345 (0.726)	-0.111 (0.588) -0.106 (0.573)
Firm's technology breadth	-0.008 (0.004)	0.025 (0.005)	0.029 (0.006)	0.025 (0.005)	0.026 (0.005)	-0.006 (0.036)	-0.045 (0.046)	-0.002 (0.036) -0.031 (0.036)

TABLE 3 (Continued)

	Second-stage DV: Drug innovation _(t, t + 1, t + 2)								
	First-stage DV: Num. of prolific inventors		Full sample				Prolific inventor sample		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Firm age	-0.008 (0.001)	0.003 (0.002)	0.002 (0.002)	0.003 (0.002)	0.002 (0.002)	0.081 (0.026)	0.119 (0.040)	0.085 (0.027)	0.082 (0.026)
Firm size (log)	-0.066 (0.013)	0.119 (0.034)	0.153 (0.048)	0.117 (0.034)	0.118 (0.035)	0.298 (0.225)	0.911 (0.317)	0.314 (0.228)	0.411 (0.232)
Mills ratio: new product	-0.273 (0.083)	0.267 (0.160)	0.559 (0.259)	0.260 (0.157)	0.291 (0.161)	0.384 (1.077)	2.502 (1.317)	0.348 (1.080)	0.307 (1.073)
Constant	0.061 (0.153)	-0.345 (0.229)	-0.713 (0.340)	-0.342 (0.227)	-0.383 (0.229)	-0.872 (1.590)	-4.589 (2.039)	-0.814 (1.597)	-1.246 (1.604)
Firm primary therapeutic area fixed effect	YES	YES	YES	YES	YES	YES	YES	YES	YES
<i>F</i>	28.93	24.25	28.05	28.24	13.81	9.13	13.53	14.80	
N	8,892	8,892	8,892	8,892	8,892	732	732	732	732

Note: The results of the tests were as follows. Underidentification: The Kleibergen-Paap rk LM statistic (24.05) rejected the null hypothesis ($p = .00$); weak identification: The Cragg-Donald Wald *F*-statistic was 12.86, which exceeded the Stock and Yogo (2005) weak ID test critical value for 15% maximal bias (8.96). Robust SEs are in parentheses (clustered by firm).

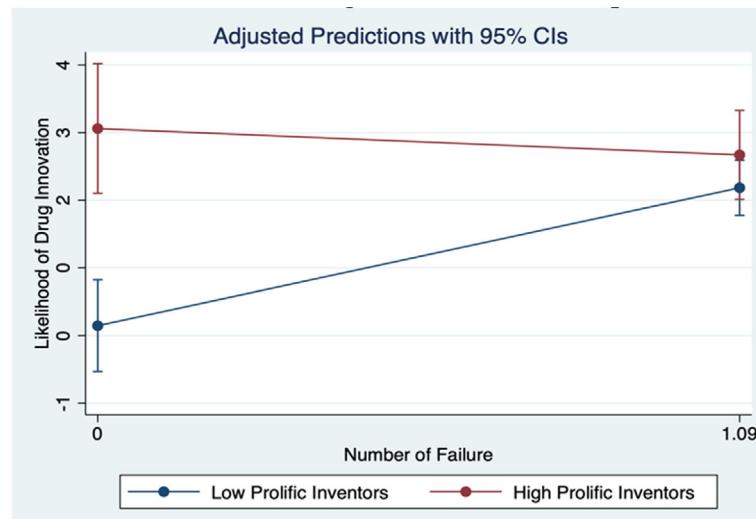


FIGURE 1 The moderating effect of number of prolific inventors.

Figure 1. As Figure 1 illustrates, at low levels of failure, firms with a larger number of prolific inventors are more likely to engage in NDI than those with fewer prolific inventors. However, at high levels of failure, firms with a larger number of prolific inventors are less likely to develop innovative drugs, as expected. In contrast, those with fewer such inventors are more likely to engage in more NDI, providing additional support for Hypothesis (H1). Interestingly, these results are consistent with the explanation that firms with less prolific inventors tend to experiment more following failure than they would otherwise, while firms with more prolific inventors experiment more when there is no failure.

4.3 | The moderating effects of the prolific inventors' characteristics

Table 3 presents the results of our examination of the moderating effect of the prolific inventors' collaborative strength and tenure on the firm's pursuit of NDI. Given that Models 3–5 for the full sample in Table 3 include firms with no prolific inventors, there is a risk of a zero-inflated bias, as the interaction terms for prolific inventors in these firms will be set to zero. Accordingly, we followed a common procedure of subgroup analysis (Kehoe & Tzabbar, 2015). Although we report the results for both the full sample (Models 4–5) and prolific inventor sample (Models 8–9), please note that tests of our hypotheses rely on the results of the subgroup analysis with prolific inventors. Our use of the instrumental variable 2SLS analysis minimizes the risk of selection bias.

Our analysis supports Hypothesis (H2) that prolific inventors' collaborative strength reduces the positive relationship between product development failure and the creation of novel knowledge ($p = .012$ in Model 8). We plotted the interaction in Figure 2. As the figure illustrates, high level of prolific inventor collaborative strength is associated with a weakening of the positive effect of product development failure on NDI. Conversely, low levels of prolific inventor collaborative strength are associated with an increase in the positive effect of product development

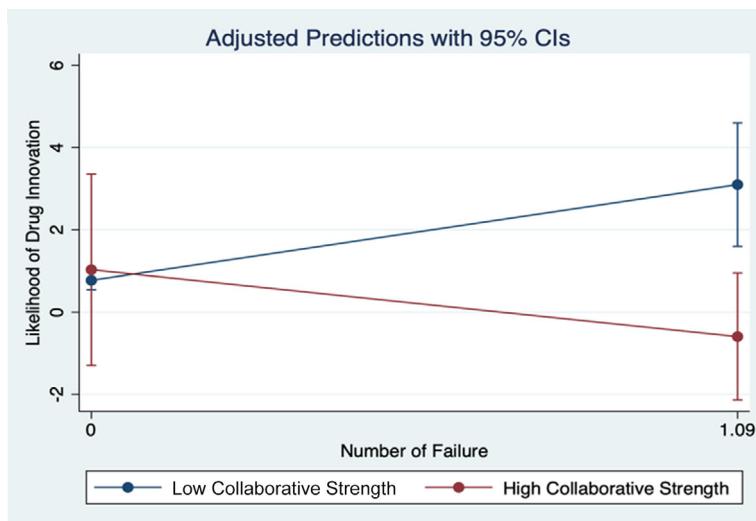


FIGURE 2 The moderating effect of prolific inventor collaborative strength.

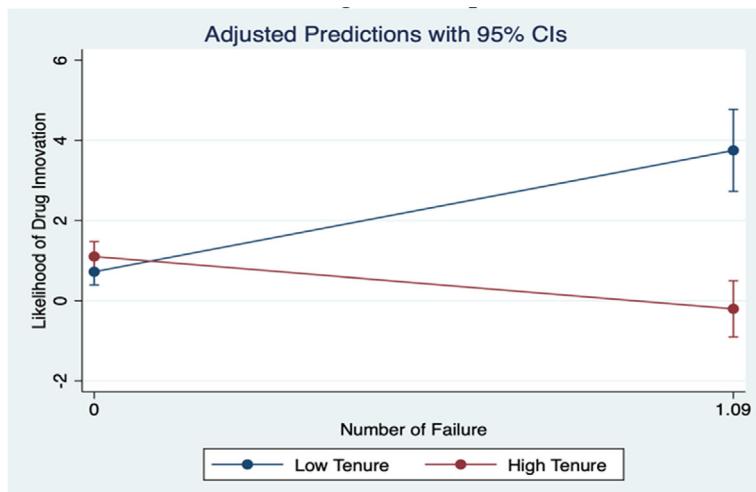


FIGURE 3 The moderating effect of prolific inventors' tenure.

failure on NDI. However, analysis using the full sample (Model 4), does not support Hypothesis (H2) ($p = .255$), potentially due to zero-inflated bias.

Hypothesis (H3) suggests that prolific inventors' tenures will reduce the positive effect of product development failure on the pursuit of novel drugs. As predicted, the interactive effect is negative ($p = .000$ in Model 9), thus supporting this hypothesis. Analysis using the full sample also shows a negative interaction consistent with Hypothesis (H3) ($p = .219$ in Model 5). Figure 3 illustrates that prolific inventors' tenure is likely to decrease the positive effect of product development failure on the pursuit of NDI. Prolific inventors with low tenure are associated with an increase in the positive effect of product development failure on NDI. Examination of all three figures (Figures 1–3) highlight that the influence of prolific inventor on novel product

innovation following product development failure is highly nuanced and depends on prolific inventor characteristics. Specifically, when prolific inventors have low collaborative strength and low tenure, the likelihood of NDI increases in the face of adversity.

4.4 | Sensitivity analysis and robustness checks

4.4.1 | Prolific inventors' characteristics

To test Hypotheses (H2) and (H3), we used the average value of prolific inventors' collaborative strength and tenure in case of multiple prolific inventors. However, an alternative way to assess prolific inventors' characteristics, is to use the maximum value of their collaborative strength and tenure rather than the average. Accordingly, for sensitivity analysis, in Table 4 (see online supplement), we used the maximum value based on the prolific inventors with the highest score on collaborative strength and tenure. For the prolific inventor sample, comparing Models 7–9 in Table 3 (using average) to Table 4 (using maximum value) indicates that there is only a slight change in the magnitude of the interaction coefficients ($p = .000$ for Model 7, $p = .001$ for Model 8, $p = .000$ for Model 9 in Table 4). These results confirm that our findings are not sensitive to measurement choices. For the full sample, results are also consistent across Model 3–5 in Table 3 (using average) and Table 4 (using maximum value) ($p = .019$ for Model 3, $p = .713$ for Model 4, $p = .162$ for Model 5 in Table 4).

4.4.2 | Analytic window for drug innovation

As recovery may take time, in Table 5 (see online supplement), we also tested our model using a five-year window for measuring our key variables compared to the 3-year window reported in Table 3. As shown, for the prolific inventor sample, there is a slight change in the size of the coefficients, but no change in level of significance ($p = .000$ for Model 7, $p = .008$ for Model 8, $p = .000$ for Model 9 in Table 5). For the full sample, results are also consistent with the 3-year window reported in Table 3 ($p = .010$ for Model 3, $p = .236$ for Model 4, $p = .145$ for Model 5 in Table 5).

4.4.3 | Alternative regression model

A major limitation of the instrumental variable approach is the reliance on identifying an instrument that is correlated with the endogenous regressor but uncorrelated with the error term. Suitable instruments are hard to find and estimation with unsuitable instruments leads to biased results (Semadeni, Withers, & Trevis, 2014). To test the robustness of our model without relying on these assumptions, we also tested our model using a two-stage generalized estimating equations (GEEs) regression model. The GEE model is a semiparametric method that makes fewer distribution assumptions relative to maximum likelihood-based approaches such as 2SLS regression. These models control for potential autocorrelation and heteroscedasticity in the data (Liang, Zeger, & Qaqish, 1986). The combination of autocorrelation correction that we use, and robust SEs provide a conservative robustness test (Henderson, Miller, & Hambrick, 2006). As shown in Models 6–8 (prolific inventor sample) in Table 6 (see online supplement), the



interactive effects of number of prolific inventors, prolific inventor collaborative strength and tenure are consistent with our main analysis reported in Table 3 ($p = .059$ for Model 6, $p = .004$ for Model 7, $p = .000$ for Model 8 in Table 6), providing robust support for our arguments, whereas Models 2–4 (full sample) in Table 6 provide partial support ($p = .714$ for Model 2, $p = .046$ for Model 3, $p = .977$ for Model 4 in Table 6).

5 | DISCUSSION

5.1 | Contributions to theory

In this study, we examined the moderating effect of prolific inventors on innovation following product development failure. Our results contribute to theory and research in several ways. First, whereas research on learning from failure has commonly attributed a firm's ability to learn and change following failure to firm-level capabilities (e.g., Maslach, 2016), we delve deeper to examine the effect of key organizational actors on these outcomes. In doing so, our theory highlights the importance of prolific inventors in shaping organizational responses to failure, focusing on the level at which learning occurs in organizations. By linking prolific inventors to learning from failure, we show how differences in the composition of the firms' human capital help explain varying firm responses to product development failure. Highlighting the role of prolific inventors in the firm's response to failure further helps researchers identify additional pathways through which firms can acquire the ability to develop new knowledge (Rhee & Kim, 2014). As such, our study opens the door to future research that seeks to improve our understanding of the role of strategic human capital (Coff & Kryscynski, 2011; Wright, Coff, & Moliterno, 2014) in learning from failure, while also highlighting the behavioral and political processes underlying innovation (Tzabbar, 2009).

Relatedly, by demonstrating that a firm's response to failure is reflected in its NDI, we further extend past research on learning from failure. This work has typically assumed that failure opens up opportunities for the creation of novel knowledge, without directly examining this relationship (e.g., Madsen & Desai, 2010; Maslach, 2016). Studying the association between failure and novel knowledge creation at the product level is particularly important because it provides us with deeper insights regarding the set of knowledge a firm typically turns to following failure. Our results reinforce and are consistent with the view that failure prompts firms to take more risks and experiment with new knowledge (March & Shapira, 1987)—with the additional insight that their propensity to do so depends of the characteristics of the firm's key inventors. In this manner our study helps link the heretofore disconnected literatures on learning from failure (e.g., Eggers & Suh, 2019; Khanna et al., 2016) and the role of prolific inventors on the firm's search and inventive behavior (e.g., Paruchuri, 2010; Tzabbar, 2009; Zucker, Darby, & Brewer, 1994).

Second, we advance our understanding of the behavior of prolific inventors and their effect on organizations. Past work has associated prolific inventors with both the desire to exploit their own knowledge, which limits a firm's ability to change its knowledge base (Tzabbar, 2009; Tzabbar & Kehoe, 2014), and the ability to explore and learn about new areas effectively, which results in breakthrough innovation (Chen & Garg, 2018; Conti et al., 2014). Challenging both views, our findings suggest that when firms face adversity in the form of product development failure, prolific inventors respond by prompting their firm to engage in a loss aversion framing of the failure (Kahneman & Tversky, 1979) and with a threat rigidity response (Chen &



Garg, 2018). This response may make it difficult for the firm to recognize new information and react to it, leading individuals and groups to become inflexible under pressure and default to existing knowledge (Almandoz & Tilcsik, 2016; Dane, 2010; Furr et al., 2012). Hence, our findings add a critical contingency factor to existing arguments by suggesting that a greater number of highly capable and motivated actors in the firm may significantly reduce the likelihood that it will engage in the creation of novel knowledge following failure. Overall, these findings highlight the importance of the social and behavioral aspects of organizational learning following failure (e.g., Eggers & Suh, 2019; Khanna et al., 2016) and the role of the firm's human capital in the process of learning. Our results also highlight the need to consider the quality of a firm's human capital on its behaviors following failure (Kor & Mesko, 2013).

Third, our theory and results provide a more nuanced understanding of the effect of prolific inventors on generating new knowledge. Specifically, our findings suggest that prolific inventors with more collaborative strength reduce the positive effect of product development failure on the creation of novel knowledge, while prolific inventors with low collaborative strength increase it. Similarly, we show that prolific inventors with long tenure are likely to reduce the propensity for drug innovation following failure whereas prolific inventors with low tenure increase it. Rather than spurring more novel knowledge creation following product development failure, we find that longer tenured and more highly collaborative prolific inventors may lead their organizations to rely on more familiar knowledge in the face of adversity. Our research reinforces the findings of studies that have examined the Not-Invented-Here syndrome (e.g., Antons & Piller, 2014; Katz & Allen, 1982) in long-standing project teams and show that such a propensity may also hamper firms with exceptional human capital, characterized by prolific inventors who have long tenures and are highly collaborative. Overall, our theory suggests that the effect of prolific inventors on novel drug development after failure varies depends on the number of prolific inventors, their collaborative strength, and their tenure.

5.2 | Limitations and future research

Despite our contributions, our study also has limitations that provide opportunities for future work. Selecting the biotech industry as our empirical context enabled us to take advantage of mandatory disclosures that the firms in this industry must make concerning their product development initiatives, thus providing us with a rich context for testing our theory. While focusing on a single sector limits the introduction of unnecessary variance into our model, it also constrains our ability to generalize our results. Furthermore, in research-intensive contexts such as biotechnology, prolific inventors are in a unique position to influence the firm's inventive trajectory—an opportunity that may be less available in other industries. Future research should examine how firms in other sectors respond to failure and the role that key individuals play in motivating these responses. Studies should also examine other contextual moderators to better understand the influence of context on the dynamics we observe in our model.

More importantly, our use of secondary data limits our ability to fully estimate the unobserved heterogeneity associated with the motivations of some firms to rely more heavily on prolific inventors. To limit the effect of unobserved heterogeneity among firms, we first tested the likelihood that a firm has at least one prolific inventor. This allows us to fully assess the quality of firm human capital associated with firms with and without prolific inventors. In addition, we explore variation in the effects of failure on firms with and without prolific inventors, thus limiting the risk of endogeneity and selection bias. Nevertheless, we encourage future research to explore alternative methodological approaches to further eliminate the possibility of endogeneity.



It is also important to note that while our theory suggests that intrafirm competition exists when firms have multiple inventors, we do not observe such dynamics directly. Our data also limits our ability to observe the extent to which there may be an involuntary departure of inventors following failure. We hope future research will fill this void.

Contrary to prior research, our tests could not discern a difference in the creation of new chemical components based on the magnitude of the failure. It is possible that it is inaccurate to estimate the magnitude of a product's failure based on the point in its development when it fails. Accordingly, future research should develop a better assessment of the magnitude of failure based on more direct measures of organizational investment of tangible and intangible resources. Finally, by employing a 3-year average count of failure, which consider multiple failure in a certain time period, it is possible that the mechanisms are more likely to occur in organizations that have experienced repeat failure.

6 | CONCLUSION

Learning is necessary for organizations to survive and grow, and failure represents an important opportunity to learn from earlier experiences. Prior research has shown, however, that organizations usually struggle to learn from failure. By examining the influence of prolific inventors on organizational actions in the aftermath of failures in product development, this study takes a first step toward unpacking the role of prolific inventors in helping or hindering organizations' abilities to learn from failure. While a large body of research on organizational learning has emphasized the importance of knowledge creation, our study explores conditions under which prolific inventors both facilitate and impede firms' creation of novel products.

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DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from proprietary databases such as PharmaProjects, TrialTrove, Thomson ONE, and Recap. Restrictions apply to the availability of these data, which were used under license for this study. Additional data used in the study are derived from the Harvard Patent Dataverse, which is available in the public domain.

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