Trials and Terminations: Learning from Competitors' R&D Failures

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Abstract

I develop a theoretically motivated approach to analyzing project continuation decisions, where firms may resolve uncertainty through news about competitors' failures, as well as through their own results. I examine the trade-offs between product-market competition and potential learning from parallel R&D projects in the setting of drug development. Leveraging the industry's unique characteristics to overcome barriers to measuring the project-level response to competitor news, I employ a difference-in-differences strategy to evaluate how competitor exit news alters a firm's own project discontinuation decisions. The findings reveal that technological learning dominates competition effects. Firms are most sensitive to competitor failure news coming from within the same market and technology area—more than doubling their propensity to terminate projects in the wake of this type of information. Second, I find evidence that firms overreact to failure news from closely related competitor projects. Finally, I grade decisions and investigate project- and firm-level characteristics that drive persistent differences in decision-making performance.

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1 Introduction

How should a firm respond to a competitor's failure? On the one hand, the loss of a competitor is positive news, opening up greater potential market share for the remaining players. On the other hand, the rival's failure might contain important, cautionary information about technological roadblocks that limit the likelihood of success. These opposing forces create a strategic dilemma for the remaining firms. By and large, canonical approaches to evaluating competitive advantage (Porter, 1979; Wernerfelt, 1984) and project selection (Scherer, 1967; Stein, 1997) do not capture this strategic dilemma. Yet, deciding how to interpret competitor exit news is a key factor shaping capital-intensive investment decisions in oligopolistic settings.

Consider the modern-day space race, in which Elon Musk's SpaceX and Jeff Bezos's Blue Origin compete to develop reusable rockets for delivering sattelites, supplies, and (ultimately) people to space. Project failures in this technology race are quite public and spectacular (multimillion dollar rockets exploding on launch or landing pads),[1] and the billionaire owners closely watch their rivals for technical lessons. In the tire industry, when Firestone recalled 6.5 million tires due to high tread failure rates, competitors Goodyear and Michelin reaped the benefits by ramping up their own advertising and production. However, the recall also had implications for the rivals' own tire development, as the entire industry faced tire design safety concerns (Daniels Fund Ethics Initiative, 2011). In the harsh environment of Arctic oil exploration, firms had many opportunities to learn from their rivals' mistakes, as a recent string of high-profile failures cost firms billions of dollars in drilling rights and operational expenses. But with roughly 90 billion barrels of untapped crude oil (Wall Street Journal, 2014), the prospect of staying to become the single firm to (literally) strike oil after the others left explains why many firms forged ahead in the face of discouraging signals.

In this paper, I examine this strategic dilemma directly, and tease apart the two conflicting pieces of information contained in a competitor's exit: (i) knowledge spillovers, and (ii) product-market competition effects. Empirically, I evaluate how biopharmaceutical firms alter their own project investments in the wake of different types of competitors' clinical trial failures. Specifically, I measure how different types of competitor failure news influence the likelihood that a firm pulls the plug on its own drug development project. In order to overcome barriers to measuring the project-level response to competitor discontinuation news, I leverage unique features of the pharmaceutical R&D setting, including the observability of development milestones, and the separability of product markets and technologies. As a whole, this paper offers the first framework to analyze how firms react to news about competition and technological failure. Furthermore, this study demonstrates how firms can capitalize on competitor news to improve the quality of their investment decisions.

[1] On YouTube, videos of SpaceX and Blue Origin's explosions and successful landings often have more than one million views.

To clarify the trade-offs and present this framework formally, I introduce a model of R&D investments that includes learning from competitor exits. The model separates beliefs about the probability of technical success from competitive factors. The extent to which firms update their beliefs following competitor exits depends on the relatedness of a firm's own development project to the failed competitor project. I evaluate R&D investment decisions as real options (McGrath & Nerkar, 2004; Folta & Miller, 2002; Nanda & Rhodes-Kropf, 2015), and show that the *potential* for competitor failure news makes projects more attractive due to the possibility of gaining additional signals about the technology's underlying quality. This general framework sheds light on the conditions under which different types of competitor failure news are more likely to lead to subsequent market exits. In particular, the analysis shows that the informativeness of the signal, baseline level of competition, degree of uncertainty, and remaining opportunities to learn are key moderating factors in the response to competitor exit news.

Learning from competitors' investments and outcomes is not a new concept in the organizational learning literature. However, scholars have missed a major strategic implication of vicarious learning by failing to separate knowledge spillovers from product-market competition effects. Past studies have evaluated how firms learn vicariously through industry rivals' successes and failures (Madsen & Desai, 2010; Baum & Dahlin, 2007; Kim & Miner, 2007; Ingram & Baum 1997, Haunschild & Sullivan, 2002; Garzon-Vico, 2012; Macher & Wade, 2016). This prior work asks how cumulative success and failure experiences impact competitors' subsequent performance on particular tasks (e.g. safety incidents, orbital launch explosions) or firm survival rates (e.g. bank failure, hotel chain failure). Set in industries with relatively stable products and technologies, the environments studied do not face the types of uncertainties common in innovation-driven sectors, where the conflicting forces of pure technical learning and product-market competition create a unique strategic dilemma.

Furthermore, by focusing on firm-level performance outcomes and the industry's cumulative failure experience, this prior literature does not capture when knowledge generated by rivals directly enters specific project investment decisions.[2] A key strategic concern for firms is to effectively assimilate external knowledge and respond appropriately to environmental signals (Cohen & Levinthal, 1994; Cockburn et al., 2000). In order to judge a firm's effectiveness in these areas, one needs to isolate well-defined learning opportunities, decision points, and outcomes. I use the timing of failure events and variation in entry timing and project life cycles to capture the project-level response to competitor exits. Additionally, I exploit a crucial distinction between competitive space and technology space first used by Bloom et al. (2013) to separate the countervailing knowledge and competition effects of learning from competitor news.

[2]Bennett & Snyder (2016) demonstrates how focusing on cumulative success and failure events as the key explanatory variable for performance leads to biased estimates of learning in much of this prior literature. Similar to their preferred approaches, this paper focuses on how the most recent failure events impact organizational actions, rather than probability of success.

While innovation scholars have argued that competition, information disclosure, and the ability to assimilate external information all have positive effects on the rate of innovation (Henderson & Cockburn, 1994a and 1994b; Ederer, 2013; Bloom et al., 2013; Boudreau & Lakhani, 2015), we still have little evidence regarding whether and when competitors respond directly to each other's R&D failures.[3] One reason for the scant empirical work is that making valid inferences about the nature of competitor learning requires a special type of setting. The analyst must be able to observe the market structure and entire set of projects, track the timing of project development and failure events, and follow the developers' subsequent choices. The setting must involve project continuation decisions with large capital expenditures at risk, so that the corresponding investments have the potential to shift firm performance. Failure news must be surprising, and disclosed promptly and publicly. Perhaps most importantly, the setting must provide a metric to assess the degree of relatedness between competing projects. Without these ingredients, scholars cannot clearly isolate the spillover effects of learning from competitive forces.

The pharmaceutical drug development setting is uniquely suited to fulfill these requirements because its regulatory structure, information environment, and large resource investments allow for observable project-level data in the context of high-stakes decisions. Selection between uncertain R&D projects is a strategic choice central to firm performance. Failure is a frequent occurrence and interpreting competitor outcomes is a game played by executives, scientists, journalists and investors alike.[4] In an instant, a failure event can shift the frontier of technical knowledge, as well as the competitive landscape for the remaining players. Additionally, drug development provides an ideal laboratory for studying learning from competitor failures because strong intellectual property protection and the high cost of clinical trials create a racing environment with substantial capital commitments.

I utilize this structured and highly competitive setting to evaluate how different types of competitor failure news influence project termination decisions. I construct a dataset comprised of all clinical development projects over the period 1997-2014, along with each project's development milestones. By linking each project to their competitors' project exit events, and using a survival model approach to control for the typical life cycle of development projects, I measure how competitor news influences project termination patterns over time. I distinguish between product-market and technological competitors, and take advantage of variation in the timing of entry and failure to causally identify the effect of competitor failure news on project exit rates.

[3] Applied economists have provided analysis on how market events like bankruptcies and product recalls influence stock market valuations of competitor firms (Lang & Stultz, 1990; Ahmed et al., 2012), or sales performance of related products (Freedman et al., 2012). However, these studies focus on third-party valuations and market demand, rather than competitors' own investment decisions.

[4] Tracking rival projects has grown into its own cottage industry with considerable resources and time spent on external competitive intelligence databases and pipeline consultants.

Using this setup, I show how the relationship between competitors in both market and technology space dictates the impact of failure news on project abandonment decisions. In my main set of findings, news of *same market, same technology* competitor failures leads to a large increase (more than doubling) in project exit rates, while *different market, same technology* competitor discontinuations led to a smaller (18%), but still meaningful increase in exit rate. On average, news of *same market, different technology* competitor failure does not impact project survival rates. However, when the level of market competition is low, or opportunities for learning from technological competitors is high, *same market, different technology* competitor discontinuations reduces developers' likelihood of pulling the plug on their projects, relative to similar projects that had not experienced this type of competitor news.

My analyses also evaluate decision-making quality in the wake of competitor discontinuations. I explore project success rates for projects that continued following different types of competitor failure news. This analysis yields evidence in support of the hypothesis that firms, on average, overreact to *same market, same technology* competitor discontinuations—vacating the space at excessive rates. I also introduce a new method for judging decision quality after competitor failure events. Grading both exit and continuation decisions, I find that persistent decision quality differences exist across firms, even after controlling for project and firm characteristics. This finding is consistent with prior evidence of persistent performance differences among seemingly similar enterprises (Syverson, 2011; Gibbons & Henderson, 2013), and highlights how a heterogeneous responses to competitor exits may be an important source of firm performance variation.

The paper proceeds as follows. I begin by laying out the theoretical framework that combines insights from real options theory, with vicarious learning about markets and technologies. Next I discuss the drug development setting, and how learning from failure plays out in the pharmaceutical industry. Third, I describe my main empirical approach, using difference-in-differences survival models to capture how different types of competitor failure news impact exit rates. Comparing the project responses across projects in different competitive and technological contexts allows for robustness exercises and testing the main predictions of the theoretical framework. I then turn to the decision quality analyses to shed light on whether firms are under- or over-reacting to competitor news, and introduce a new approach to "grading" decision quality after competitor failures. Finally, I discuss the implications of the results and conclude.

2 Theoretical Framework

The theoretical framework introduces a general model for updating project portfolios in response to competitor failure news. Given that uncertainty and inappropriability may lead to underinvestment in knowledge production (Arrow, 1962), why do firms invest in uncertain projects? The existing

literature provides a number of reasons why managers may give the "green light" to funding R&D efforts. In a standard economic model, firms seek to minimize competition by engaging in R&D when the opportunities for monopoly power or first-mover-advantages are strong (Rosenberg, 1990). In internal capital markets, firms may choose to invest in uncertain projects after ranking all projects according to their expected value (Stein, 1997; Lamont, 1997; Guedj & Scharfstein, 2004). In addition to maximizing returns on investment, firms may also invest in uncertain projects in order to gain external legitimacy among peers and the labor market (DiMaggio & Powell, 1983, Haveman, 1993), or to build technical capabilities and absoptive capacity (Cohen & Levinthal, 1990; Henderson & Cockburn, 1994).[5]

While the prior literature is instructive for understanding why and how firms engage in uncertain projects like R&D, they generally treat the investment decision as a static process. The model below aims to move beyond the initial decision to invest, because firms continue to re-access make project investment decisions as new and different types of signals arrive. Additionally, the theoretical framework proposes that more competitors may increase project continuation values, when uncertainty is high and vicarious learning opportunities are present.

By treating R&D projects as real options investments, the model accounts for the informational benefits of competition. The tension throughout the framework is between technological learning (probability of success) and the competitive environment (market share conditional on success). The framework differs from prior literature on learning from competitors in two ways. First, it addresses uncertainty about own and competitor projects. Second, it allows the impact of competitor news to vary by technological and market distance.

2.1 R&D Projects as Real Options

Previous literature has provided some evidence that firms' R&D entry strategies are consistent with real options reasoning (McGrath & Nerkar, 2004; Folta & Miller, 2002). However the literature fails to address how firms in changing environments update and alter these investment decisions.[6] Even if a firm exercises a growth option and enters a market, how does the firm determine when to continue, reinvest in, or terminate R&D real options as technical knowledge and the competitive landscape change? This updating process is essential to the success of a real options valuation approach.

The updating process can be seen as breaking a project into smaller stages that consist of intermediate experiments that each resolve some uncertainty and have an option to terminate or

[5] In additional to the rational explanations for firms' investment in R&D, Malmendier & Tate (2008) and Galasso & Simcoe (2011) have shown that CEO overconfidence predicts their firm's willingness to risk capital on more uncertain projects.

[6] Dixit (1989) provides a model explaining investment inertia, but focuses on general uncertainty, rather than changing beliefs about a market or technology.

continue. Real options reasoning allows entrepreneurs to take on more uncertain exploration paths (Nanda & Rhodes-Kropf, 2015) and even develop multiple alternative paths simultaneously (Nelson, 1961; Scherer, 1967). While the prior literature on R&D real options focuses on the guaranteed right to continue, expand, or terminate a project after initial experiments are complete, here I consider how the *potential* for receiving competitor news (prior to learning one's own project results) may increase the value of the real option. If a firm knows it will have the ability to reassess its R&D portfolio, then the potential of receiving competitor news might change project priorities.

I ground these difficult decisions in an investment model for staged R&D projects, where firms may resolve uncertainty through their own experimental results or news about competitors' outcomes. I consider the trade-offs between product competition and potential learning from parallel R&D projects. The central friction is that competitor failure news may reveal flaws in a technological approach, but also opens up potential market share for remaining competitors. This model yields two key insights: 1) the potential to learn from competitor results may change the overall value of an R&D project and enable investments in projects that would otherwise seem too risky, and 2) the impact of competitor news on investment choices varies with the informativeness of competitor signals, the level of competition, and the potential for future competitor learning.

In addition to drug development, the framework generalizes to other settings where competitor results may contain a combination of technical knowledge and market competition information. Applicable settings share certain characteristics that enhance the role of competitor learning. Relevant industries share high uncertainty in project quality, large capital commitments, publicly observable actions and outcomes, and the potential for oligopoly. Additionally, relevant production settings will have well-established demand and product categories.[7] Outside of pharmaceuticals, applicable settings may include the automotive industry, oil and mineral exploration, aerospace technology, venture capital investing, and medical devices.

2.2 Model

My general model of R&D investment is relevant for decisions in environments with both informational and payoff externalities. To simplify, I define projects as a single experiment or "stage" of R&D (e.g. phase II clinical trial), and consider the firm's dynamic choice to stop or continue the development project. In the model, competitor failure events create new decision points, where the firm may reevaluate their project investment choices.

[7] If a product is the first of its kind, then failure signals may include information about demand, as well as information about the technology and competition. For example, when Google discontinued sales of its controversial wearable device Google Glass, the failure might have said as much about consumer preferences and the product's marketing as the technology itself. Google Glass's failure is very different than when a firm cancels clinical development of a new drug to treat a well-known and prevalent disease.

At the time of the initial investment, there are q parallel projects,[8] each controlled by competing firms in market i and technology j. For simplicity, I assume that q is known to all the participants, with no additional entry throughout all periods.[9] Firms may learn from their own project results. In any given period, the likelihood that the firm discovers its own project's true quality (through its own signals and experiments) is represented as λ, and the cost of continuing in any period is c.

Since failure news is common in uncertain fields, firms with many competitors (high q) expect to eventually learn of competitors' failures. As time passes, if the developer does not learn about competitor failures, then the developer may assume that these competing projects are performing well and that the underlying technologies are good.[10] The extent of this positive belief updating about the probability of project success (p) depends on the level of q: lack of failure news from any competitor is more informative when many other firms have had the opportunity to fail. The probability of learning about a competitor's result before one's own project experiment finishes is represented an increasing concave function $g(q)$.[11] If the developer stops a project, it recovers $\overline{V}$, which represents both direct costs and the opportunity costs associated with continuing.

While firms update their beliefs about the probability of success, firms simultaneously adjust their beliefs about the expected level of competition. When a market competitor drops out, the expected number of competitors decreases (e.g. $q-1$) and the potential payoff may increase. If the exiting competitor is in a different market, then the expected competition is unchanged. If the exiting competitor was in the same technological area as the focal project, then the real options value component of continuing also decreases, since the number of opportunities to gain cheap signals from competitors is diminished. The overall continuation value of the project depends on updated beliefs regarding probability of success, the updated expected payoff (conditional on success), and the remaining real option value from potential competitor learning.

The value of continuing a project is a function of beliefs about project success, as well as the number of competitors: $V(p,q)$. The firm has an uncertain belief about whether the project will be developed successfully. In a basic sense, the firm wants to answer the following question: will the technology succeed as an application for a specific market? For example, will a specific type of beta-

[8] The number of competitors could be a vector, where each component is a different type of competitor (e.g. same or different market, same or different technology). For simplicity, I discuss q as a single value representing the number of same market and same technology competitors.

[9] This assumption is not so different from the empirical reality in my research setting, phase II clinical trials. In clinical drug development, firms are well aware of their competitors' projects and can track their competitors' progress through patents, research publications, trial registries, financial statements and pipeline disclosures.

[10] The assumption contrasts other theoretical models of R&D competition (Malueg, 1997; Akcigit & Liu, 2015), which assume that no news (about a rival's project) is bad news regarding the competitor's project. Here, I argue that no news is good news (about the underlying technologies) when failures are hard to hide (as is the case with public companies and large clinical trial failures). This setup also matches the intuition of Gross (2016), which uses logo design contests to show that the disclosure of more intense competition leads to reduced effort within those contests.

[11] For example, $g(q)$ might be a geometric function like $g(q) = 1-(1-q)^2$.

secretase enzyme inhibiting drug successfully protect against the progression of Alzheimer's disease? At the time of initial investment, a firm believes the focal project will succeed with probability p^0, and the firm may update this belief over time as new information arrives (this updating process is described in more detail below). Conditional on succeeding in development, the firm's expected profits are a decreasing function of the number of competitors it faces: $f(q)$.[12] For simplicity, I assume that firms do not discount for the time value of money.

Sequence of the game. The generality of the model allows one to think of it as an infinite game, with intervals for each opportunity to get signals. If a firm receives a signal from its own project's results, then its own technological uncertainty is resolved and the firm can choose to move forward with the project or exit development. Once competitors disclose failure news, firms update their beliefs about both p and q, and enter a new phase of the game. In total, the game has the following steps:

1. Firm decides whether or not to continue to invest in the project, or exit and receive $\overline{V}$
2. Receive own project quality signal with probability λ, and continue or exit and receive $\overline{V}$
3. Receive competitor failure news with probability $g(q)$, and continue or exit and receive $\overline{V}$

Unlike static models of auctions where participants have correlated signals (Hendricks & Porter, 1988; Kagal et al., 1987), the firms in this model have additional uncertainty about if and when competitor information will be revealed, as well as which type of competitor will provide a quality or market signal. This uncertainty around the timing of competitor information is key to the central strategic dilemma of learning from competitor failures: firms have to consider the likelihood of learning from competitors as well as the implications of a rival dropping out.

Continuation Value. For ease of exposition, I first consider project continuation value without the possibility of competitor learning, such that the firm can continue with an uncertain project at cost c, or exit and recover $\overline{V}$. If the firm does not see an internal signal regarding its own project quality, then it infers nothing about the underlying project quality (no news about one's own project is truly no news).[13] If the firm does not resolve uncertainty about the project's quality in a given period, then the firm can accept the same gamble in the next period. The value of continuation is strictly increasing in p, as a stronger belief in success is unambiguously good for the project's potential:

[12] The seminal work of Bresnahan & Reiss (1991) suggests that this decreasing function, $f(q)$, is likely to be convex since the entrance of firms has a much greater impact on competition when the starting point is a small number of firms.

[13] This assumption is realistic in this study's empirical setting, since the researchers do not see the intermediate data in clinical trials (with the exception of the data safety monitoring board). The developers will not know the outcomes of their trials until the results are unblinded at the end.

$$V(p,q) = \max\{-c + \lambda \underbrace{[pf(q) + (1-p)\overline{V}]}_{\substack{\text{value if learn from} \\ \text{own project}}} + (1-\lambda) \quad \underbrace{V(p,q)}_{\substack{\text{continuation} \\ \text{value if do} \\ \text{not learn from} \\ \text{own project}}} \quad , \overline{V}\} \tag{1}$$

The firm is indifferent between continuing and stopping when both components of the right hand side are equal $\overline{V}$:

$$\overline{V} = -c + \lambda[pf(q) + (1-p)\overline{V}] + (1-\lambda)\overline{V}$$

Next, I incorporate the possibility of vicarious learning into the model. Firms can base their actions on both their own signal and their competitors' failures (or lack thereof). In a standard model of competition, more competitors would have a strictly negative relationship with perceived project value, because increased competition puts downward pressure on product prices and potentially reduces market share. However, competitor learning and real options reasoning both serve to introduce a countervailing force: more competitors also increase the likelihood of receiving competitor news. In particular, competitor failures create new decision points—allowing firms to abandon their own project earlier and recover $\overline{V}$, rather than continuing to spend on a project that was unlikely to result in profit. Because competition and option value have opposite effects, the net impact of one less competitor on the continuation value of a project is unclear, and may depend on the initial stock of competitors.

Specifically, learning from competitors can change the continuation value in three different ways. First, when a competitor fails, firms may revise their belief about their own project's probability of success downward based on the competitor news. Conversely, firms may increase their belief in the likelihood of project success based on the absence of competitor failures. Second, a competitor's exit increases the firm's expected payoff conditional on success: $f'(q) < 0$. Third, the loss of a competitor reduces the potential future opportunities to learn from a competitor failures (or lack thereof), reducing the subsequent option value component of continuing.

To see the value of learning, I rewrite the project valuation equation in (1) with the possibility of learning from competitor project outcomes. After updating beliefs, the developer compares this continuation value to the alternative payoff of stopping the project ($\overline{V}$). Including these learning effects, the project value can be written as follows:

$$V(p,q) = \max\{-c + \lambda \underbrace{[pf(q) + (1-p)\overline{V}]}_{\substack{\text{value if learn} \\ \text{from own project}}} + (1-\lambda)\underbrace{[g(p,q)V(p^-,q^-) + (1-g(p,q))V(p^+,q)]}_{\substack{\text{project value learning from competitors} \\ \text{if do not learn from own project}}}, \overline{V}\} \quad (2)$$

Here, the superscript notation on p and q represent the expected belief updating about probability of success and number of competitors following competitor failure news (or lack thereof). The first section of the equation is the same as the simple version with no competitor learning in equation (1). However in examining the the second component of (2), the value of learning from competitors, one can see that this version yields a continuation value strictly greater than that in equation (1). The second component, the continuation value if the firm does not receive a signal from their own project, represents a gamble between learning that the project is worse than originally believed (p^-) and has less competition (q^-) vs. if the project is more promising than originally believed (p^+) with the same level of competition (q). The extent to which firms will update their beliefs about the probability of success (p) depends on both the product market and technological distance between a focal project and its R&D competitors. Appendix A provides more detail about how these updating values (p^- and p^+) will differ depending on competitor project relatedness in terms of two key dimensions: product market and technological space. The extent of the updating will also depend on the strength of the prior belief (e.g., more difficult to move p when firm has more internal evidence about their project quality).

The technological learning effect can be isolated by graphing the option value of a project by p while holding q constant (Figure 1). In both valuation approaches, the lower bound is $\overline{V}$, since the firm will exit the project if the continuation value ever drops below that value. By adding in competitor learning, the model introduces a new gamble with a higher upper bound of the project continuation value (due to the possibility of no failure news), without changing the lower bound.

Considering the point at which the firm would be indifferent about continuing under the simple approach in equation (1) reveals the value of competitor learning value. With the prospect of learning from competitors' failures, that same project may still be worth $\overline{V}$ if the developer receives bad news from their own project results, or if the firm updates its own beliefs downward (p^-) after learning from a competitor failure. However, no competitors failing could lead the firm to updating their beliefs upward so that continuation becomes strictly more attractive than exiting. The expected value of the project would now lie somewhere along the dashed line in Figure 1b, at a value higher than the single firm valuation approach. The same logic could make a project with a continuation value less than $\overline{V}$ under the setup in equation (1) transition to to a value greater than $\overline{V}$ after accounting for the possibility of learning from competitors.

In the graphical depiction in Figure 1, I fix the value of q to isolate the learning effects from the competition effects. The relationship between the level of competition and V will depend on the relative magnitude of the real option value of continuation (i.e., positive value created by possibility of learning from competitors and stopping early) and the negative impact of increased competition on payoffs (conditional on success). Therefore, the impact of a reduction in q on V is ambiguous and will depend on the baseline level of q, project relatedness and uncertainty about the technology.

To summarize, this model provides testable implications for the setting of drug development. In particular, the model predicts that the impact of competitor news will vary along four key dimensions. First, the stength (technological informativeness) of the signal will determine the extent of belief updating about the probabilty of success p. Second, the baseline number of market competitors q impacts the response to competitor exit news based on the potential changes in payoffs. Third, project continuation values are increasing in the remaining same technology competitor learning opportunities. Finally, the response to competitor exits depends on the baseline amount of uncertainty (i.e., strength of prior beliefs) about one's own project. In the empirical analyses, I address how each of these factors moderates responses to competitor failure news.

3 Setting

3.1 The Drug Development Process

This study's setting is the drug development industry. Drug development is a multi-stage process for research & development with a regulatory approval process that proceeds in well-known stages. I study both small molecule drugs and large molecule drugs (biologics), but exclude vaccines, which undergo a slightly different regulatory process. After thousands of European babies suffered birth defects due to their mothers taking the drug thalidomide in the 1950s, the Food and Drug Administration (FDA) in the US (and its counterparts in Europe and Japan) has required drug companies to provide evidence that their drug is both safe and effective in humans, before the drug may gain regulatory approval.

In the modern format and throughout the period studied here, the FDA defines five steps in the drug development process. The first is discovery and development, where scientists may screen thousands of existing compounds, create new chemical structures, and use biological assays to determine what drug candidates might be effective in treating a disease. In the second step, preclinical research, developers engage in both *in vitro* (e.g. in a test tube) and *in vivo* (in a living organism) tests of their drug candidates—looking for signs of potential toxicity, as well as signs of success against the disease of interest. If a drug project survives through the first two stages, the developer may begin clinical research, where humans become the test subjects.

Pre-approval clinical trials have three phases, with increasing degrees of rigor and cost. Phase I trials typically have between 20 and 100 healthy volunteers, last a short period of time, and are intended to test safety and dosage. Phase II trials, which are the focus of this study, may involve several hundred people who have the condition (disease) of interest, and typically require comparisons to a control group "treated" by a placebo or the existing standard of care. These trials may last months or years and serve as the first real test of the drug's efficacy in humans (in addition to monitoring safety). Phase III is essentially a larger scale version of the Phase II trials, usually involving more participants (often thousands) and tracking them over a longer period of time. Trial costs range from thousands of dollars in phase I, to hundreds of millions in phase III (FDA; Manhattan Institute, 2012).

Prior to the Federal Drug Administrating Modernization Act in 1997, there was no centralized resource for publicly accessible information on current and past clinical trials. This act led to the formation of clinicaltrials.gov, a central repository for clinical trial information that required developers to post information about phase II and later clinical trials. While initial compliance with trial registration rules was low, registration rates accelerated after the International Committee of Medical Journal Editors (ICMJE) initiated a policy whereby trials must be registered as a prerequisite for journal publication (Gil, 2012). Trial registries now provide the bulk of information about where drug development projects stand in the process, though companies also release information about development time lines and trial outcomes via company documents (e.g."pipeline tables" with the status of drug candidates), investor relations materials, financial files, and conferences (see Discontinuation Disclosure section, and Appendix C for more on information disclosure). Only more recently, starting with the Food and Drug Administration Amendments Act (FDAAA) of 2007, have regulators also pushed for greater mandatory (and structured) disclosure of clinical trial results.

Often, the earliest steps of drug development are conducted in smaller firms or in collaboration with academic researchers, while the scale and cost of the clinical trials and marketing activities often require the capital that only larger pharmaceutical or biotechnology firms can provide. The size of the firm and origin of the project has been shown to impact how the developer decides whether to continue a project (Guedj & Sharfstein, 2004; Hermosilla, 2015).[14]

After completing the gauntlet of clinical testing, the developer can file a New Drug Application (NDA) that presents the full set of preclinical and clinical testing results. At this point, the FDA assigns a review team to evaluate the findings, inspect clinical trial sites, and eventually make a recommendation regarding approval. Despite the years of testing and data collection, these decisions often remain quite uncertain. Surprising rejections reverberate throughout the industry, and change

[14]Contract research organizations (CROs) are also retained at different points throughout the development process to run experiments and trials on developers' behalf. The decision to outsource projects depend on both the specialized knowledge required for the R&D and the governance structure of the firm (Azoulay, 2004; Guedj, 2005).

firms' subsequent willingness to invest in and continue projects (Blankshain et al., 2013). In the fifth and final step, developers continue to provide post-approval safety and monitoring data (e.g. Phase IV clinical trials, adverse event reporting, and other post-marketing surveillance).

Drug development projects fail to reach approval for a variety of reasons. Safety and efficacy concerns make up the vast majority of clinical trial project closures. Cook et al. (2014) studied 142 drug development projects at AstraZeneca and investigated reasons for failure. The authors found that about half of clinical trial safety failures were related to the drug's primary biological target, while the other half of safety failures were attributable to off-target side effects. The study also found that the most common reasons for efficacy failures included poor target validation (no causal linkage between drug target and clinical impact), dosage limitations, bad selection of indications, and weak evidence from previous phases.

3.2 Failing to Learn, or Learning to Fail?

The drug development industry has a bounty of anecdotes about failure to learn from competitors. Industry scientists and executives are quick to relay stories typifying decision-making hubris, the sunk-cost fallacy (Lowe, 2015), and confirmation bias. Here, the usual narrative is that firms failed to learn from their rivals' failures in the same drug class, since they were blinded by their own convictions, organizational inertia, or dearth of alternative projects. In interviews for this project, one biotech venture capitalist summarized this narrative succinctly by saying that "firms need to taste their own failure before they act."

One famous example is the the continuing parade of failures of cholesterylester transfer protein (CETP) inhibitors for the high cholesterol market. In November 2006, Pfizer CEO Jeff Kindler told investors that Pfizer's phase III drug Torcetrapib would be "one of the most important compounds of our generation." Just a week later, Pfizer announced it was halting all clinical trials of Torcetrapib after finding that the drug had increased death rates among treated patients. In response to the news, Pfizer's stock plummeted, and the firm lost a staggering $21 billion in market value. Despite a Pfizer's high-profile failure, a number of competitors forged ahead with CETP inhibitors and subsequently spent many millions of dollars on (ultimately unsuccessful) clinical trials of their own. When Roche and Eli Lilly eventually pulled the plug on their CETP inhibitor trials in 2012 and 2015, the companies immediately lost $3.3 billion and $5.05 billion in market value, respectively. Despite these R&D disaster stories, the prize of becoming the next blockbuster cholesterol remains a strong draw. As of 2016, Merck's CETP inhibitor (Anacetrapib) is moving ahead with phase III trials.

Another often-mentioned example of failing to learn from failure is in the area of Alzheimer's drugs. The development of β-secretase (BACE) inhibitors for treating Alzheimer's represents a recent and salient case. Robert Vasser, as Northwestern University Medical School professor, led

a team that first cloned and characterized the β-secretase in 1999. Soon after, Merck & Co., AstraZeneca, Eli Lilly, and others rushed to develop their own patented BACE inhibitors and enthusiastically adopted this new potential approach to treating Alzheimers by inhibiting the BACE enzyme and reducing the production of amyloid plaques in the brain. Over 15 years later, some of the firms continue to invest in BACE inhibitors and evaluate their effectiveness, others have dropped out after reaching late stage clinical trials, and not a single BACE inhibitor drug has reached approval. The most recent example of BACE inhibitor failure is Boehringer Ingelheim and Vitae's Pharmaceuticals' development partnership. Despite previous high-profile BACE inhibitor failures from industry leaders such as Myriad Genetics, Eli Lilly, Elan, Pfizer and Johnson & Johnson, the market was still surprised by the failure announcement in March 2015, and Vitae lost 20% of its market value in the day following the news. However, Merck, AstraZeneca and Eli Lilly all continue to develop other BACE inhibitor compounds despite the warning signs. Depending on ones view of the area, the BACE case is either a story of irrational exuberance and disappointment in Alzheimer's treatment, or another step towards better understanding of the disease and treatment paths.[15]

However, an alternative story also plays out throughout the industry and media. In this narrative, firms intensely follow their competitor's experiments and exhibit "quick trigger" behavior and fear of looking foolish while others exit. The disclosure of one firm's failure may lead rivals to quickly exit their own project or even an entire field. For example, after Pfizer released disappointing data about one of their compounds that used a particular target and approach (SMARCA4 ligands to fight tumor cells), "a number of [related drug development] programs (in academia and industry both) came to a juddering, dust-spewing halt once people saw the data" (Lowe, 2015). In interviews for this project, industry scientist also mentioned the case of nerve growth factor (NGF) inhibitors, a class of pain drugs thought to be quite promising, but whose overall development stopped abruptly in 2010 after the FDA put a hold on clinical development for Pfizer and Janssen's NGF compounds, following safety concerns related to patients having joint damage after taking the drug. While these stories imply that firms closely monitor their rivals' failures and hint at sources of flawed decision-making, they do not provide clear answers about how firms respond to each other's failure news and what forces drive firms to update their R&D portfolio in response to the news. In the empirical analyses below, I use the unique features of the drug pipeline data to answer these questions.

[15] An October 2016 article in STAT News described how after all the Alzheimer's drug failures, firms still watch each others' trials closely, and that a late-stage trial success "would go a long way in validating the idea that amyloid plaques are integral to disease progression, bolstering the odds of success for Biogen, Merck, Roche, and others working in the same field." However, the article also noted that a trial failure could "have a chilling effect on other drug developers targeting amyloid plaques," and that a single late-stage failure could have "ripple effects in other companies," who might question the direction of their own drug development approach (Garde, 2016).

4 Data and Sample Construction

The main empirical goal of the paper is to identify how R&D failure news influences competitors' project continuation decisions. To do so, I need a comprehensive dataset with project development histories and disclosures, as well as the ability to link projects by their product market and technological similarity. This section details my construction of the phase II drug development panel dataset used in the main empirical analyses.

4.1 Drug Pipeline Data

The starting point for my sample construction is the drug development records in Cortellis, which contains development information for over 64,067 drugs (as of May 2016). The Cortellis platform aggregates information from public records (e.g., patent filings, company press releases, financial filings, clinical trial registries, FDA submissions, etc.), and employs professional analysts who curate content.[16] At the minimum, drug reports contain drug name(s), development firms, and a list of key historical development milestones by firm, country, therapeutic indication, development status and date. Each milestone date/event is linked to its applicable disclosure information (e.g. press release, company investor literature or pipeline documentation, financial filings, etc.). Most records also have detailed write-ups summarizing the drug's development history, trial outcomes, conference presentations and journal publications.

A key to my main analyses is using these milestones to construct full drug development histories for each drug-indication (development "project"). These histories include which firms were actively developing the drug, and what stage of development (discovery, preclinical, phase I/II/III clinical trials, registration, approval, launch) the project was in at any given point in time. They also include event dates for development discontinuation, suspension, product withdrawal announcements, and "no development reported" if Cortellis reports no change in development for an 18 month period.

4.2 Market and Technology Groups

In my analysis of competitor reactions, I separate drugs by two different dimensions of relatedness:[17]

Therapeutic Indications (Market). A therapeutic indication is the medical condition treated by a drug. Firms may develop a single drug to treat a number of separate indications—though firms often consider one to be the "lead indication," when the market size, patient population, or potential

[16] Thomson Reuters sold Cortellis to Onex and Baring Private Equity Asia in October of 2016, as part of a larger deal involving a number of Thomson Reuters' scientific research databases.

[17] The distinction between spillovers across these two dimensions, market and technology, was first used in Bloom et al. (2013). In that paper, the authors look at market and technology at a higher level (using industry codes for product markets and patent technology classes). In this study, I magnify more fine-grained distinctions between market and technology groups to isolate project-level spillovers.

for clinical success make it most appealing for initial development and testing. Approximately 28% of all drugs in the Cortellis data list more than one development indications (34% of drugs that reached phase II clinical trials undergo phase 2 trials for more than one indication). Cortellis indication names are usually quite specific (e.g. "Congenital ichthyosiform erythroderma"), but also include some more vague categories (e.g., "joint pain," "stomach pain").

In some cases, two or more distinct Cortellis indication categories are actually referring to the same or highly similar conditions. For example, a drug treating "liver disease" is likely in competition with drugs treating "liver cirrhosis." To account for these category issues, I map Cortellis indications to their International Statistical Classification of Diseases and Related Health Problems ICD-9 condition codes, and use these ICD-9 groups to delineate different therapeutic markets.[18]

Target-Actions (Technology). Roughly 65% of drug records also contain information about the drug's primary (and secondary, if applicable) biological mechanisms of action. A biological target is anything within the body on which the drug acts and influences its function. For example, a drug may bind to and inhibit the function of a specific protein, or a drug might function as an agonist by activating and increasing function in a receptor. In these cases the target is defined by the biological pathway or product, and the action is determined by the functional change or mechanism (e.g., "inhibitor," "agonist," "antagonist" etc.). Though two drugs may differ in their compounds' molecular structures, by attempting to treat a condition through the same target-action, their developers are essentially testing the same hypothesis about how a biological process can be altered to achieve a clinically desirable outcome.[19] Some target-actions are useful for more than one medical condition. For example, Avastin (bevacizumab) is an angiogenesis inhibitor developed by Genentech that was originally explored as a cancer drug, but also proved promising as a treatment for age-related macular degeneration. A single drug compound (or a combination drug made up of multiple drug compounds) may also act on multiple known targets. In the set of Cortellis drug records that have at least one target assigned, approximately one out of five has more than one primary target-action assigned (with a maximum of 13 assigned in the data). Krieger, Li and Papanikolaou (2016) use chemical informatics techniques to show that a given drug candidate is more likely to be structurally similar to another drug when the pair shares a target-action.

[18] Assigning ICD-9 codes to the Cortellis indication names is a challenge that requires knowledge about both the medical conditions, and about how health care providers classify conditions. A professional medical biller coded the concordance between Cortellis indications and ICD-9 codes in the fall of 2015. ICD-9 codes have different levels of granularity, where each number represents a different medical conditiona and with sub-categories denoted by decimals. The medical biller assigned codes to integer categories (e.g., an indication with ICD-9 of 202.5 is categorized as 202).

[19] Drugs may also have "off-target" effects, which represent the collateral damage incurred to other biological functions in the process of trying to act on a focal target. Often, these off-target effects are the source of toxicity issues for investigational drugs.

4.3 Sample Inclusion Criteria

In order to capture the project-level response to competitor failure news, one needs a data set that captures relevant competitor failure disclosures and their timing. The first step is to use the development history events to create a full panel data set of drug-indication-date for all drugs. Drug project observations are eligible for inclusion in the final analysis data set starting with the earliest date after entering phase II clinical trials, until they begin phase III trials. I use phase II development projects because phase II trials are the first real test of a drug's efficacy in humans, require major capital investments,[20] and have levels of uncertainty much higher than phase III projects.[21] Next, I focus on failure disclosures that are potentially relevant to competitors. I identify the potential set of "treating" failures by defining "frontier discontinuations" as drug project discontinuations that occurred after phase II trials began, and before any drug projects within the given indication-target action had reached approval and market launch. This criteria is important, because it excludes early (e.g. preclinical, phase I) failures that are unlikely to influence decisions for later stage projects, as well as failures in technology areas that are already validated through the regulatory process and in the product market.

To establish competitor failure news events, I merge the frontier discontinuation dates with the full set of phase II development histories. A phase II project experiences a competitor discontinuation if it shares either a market or technology with the failing competitor, if the pair of projects were ever simultaneously active for at least one quarter, and if they entered phase II within 10 years of one another. A frontier discontinuation event may only "treat" competitor projects if its discontinuation date was prior to the discontinuation of the competitor project.[22]

The analysis data is limited to 1997-2014, since the Cortellis coverage of development histories is less reliable in earlier time periods, and project data were compiled in 2015. Project-quarter observations are censored out of the panel once the project was discontinued, graduated to phase III, or after 32 quarters elapsed since the project entered phase III. Some projects are never officially discontinued, and continue to be listed as though they continue in phase II despite no development reported for long periods of time. These "zombie projects" make up most of the projects that I include in the panel for a full 32 quarters before censoring out their subsequent project-quarters.

[20] Cost estimates for trials vary, with the average cost of Phase II trials reported as anywhere from $13 million to $80 million, while phase I cost estimates range from $4 to $8 million (Sertkaya et al., 2014; Adams & Brantner, 2006; https://lifescivc.com/2014/11/a-billion-here-a-billion-there-the-cost-of-making-a-drug-revisited/).

[21] 16% of phase II and 50% of phase III projects eventually reach approval, according to Hay et al. (2014).

[22] Since the analysis panel is at the quarter level, some "treating" and "treated" projects share a discontinuation quarter, but only if the "treating" project disclosed failure at an earlier date within the quarter.

4.4 Disclosure of Discontinuations

The decision to halt a drug development project is one that impacts potential consumers, employees, investors, and competitors. However, the news of project discontinuation may be revealed through different mechanisms with varying degrees of detail. The shut-down decision is most often reported in company press releases, updated drug development pipeline documents (usually posted on the firm's website), and financial filings. Cortellis tracks these disclosures and links them to drug development projects (drug-indications). These announcements contain different levels of information about the events leading up to the decision, and only a small fraction of the discontinuation announcements are preceded by early clinical trial terminations (as documented in trial registries). When the rationale for discontinuation is included in the disclosure, the most commonly cited reasons for stoppage are (disappointing) efficacy results, safety issues, shifting company priorities, or funding issues. On a few occasions, termination announcements also mention results from other development projects. In Appendix C, I provide examples of discontinuation disclosure statements that have different levels of transparency.

Public companies have more incentives to report their project disclosures to the entire market in a timely fashion. Regulation Fair Disclosure, enacted by the U.S. Securities and Exchange Commission in 2000, requires that publicly traded firms disclose all material information to investors. In practice, this regulation means that firms must disclose via press releases (or social media, as of April 2013) any information that might impact the stock price.[23] While I cannot ascertain the exact coverage of discontinuation disclosure, one can expect that public firms (who run the vast majority of phase II trials) will err on the side of caution and disclose project exits in a timely fashion. Small biotech firms may be theoretically less likely to make official announcements shortly after the decision to abandon the project is made; however, the Cortellis database includes discontinuation disclosures from all types of firms.

4.5 Analysis Data

The final analysis data set contains 6,182 drugs, 325 ICD9 indications (markets), and 10,637 drug-indications (projects). Projects may experience relevant competitor failure events in three different ways: 1) same market, different technology, 2) same market, same technology, and 3) different market, same technology. 95% of the projects eventually experience at least one competitor failure

[23] In the supreme court case of Matrixx Initiatives, Inc. v. Siracusano (2011), the limits of this rule were clarified after a pharmaceutical company failed to disclose news that its drug may cause adverse events. In the unanimous decision, Justice Sotomayor wrote in favor of the existing standard that the"materiality requirement is satisfied when there is 'a substantial likelihood that the disclosure of the omitted fact would have been viewed by the reasonable investor as having significantly altered the total mix of information made available.'" While this decision did not result in a "bright-line rule" regarding materiality of clinical trial results or adverse event information, it did reaffirm that public companies need to announce significant negative events involving drug development.

within the same market, 10% ever experience a competitor failure within the same market and same technology, and 43% experience a competitor failure within a different market, but same technology. For each competitor failure experience type, I createda series of variables that captured the type, status and timing of news.

First, I create dummy variables for whether a given drug project had experienced each type of competitor failure as of a given quarter. Next, I generate a set of count variables for the number of times a given phase II project has experienced a competitor failure within each category as of a given date. Last, I create treatment "window" indicator variables, that equal one when a project is within a defined time range (one, two, or three quarters) following the competitor failure news. The descriptive statistics for the analysis sample are summarized in Tables 1 and 2.

In my main analyses, the outcome variable is whether or not the focal project's developer has discontinued the project. The average likelihood of a project being discontinued in a given quarter is 1.2% (conditional on surviving up until that point). 37% of the projects which were not right-censored by the end of the analysis period (e.g. had the opportunity to complete 32 quarters in phase II, exit, or graduate to phase III prior to the third quarter of 2014) are actively discontinued during the sample period, while 20% of those projects graduated to phase III development.[24]

5 Results

In this section, I empirically investigate how competitors' failures impact project exit decisions. I treat competitor project terminations as information shocks to both the competitive environment and technological space. In the main analyses, I employ a panel difference-in-differences survival model approach to answer the primary questions about if and when firms change their project investments based on competitor news, while controlling for differences across time, therapeutic markets, and project age. The resulting estimates allow me to evaluate the relative impact of different types of competitor failure news on related project exit choices. After establishing this method and the central findings, I examine key subsamples to test the robustness of the results, and connect the results to the predictions of my theoretical framework. Next, I present an approach to measuring aggregate under- or overreaction to competitor failure, and summarize the findings.

[24]For my primary outcome measure, I use a conservative definition of project discontinuation, since many projects continue on-paper even though the firm does not commit any new resources to the project (e.g. no additional trials). In order to check whether the results hold under a less conservative definition of project "death," I created an alternative outcome variable that defines discontinued projects as those officially discontinued, plus those that completed their final phase II trial for a given drug-indications and do not have any subsequent development. Under this more inclusive project discontinuation definition, the average likelihood of a project being discontinued in a given quarter is 4% (conditional on surviving up until that point), and 51% of the non right-censored projects are discontinued during my phase II sample period (the first 32 quarters of phase II development. The main econometric results are qualitatively the same under the conservative and alternative discontinuation definitions, but I report the findings using the more conservative definition in the results section.

Finally, I introduce a method for evaluating (post-rival failure) decision-making. I describe the decision quality measures, and explore how firm characteristics correlate with decision-making performance.

5.1 Non-Parametric Analysis

I first assess project discontinuation decisions in phase II using simple comparisons of averages. The econometric approach that follows aims to control for many factors that might impact project exit rates, and to isolate the independent impact of competitor failure news on firms' continuation decisions; however, as a first step, I explore the overall patterns of continuation and exit for projects throughout phase two that are proximate (in time) to competitor failure events. The goal of the empirical exercise is to identify whether each type of competitor failure news influences project exit rates. To do so, I first need to establish the "typical life cycle" for projects in phase II.

Figure 2A shows the overall cumulative hazard rate of projects by the number of quarters spent in phase II (up to 32 quarters). The intuition for the cumulative hazard rate is that it represents the project death rate for a given project age, conditional on surviving until that point in time or later. The curve has a slight "S" shape—indicating that the rate of project death starts slowly, but increases through roughly 15 quarters into phase II. After that point, the death rate slows for the projects that remain in phase II (without exiting or graduating to phase III) after four years. While the cumulative hazard estimates in Figure 2A are the average of all phase II projects in the analysis sample, I also evaluate how the hazard rates differ for various subgroups (e.g. by firm size and portfolio characteristics) in Appendix E, Figure 1. In line with prior studies (Guedj & Sharfstein, 2004), I find that smaller firms are much less likely to abandon projects, and that firms with relatively high market or technology project concentration are also less likely to abandon projects throughout phase II.

Figure 2B shows the average quarterly project survival rate. This figure also distinguishes between projects that are proximate (in time) to *same market, same technology* competitor failure news, and projects which have not recently experienced such news. Overall project survival rates have roughly a "V" shape, remaining above 99% for the first year in phase II before declining the 97-98% range until increasing again after about four years in phase II. Furthermore, the figure reveals that the survival rate is almost always lower for projects in the time window after a *same market, same technology* failure news events. In other words, the average project death rates show a marked difference after close competitors' failure signals.

5.2 Econometric Framework: Measuring Project Updating After Competitor Failure

My baseline regression specification aims to capture project-level response to a competitor's project termination. While other empirical approaches in the learning literature address how cumulative failure in the firm or industry impact the likelihood of a project or firm's success (Kim & Miner, 2007; Rao, 2014; Haunschild & Sullivan, 2002), these prior analyses do not leverage the timing of disclosure announcements, assert strong assumptions about the decaying value of competitor news over time, require structural modeling for interpretation, or are limited to cross-sectional correlations. My method focuses on the dynamics of updating project investments after competitor news. Here, the timing of both competitor exits and the focal project's termination are key to identifying the role of vicarious learning in decision-making.[25]

The baseline specification is a panel difference-in-differences proportional hazard model, using the development panel data for phase II projects. The dependent variable is an indicator for whether or not the focal project was terminated in a given period. Using hazard models on panel data is appropriate in this setting, because survival analysis accounts for projects' natural death rates at different project ages, and estimates how given independent variables shift the hazard of project death. Variation in the timing of the information shocks (competitor discontinuation events) allows for the not-yet treated observations to serve as a plausible control group for the treated groups. Furthermore, by stratifying the baseline hazard rate for different fixed characteristics (e.g. therapeutic market), I can estimate treatment effects relative to the most relevant counterfactual propensity for project exit. In other words, the survival model framework allows one to ask "how does recently experiencing competitor failure news influence the propensity to exit, when compared to 'untreated' projects of the same stage, age and market?"

One key aspect of this method is the "no-anticipation" assumption (Abbring & Van Den Berg, 2003), which is satisfied in the clinical trials setting since firms believe that their rivals are unlikely to invest in high-stakes clinical trials with the expectation of failure.[26] I can also test this assumption empirically, by assessing the extent of any pre-trends leading up to competitor discontinuation events (see Figure 3 and Appendix D). The main specification is analogous to hazard models in

[25] Overall experience with failures within an industry, firm or department may result in organizational changes and learning. However, long-term failure experience may also correlate with *strategic choices* regarding market entry and risk tolerance, as well as scientific or technical evolution. In order to link specific competitor news events to project-level decisions, it is important that the econometric framework dynamically accounts to timing of exogenous (surprising) events, as well as the changing market environment.

[26] To the extent that any information leakage occurs, or news about disappointing trial outcomes circulates prior to discontinuation announcements, then the information effects coefficients should be biased towards zero. Therefore, one might consider the information effects captured in this approach as conservative estimates of competitor response to failure news.

Rao & Dutta (2012), Gans et al. (2008), and Aral & Walker (2012), where the timing of both treatment and response is of central importance in interpreting the results.[27]

In practice, I use a cox proportional hazard model specification, using drug-market-quarter level data:

$$h_{i,k}(t,X) = h_{0k} \times exp[\beta_1(SAME\ MKT,\ DIFF\ TECH\ NEWS)_{k,-q,t} + \beta_2(SAME\ MKT,\ SAME\ TECH\ NEWS)_{k,q,t} + \beta_3(DIFF\ MKT,\ SAME\ TECH\ NEWS)_{-k,q,t} + \gamma_t]$$

where h_{0k} is the baseline hazard rate of project exit, stratified by therapeutic market,[28] and γ_t represents time-period (quarter) fixed effects. i represents the focal drug project, k represents the therapeutic indication (market) and q represents the drug target-actions (technology) of the focal project. β_1, β_2, and β_3 are the coefficients on the three different types of competitor project discontinuation news : 1) same market, different technology, 2) same market, same technology, and 3) different market, same technology.

In the preferred model, the competitor discontinuation ("treatment") variables are equal to one if the focal observation is within two quarters since the competitor failure news–allowing for treatment to turn on and off for multiple treatment spells. I also consider specifications where competitor discontinuation news is an absorbing state (that is, where the variable takes on the value of one after the first competitor discontinuation event in that category), or varies by "treatment intensity" (cumulative number of competitor failure events in each category since the focal project entered phase II). Separately, I also evaluate a fully dynamic version, where each competitor failure event type is interacted with indicator variables for number of quarters until the competitor news event. In Appendix D, I outline alternative regression approaches—including an ordinary least squares version of the main specification, and a dyadic approach with a separate panel for each treating-treated pair. The results from these alternative models and data structures produce the same overall patterns of response to competitor exit news as those presented immediately below.

5.3 Impact of Failure News Results

Table 3 presents the estimates from the main regression specifications. In the first column, I report the results of a naive specification, in which I group competitor discontinuation news events into a single independent variable that takes on a value of one after any type of competitor failure. Under

[27] Rao & Dutta's (2012) empirical setup is additionally relevant because it allows for multiple treatment windows (religious festivals' impact on propensity for military mutiny events).

[28] I do not also stratify by technology (target-action) because while a single drug project has only one therapeutic market, it may use multiple technologies. Running a similar hazard model specification on a data set at the drug-market-technology-quarter level yields similar results, but with a less intuitive interpretation.

this grouped competitor news variable, the results show no significant change in the propensity of project exit following competitor discontinuation. However, this null result does not hold up once I separate different types of competitor discontinuation news.

Columns 2 through 5 in Table 3 separate the project exit impact for each type of competitor news. Column 2 reports the coefficients from the version with absorbing treatment states, while column 3 uses treatment intensity (count of cumulative competitor failures), and column 4 uses the preferred treatment definition: the "window" of two quarters since the competitor failure disclosure. Column 5 tests the "no-anticipation" assumption by including indicator variables for quarters prior to each type of treatment, and shows that competitor failure news (of all types) has no significant impact on discontinuation rates prior to the announcement period.

Generally, the relative impact of each type of failure news is the same across models. Competitor news from the *same market, different technology* group yields no significant change in hazard rate of project exit, with magnitudes close to zero. *Same market, same technology* competitor discontinuations lead to large and highly significant ($p < 0.01$) increase in the hazard rate of project exit, while *different market, same technology* discontinuation news lead to a smaller, but still statistically significant increase in the probability of project exit. Wald tests confirm that the *same market, same technology* coefficient is significantly larger than the *different market, same technology* coefficient in each model. Focusing on column 4, one can interpret the *same market, same technology* coefficient as representing a 0.677 increase in the log hazard (107% increase in probability) of project exit following a closely related competitor's project discontinuation. Here, the *different market, same technology* coefficient implies a 0.181 increase in the log hazard (18% increase in the probability) of project exit following a technological competitor's discontinuation disclosure in another therapeutic area. Wald tests confirm that the *different market, same technology* coefficient is significantly less than the *Same market, same technology* coefficient ($p < 0.01$). The coefficients from column 4 are also depicted as bars in Figure 3.[29]

Figure 4 shows the dynamic effects of experiencing a competitor discontinuation event for the main specification interacted with indicator variables for time until (or after) the project's earliest treatment event using six-month increments. The estimates are much noisier than their two-period counterparts in Table 2, since this version requires slicing the data into much thinner pieces. However, the same general pattern of relative treatment magnitude holds. While the pre-treatment estimates do not appear perfectly flat around zero, they do not reveal any clear trends as the first competitor discontinuation date approaches.[30]

[29] Testing the proportional-hazards assumption yielded non-significant results—implying that the proportionality assumption holds.

[30] An alternative version of Figure 4 applies an analogous ordinary least squares model, rather than the hazard model approach, and yields very similar patterns (see Figure D1).

In Appendix E, Figure 2, I display the relative impact of the technological learning channel by graphing the predicted probability of project discontinuation by project age (quarters in phase II), compared to the counterfactual discontinuation rate if one were to "turn off" the ability to learn from competitors. The predicted discontinuation is based off the main econometric specifications' average predicted discontinuation value (corresponding to Table 3, Column 4) for observations treated by *same market, same technology* or *different market, same technology*. The counterfactual predicted value removes the effects of those types of news (as estimated in their coefficients) and shows that the discontinuation rates would be roughly 25% lower if one were to shut off the ability to learn from any technological competitor news.

5.3.1 Robustness Checks on Primary Results

A subset of additional analyses are particularly helpful for testing the underlying assumptions and reliability of the main competitor news response results. First, one might be concerned about how the timing of competitor news coincides with firm's choices of entry order. In drug development, the limitations and looming expiration of patent terms create a sense of urgency to push forward with development, rather than a "wait and see" strategy. However, firms might still choose particular entry timing in order to capitalize on informational, regulatory or first-mover advantages. For example, firms might engage in "me-too" or copycat innovation, sacrificing first-mover advantage in exchange for reduced risk and allowing the leaders to establish regulatory and marketing pathways (Stern, 2016).

In order to test whether entry order decisions are playing a role in the main competitor news response results, I interact each competitor failure type (the absorbing state version) with the focal (treated) firm's phase II entry position relative to their first treating project (follower, neck-in-neck, leader), and stratify the baseline hazard by overall competitor failure type groups (e.g. ever experienced same market, same technology competitor discontinuation) as well as by therapeutic market. Figure 5 displays the results of this regression. The results reveal that the relative magnitudes of the competitor failure news coefficients are nearly the same for followers, leaders, and projects that are neck-and-neck (enter phase II within a year of one another). The magnitude of the *same market, same technology* and *different market, same technology* are actually greatest among the leader group (those who entered phase II prior to their first "treating" projects). This result means that even when a failed project entered phase II after related projects, the project's discontinuation still influences competitors' exit decisions.

Additional robustness tests also supported the findings in the preferred specification. Limiting the analysis sample to smaller project age ranges (e.g. first 16 quarters in phase II, 4-12 quarters into phase II, etc.) yielded the same qualitative results as the primary specifications. Using an alternative outcome variable that includes projects that never report any additional development

(e.g. no new trials and no progression) as "discontinued" observations also yields results qualitatively similar to the preferred specification. The results did not significantly differ when I compared discontinuation signals accompanied by a press release to those without press releases, and when I excluded the set of "treated" projects that were proximate in time to their own trial end dates.

5.4 Heterogeneous Effects and Testing Theoretical Predictions

While the average response to technological competitors' discontinuation substantiates that vicarious learning is part of the decision-making process, the diversity of competitive environments, firm characteristics, and types of information disclosure demands closer examination. These additional factors directly relate to the theoretical framework: the level of market competition influences the trade-off between technological learning and market opportunity; the remaining technology learning opportunities moderate the option value of continuation; the level of project uncertainty changes the level of potential belief updating; firm size and pipeline characteristics determine the opportunity cost of continuing vs. abandoning a given project; and a firm's expertise and experience in a therapeutic area may temper its ability to discern project similarity and parse competitor signals. Variation in the timing and order of competitor failure disclosures also allows investigation into the relative strength of different disclosure signals, and the possibility of cascading exit behavior. Below I explore some of these areas using variation in the phase II project analysis data.

Competitive Environment and Response to Competitor Failure. Figure 6 shows the regression results when I group the analysis sample by the level of competition and evaluate the response to competitor failure within each subset. First I run the main hazard model specification on subsets of the analysis sample in order to compare the competitor failure news treatment effects for projects in the bottom quartile (low) vs. top quartile (high) in terms of number of potential market competitors in any stage of active development. This split reveals that the *same market, different technology* effect is negative and highly significant when the level of market competition is low (first bar in Figure 6, Panel A). In other words, firms are more likely to continue after a *same market, different technology* competitor failure when competition is low, even though the effect is not significant for the high competition scenario.

Next, I evaluate the competitor failure response for projects with low vs. high levels of closely related potential competitors (development projects that share the same market and technology). The notable difference in this comparison is that the *different market, same technology* effect essentially disappears for the group in the top quartile in terms of market-technology development competitors (last bar in Figure 6, Panel B). Finally, I evaluate the subset of phase II projects that are in therapeutic markets that had low vs. high levels of previously approved drugs. Similar to the result for development same-market competitors, the projects with low prior approved drug

competition exhibit a significant decrease in propensity to discontinue following a *same market, different technology* competitor failure event.

The set of competitive environment findings confirm the theoretical intuition that facing one fewer competitors will influence decision-making under certain market structures. The value of the *same market, different technology* coefficient is more negative when the baseline level of market competition is smaller (across all three definitions of number of competitors). This result supports the notion that payoffs have a nonlinear relationship with the number of competitors (Bresnahan & Reiss, 1991). The potential for monopoly or duopoly profits (if the drug development project reaches the market) is far more likely in situations with few product development or market competitors. That said, low levels of competition do not significantly moderate the technological learning effects.

Remaining Learning Opportunities and Response to Competitor Failure. In addition to number of current or potential market competitors, the number of remaining technologically similar projects might also impact firm responses to competitor failure news. In the theoretical framework, I noted that firms might make entry and continuation decisions with the number of potential competitor learning opportunities in mind. To test whether the remaining technological competitor learning opportunities influence the response to competitor news, I interact each of the three treatment types with an indicator variable for whether or not the focal project had at least three technological competitors remaining.

Figure 7 graphs the coefficients for each competitor failure news type, separated by remaining technological competitor learning opportunities. The *same market, different technology* coefficients show that when a project has a high number of same-technology competitors remaining, the firm is significantly more likely to forge ahead with the project following a same market competitor failure, compared to projects that had not experienced competitor failure news, as well as those that experienced the same type of competitor failure but had low levels of remaining technological competitors remaining. The other notable result from these comparisons is that the *different market, same technology* effect essentially disappears for projects with high remaining technology competitor learning opportunities. This result shows that the exits driving the overall *different market, same technology* effect mainly involve projects that had low remaining learning opportunities, while projects with more learning opportunities were more likely to continue.

These findings are consistent with the theoretical framework, in that more technological learning opportunities increases the attractiveness of continuing a project. A developer's belief about a project's probability of success is likely unchanged after a *same market, different technology* failure. If the project has few same technology competitors remaining, then the developer does not expect to gain any more relevant technology insight from others and the competition effect does not appear to be strong in this scenario. However, large number of remaining technology competitors may provide further information as their experiments complete over time. The combination of a more attractive

competitive environment (one less potential rival) with many potential learning opportunities still intact makes the continuation option even more attractive than it was prior to the competitor failure. An additional explanation for this strong negative effect on project termination is that a *different technology* competitor's exit may appear to validate competing hypotheses about which drug target is most promising.

A similar logic helps explain the *different market, same technology* results, where the existence of more remaining competitors using the same drug target kills the response to this type of competitor discontinuation news. Here, developers might be more hesitant to pull the plug quickly or down-weight any one given competitor failure if the developer believes more competitor signals may arrive in the future. Observing that other firms using the same drug target remain committed to their projects might also lead to a positive feedback loops, such that developers believe that their investment in the treatment approach or clinical hypothesis is validated by others.

Project Stage, Uncertainty, and Relevance of Signal. An important assumption of the empirical approach is that the informational value of competitor failure is only relevant when the initial failing project is in the same, or a more advanced stage of development. According to this approach, projects that are significant laggards in development are considered irrelevant to the decision-making process, and more-advanced projects have already resolved enough uncertainty in order to ignore the earlier stage projects. To test this assumption, I set up a "placebo"-like test where I evaluate whether phase III projects are more or less likely to exit following news of a phase II competitor's failure.

As in the main analysis, the goal is to determine whether the propensity for a project to abandon development changes following each type of competitor failure, and controlling for project age, date, and therapeutic market. In Figure 3 of Appendix E, I present the event study results of this analysis. As in the Figure 3 event study, the three panels display the coefficients of interaction terms for each type of competitor news event, multiplied by the number of quarters before or after the news event of that type (for each focal project). For all three competitor news types, the trends are fairly flat and none of the coefficients are significantly different from zero. In summary, phase III project investments do not appear to respond to phase II competitor failures, regardless of the market and technology relationships.[31]

This null result supports the notion that the informational content of a failure, rather than existence of a disclosure event, is the relevant factor in competitor response to failure news. The lack of response of phase III projects to phase II news result also supports the prediction from the theoretical framework that developers only update their expectations about R&D success when

[31]The primary analyses use both phase II and phase III failure news as relevant signals for phase II projects. I also tested whether competitor failure news originating from a phase III competitor had a different effect than the same type of news stemming from a phase II. Comparing the main specification coefficients for response to each type of news originating from phase II vs. phase III failures produced no statistically significant differences.

their own project uncertainty is high and competitor news arrives from projects at similar, or more advanced stages. If developers have already cleared certain development hurdles, then they do not consider earlier stage projects as providing new vicarious learning opportunities.

Additional exploration of heterogeneous effects can be found in Appendix E, which describes how the failure responses differ depending on the concentration of the developing firm's portfolio, the temporal clustering of failure events, the level of a developer's technology experience, a firm's commitment to the focal drug, and the strength of the competitor signal.

5.5 Overreaction Analyses

In the first set of results, I used the survival models to show how some types of competitor failure news do, in fact, alter project exit decisions. A natural follow-up question to ask is whether these responses to failure news are under-reactions, overreactions, or properly rational reactions? Answering this question is especially challenging due to the complexity of drug development decisions, variation in firm strategies or outside options, and the lack of counter-factual experience.

In order to begin to evaluate the extent of under- or overreaction, I use therapeutic market-level information detect whether, on average, firms excessively exit following competitor failures, or ignore competitor signals and forge ahead with projects at their own peril. My approach uses cross-sectional regressions to evaluate how project success rates correlate with different types of competitor failure news treatment intensity (number of competitor discontinuations), while controlling for therapeutic market and the quality of drug development projects.

To illustrate the intuition behind this analysis, consider a set of projects with a uniform distribution of their ex-ante probability of success (project quality prior). Assume that projects with initial probability of success greater than 30% are deemed worthy of the investment required to start phase II trials. The average probability of success for the continuing projects is then roughly 70%. A number of quarters into their phase II development, the projects each receive news that a same-technology competitor has stopped development due to disappointing results regarding their drug's efficacy. Assuming this news contains some relevant information with regards to the underlying technology's true utility, the developers will downgrade their beliefs (updating). If the developers are rational updaters, then some projects with initial probability of success just over 30% will leave after updating their beliefs to a point below their continuation threshold (selection). After updating and selection, the remaining projects will have a slightly lower average probability of success.[32] However, if the failure news led to a panicked flight away from the technology area, then the excessive exit might result in no change, or even an increase, in the average probability of

[32]The extent of this downward updating for any given project will depend on where projects arrived on the initial quality distribution. Though the example uses a uniform distribution of project quality, other assumptions about the distribution of project quality produce the same intuition. Some extreme multi-peaked distributions (e.g. bimodal) may result in no change in average project quality after technological competitor failure; but single-peaked

success for the remaining projects. In the under-reaction scenario, if the firms ignore the competitor news and too few or zero firms exit, then we would expect the success rates for the remaining firms to fall below relevant historical averages, since projects that "should have" left ignored relevant signals.

To execute this analysis, I start with the set of projects in the analysis data set. For each project, I keep a single observation: the last quarter when the project would continue to be active in phase II for two more quarters. From this sample, 90% have experienced at least one *same market, different technology* competitor failure, 9% have experienced at least one *same market, same technology* competitor failure, and 38% have experienced at least one *different market, same technology* failure while in phase II. The analysis focuses on the same-technology treatment intensity because the *same market, different technology* treatment a) lacks variation in the sample, b) does not have implications for changes in probability of success (as in the example above and in my theoretical framework), and c) does not, on average, lead to changes in product exit rates (as seen in the propensity analyses described above).

The econometric framework is a logistic regression estimated as follows:

$$\begin{aligned} Prob(Y_{i,k}) =& \beta_0 + \beta_1(Treatment)_{k,q} + \beta_2(Treatment)_{-k,q} \\ &+ \beta_3(\hat{quality}_{ik}) + \gamma_k + \epsilon \end{aligned}$$

Once again, i represents the focal drug project, k represents the therapeutic indication (market) and q represents the drug target-action (technology). I analyze two different binary outcome variables, Y: (i) Whether the project eventually reached phase III, and (ii) Whether the drug was ever approved (launched). The independent variables are a constant term, β_0, count variables for the number of *same market, same technology*, and *different market, same technology* failure news events experienced, a measure of project quality as of the start of phase II, and indicator variables for each therapeutic market. The quality measure, $\hat{quality}_{ik}$ is the predicted value based on results of a penalized logistic regression with a lasso penalty term:

$$\hat{quality}_{ik} = Prob_t(Y_{ikq}) = \alpha_0 + X_{ikqt}\alpha_1 + \epsilon$$

where X_{ikqt} is a set of characteristics of the drug project, technology and market as of the time of phase II entry (e.g. entry order, number of previously approved drugs in the market, number and percentage of previously failed drugs in the technology or market, etc.).

Table 4 reports the results of the logistic regressions for each outcome (graduation to phase III, and eventual drug launch). Columns 1a-1c show the key regression coefficients for the outcome of

distributions should all share the characteristic of a decreased average probability of success following belief updating and selection.

graduation to phase III. Here, the coefficient on the count of *same market, same technology* failure news events are negative, but small and statistically insignificant. The *different market, same technology* failure news events coefficients are all negative and significant at the 1% level. The regressions with the drug product launch outcome are in columns 2a-2c. The *same market, same technology* failure news coefficients are positive and the *different market, same technology* failure news coefficients are all negative, and statistically significant at the 1% level. When I include the quality controls, the *same market, same technology* failure news coefficients more than quintuple in magnitude and become statistically significant at the 10% level.

In total, this analysis shows that success rates stay about the same or go up after more *same market, same technology* competitor discontinuation events, and go down after *different market, same technology*. Based on the intuition described above, these results indicate a moderate level of overreaction for the *same market, same technology* news events, on average. These results rule out overreaction for the *different market, same technology* events, but cannot determine whether these responses are perfectly rational or under-reactions.

5.6 Decision Grading Analysis

Another way to evaluate reactions to competitor failures is to grade each decision based on observed project outcomes. Failure disclosures provide a key decision point, where developers can re-access their investment priorities. Figure 8 shows how I assign simple positive and negative decision grades to each decision and outcome type. If a project experiences competitor failure news and its developer chooses to continue, then I grade that decision based on the eventual outcome (i.e. reached approval or failed). The more complicated scenario is when the developers kill their own project in the wake of a competitor termination. While I cannot see the counterfactual (what would have happened had the project continued), I use the outcomes of technologically similar projects that did continue development as a proxy measure for the the focal project's true quality. In other words, did similar projects validate the scientific and clinical hypotheses involving these drugs. If the majority of subsequent developers end up failing, then I consider those failures as validating of the focal project's decision to exit. And if the majority of similar projects succeeded, then I characterize the focal project's exit choice negatively. If no other subsequent technology competitors have continued or completed their development, I assign a neutral grade.[33]

This method is inherently crude, and does not capture any of the nuance around competitor signals (e.g. safety vs. efficacy failures, problems with the primary drug target vs. unanticipated

[33] A limitation of this grading system is that some of the most influential failure events will generate only "neutral" grades. If the failure signal is so strong that all concurrent similar projects wisely exit and all future attempts are correctly thwarted, then I can still only assign a neutral grade, since no subsequent projects are available to estimate a counterfactual outcome. This problem is moderated by the fact that exit (in the wake of competitor failure news) is still a relatively rare event, so few decisions grades are affected.

off-target effects, etc.). However, by assigning these grades to every decision and aggregating across all events, I can evaluate whether any project or firm characteristics correlate with overall patterns of good or bad decision-making. Furthermore, the noisiness of the measure should decrease the probability of any one firm's decision-making consistently scoring very high or low through time.

To run this analysis, I use an ordered logistic regression framework. The probability of a given outcome type can be written as follows:

$$p_{ij} = Pr(y_i = j) = Pr(\phi_{j-1} < X_i\beta + u < \phi_j)$$

where i is a distinct project decision observation, j is the decision grade ($bad = 1$, $neutral = 2$, $good = 3$), ϕ is the latent variable (ϕ_0 is $-\infty$ and ϕ_3 is ∞), and X_i is the vector of project and firm characteristics associated with decision i at the time of the decision.[34]

I run two versions of the ordered logit regression, one for the "stayers" and one for the "leavers," since the assignment of decision grades is different for projects that continue and projects that leave at their respective competitor news decision points. Table 5 describes the sample of 35,545 decisions following *same market, same technology* and *different market, same technology* competitor failure news, and summarizes the grading outcomes for both stayers and leavers. Unsurprisingly, decisions to leave are far less common than decisions to stay after competitor discontinuations, and "good decisions" are relatively uncommon (2%) within the stay decision category.

Table 6 reports the ordered logit regression results. Across both the stayer and leaver groups, I evaluate how decision making quality correlates with a number of project-level and firm-level measures at the decision point in time: the size of the firm (proxied by the number of patents owned), the novelty of the drug compound (see Appendix B for detailed description of this measure), the firm's concentration of projects committed to the given market or technology, and the proximity in time to a approved drug losing its patent protection (within two quarters, in either direction, of expiration), and whether the project was originally developed within the firm (rather than in-licensed or acquired through mergers). In each regression, I included year fixed effects in each model, and run the ordered logit specification with and without firm fixed effects. I also analyze the subset of stay decisions for large firms (more than 100 patents owned) only, but do not run the equivalent regression for the leavers because of the relatively few number of leave decisions.

Within the small leaver group, I find that being close in time to an approved drug patent expiration, or having a R&D portfolio with a high concentration of projects in the focal project's technology area both have are significantly and positively correlated with decision quality (Columns

[34] As robustness checks, I also ran standard (binary) logistic regressions, in which I eliminate the neutral outcome category. These alternative versions yielded similar results, in terms of the distribution of firm decision "performance."

1 and 2). After including firm fixed effects (Column 2), I find that those relationships are stronger and I also find that "homegrown" compounds are associated with better decision-making.

Among the stayers, the project characteristics have generally stronger correlations with the decision quality outcomes (Columns 3-5).[35] However, these correlations are also more sensitive to the model specification. For example, in the full sample, drug compound novelty is negatively correlated with stayer decision quality ($p < 0.01$). However, this relationship flips to positive and significant when I include firm fixed effects or limit the sample to large firms. The one independent variable whose coefficient direction is stable across all three stayer decision-quality models is the concentration of projects within the focal market, which is positively correlated with stayer decision-quality. In general, firm fixed effects have a large influence on the coefficients in the stayer models—implying that firm-specific factors (e.g. decision-processes, expertise, risk tolerance) may play an important role.

Since the firm fixed effects clearly have an impact on estimation of decision performance, I separately analyzed the fixed effects and searched for firm level patterns. In Figure 9, I chart the overall variation in decision performance by firm. Figure 8 displays the distribution of firm fixed effects for the stayer (Panel A) and leaver (Panel B) groups. These estimates are generated by taking the firm fixed effects from the ordered logit models described above. Some firm estimates are much more precise than others since they have many more decision points, or because their decision quality is truly more or less persistent over time. Before plotting the firm decision-quality fixed effects, I weight them by a Bayesian shrinkage factor that adjusts for the signal to noise ratio (Kane and Staiger, 2008; Friedrich, 2016).

The results show a wide range of decision-making performance across firms—with some firms exhibiting persistently good or bad decision quality in both the leaver and stayer groups. Notably, the stayer group shows less overall heterogeneity, with most of the firms yielding weighted decision scores close to zero, but still a long tail on the negative score side. The leave decisions are more spread out, despite fewer firms in that sample (less firms ever make a leave decision in the wake of technological competitor failure event). This variation implies that firms have their own unique processes for interpreting competitor news, and that this organizational variation influences the quality decisions over time. These persistent decision differences also support the idea that competitor learning is a capability or skill that may be improved across a range of competitive environments.

In order to better understand these persistent decision-making performance differences, I evaluate the within-firm correlation in stay and leave decisions for firms who appear in both analyses. I find a statistically significant negative correlation between the two types of decisions (correlation

[35]The stayer group regressions also have much more power with nearly 33 times more observations than the leaver group.

of -0.38, $p < 0.05$). I plot this trend using a binned scatter plot in Figure 10. This correlation suggests that some firms are being quite conservative in their decisions after a competitor failure, while others are relatively aggressive. For example, a firm that only would stop its own project in the most obvious situations (e.g. the target clearly does not work for that disease), would appear to perform well on its leave decisions, but would have an excess rate of failure for projects after stay decisions.[36] Large discrepancies in stay and leave decision-quality scores would represent an imbalance in the approach to failure news.

These analyses represent only a first step towards understanding the sources of heterogeneous decision-making quality across firms. The results suggest that some institutional differences and R&D strategic choices (e.g., diversity of projects) explain some of the firm-level variation. At the same time, this set of easily observable firm characteristics has fairly low predictive power when it comes to explaining the overall dispersion of firm decision performance. Additional variables such as organizational structure, management practices, research scientist incentives, and executive characteristics might help to further explain this variation. However, these decision-making results are also in-line with the literature on productivity that finds large dispersion in performance at the organizational level (Henderson & Cockburn, 1994; Syverson, 2011; Gibbons & Henderson, 2013).

6 Conclusion

One of the key challenges in R&D is selecting among project investment opportunities. Developing new innovations is an inherently uncertain process and requires judgments about both the expected value of the technology and the potential of a given R&D investment to reduce uncertainty. In this paper, I present a model where the existence of technological competitors increases the attractiveness of a R&D investment by providing new opportunities to learn about both the quality of a technological hypothesis and the competitive landscape. Though greater competition decreases the payoffs for successful projects, it may also offer actionable information and an opportunity to reevaluate project commitments.

While prior studies have emphasized how the ability to learn from external research and competitors is generally valuable (Cohen & Levinthal, 1994; Henderson & Cockburn, 1994a and 1994b; Boudreau & Lakhani, 2015; Bloom et al., 2013; Kim & Miner, 2007; Ingram & Baum, 1997; Haunschild & Sullivan, 2002; Macher & Wade, 2016; Lane & Lubatkin, 1998), this paper empirically demonstrates the circumstances under which competitor failures directly enter into project selection decisions. The paper exploits the unique characteristics of the drug development process to identify the development histories of parallel competing projects, and distinguish between market and technological competitors. I find that competitor discontinuations do influence the probability

[36] Put differently, a firms decision-making "style" could be represented as the ratio between its stay and leave decision scores.

of project exit, but that the extent of this response depends on projects' relatedness in both market and technology space.

This paper also shows that the response to competitor failure events varies by the competitive environment and project characteristics. I find that the market competition effects are stronger when baseline competition levels are low. However, the market competition considerations do not supersede the more powerful technological learning effects that make close competitors more likely to exit after competitor failure news. Additionally, I find that the potential for future competitor learning, project-specific uncertainty, the developer's portfolio diversity, and technological expertise all influence the magnitude of responses to competitor failure news.

I also explore whether the level of response to competitor project failures is prudent or predictable over time. First, I use the average success rates of projects that forged ahead in order to evaluate whether rivals' failures leads to excessive exit. I find evidence of overreaction to competitor failure news, but only when the news comes from *same market, same technology* project discontinuations.

Finally, I introduce a method for grading continuation and exit decisions in the wake of competitor failure news. I evaluate which projects are correlated with better decision quality, and find that characteristics such as drug novelty, proximity to an approved drug's patent expiration, R&D focus, and being "homegrown" are associated with better decision-making. However, I find persistent decision quality differences across firms that are only partially explained by observable firm characteristics. Moreover, the negative correlation between stay and leave decision scores suggests a wide range in decision-making styles and effectiveness.

This study's findings contribute to both the organizational learning literature and research on R&D spillovers. Failure disclosures provide clear decision points and learning opportunities, and this study shows how one can use these events to understand how competitor news directly enters into the decision-making process. Future vicarious learning analyses need not be limited to failure events, as firms also learn from their rivals' successes. The challenge in studying successes (especially in the drug development setting) is that firms may not disclose good outcomes in a single news event, but rather over the course of multiple announcements. Empirically identifying the impact of positive competitor R&D news, and comparing it to the response to failure news is an important area for future research.

In the end, the theoretical model and empirical results present a simple recommendation for R&D managers: when comparing projects, managers should anticipate the value of learning from competitors, and include these factors in their valuation models. Preparing for shifts in the competitive and knowledge landscape will give firms a more realistic picture of a project's development path, and change the relative attractiveness of investment options. Furthermore, my findings show

that firms can use publicly available information on competitor type, rivalry level and portfolio focus to forecast responses to competitor news.

Firms may also use their proprietary data to gain insights that go beyond the scope of this study. While my analysis is limited to publicly available knowledge, firms have finer-grained information about their own projects and competitors. From individualized project quality measures (e.g. ex-ante probability of success) and comprehensive information about project relatedness, to precise reasons for project failure, firms can use proprietary data to document competitive responses to project outcomes, and evaluate their own decision-making quality. Firms might even choose to set up formal decision processes or reviews following competitor disclosures, in order to quantify and track the components of these decisions over time. The flow of information about competitor projects combined with the deluge of internal data should allow the modern R&D organization to continuously evaluate its project portfolio with respect to internal and external information. Furthermore, such internal data could help social scientists uncover the reasons behind variation in firms' R&D productivity.

If "strategy is centrally concerned with the process of how firms and managers respond to and exploit environmental signals" (Cockburn, Henderson, & Stern, 2000), then reacting to competitors' project failures is of principal importance to firms that are juggling uncertain projects. For these projects, novel information may drastically change the direction and payoffs of capital investments and R&D efforts. How firms can improve their competitive advantage by controlling and reforming their response to external signals continues to be a key question for managers and an exciting motivation for scholars.

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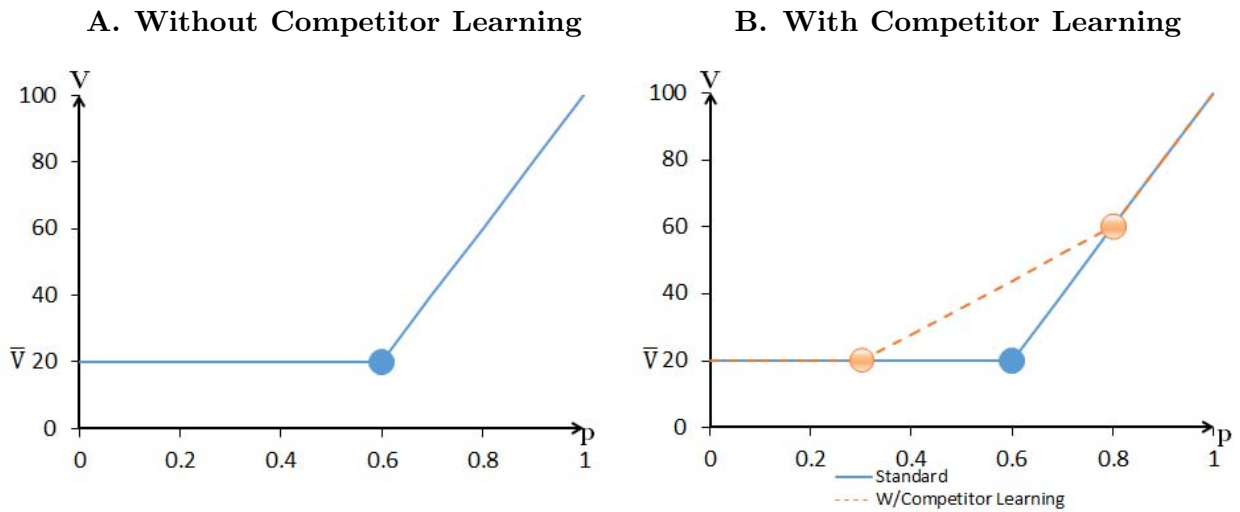
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Figure 1: Option Value of R&D Project Continuation, by Project Likelihood of Success



Note: The solid blue line represents the option value of a hypothetical R&D project, where the firm may continue the project or exit and recover its opportunity cost value ($\bar{V}$). The x-axis is the firm's belief in the project's probability of succeeding, and the y-axis the project's option value holding the level of competition (q) constant. Panel A shows the standard version of the project's option value, and the blue circle highlights the point at which the firm is indifferent between continuing and exiting. Panel B introduces the prospect of competitor learning, with the two orange circles indicating the potential project values depending on whether or not the firm receives news of competitor failure. The project's expected value would be somewhere between those two points on the dashed line.

Table 1: Descriptive Statistics, Phase II Projects that Experienced Competitor Failures

	Count	Mean	Std. Dev.
Discontinued in First 32 Quarters of Phase II	10,637	0.24	0.43
Experienced Competitor Failure in *Same Market, Different Technology*	10,637	0.95	0.21
Experienced Competitor Failure in *Same Market, Same Technology*	10,637	0.10	0.31
Experienced Competitor Failure in *Different Market, Same Technology*	10.637	0.43	0.49
Active Quarters in Phase II	10,637	21.91	9.01

Note: The analysis data set contains 10,367 phase II drug-indications (projects) that entered phase II between 1997 and 2014. The projects consist of 6,182 drugs, and 325 therapeutic market (ICD-9 codes). Approximately 28% of all drugs in the Cortellis data list more than one development market (34% of drugs that reached phase II clinical trials undergo phase II trials for more than one indication). 65% of drugs have at least one technology (target-action) assigned in the Cortellis database. A phase II project experiences a competitor discontinuation if it shares either a market or technology with the failing competitor, if the pair of projects were ever simultaneously active for at least one quarter, and if they entered phase 2 within 10 years of one another. A project can only experience a competitor discontinuation event if the competitor's discontinuation date was prior to the discontinuation of the focal project.

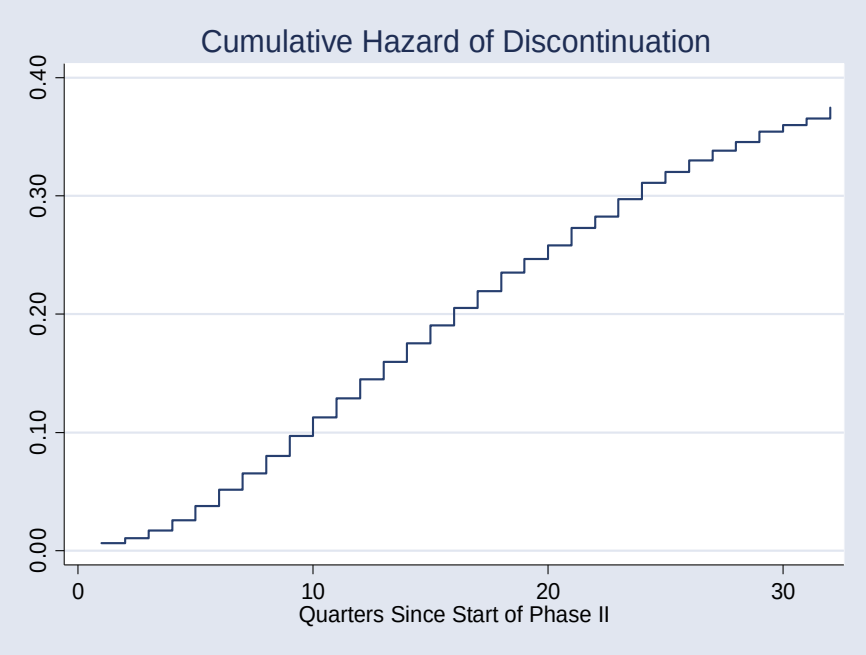
Table 2: Descriptive Statistics, Phase II Project-Quarter Panel

	Count	Mean	Std. Dev.
Within 2 Quarters of Competitor Failure in *Same Market, Different Technology*	254,069	0.54	0.50
Within 2 Quarters of Competitor Failure in *Same Market, Same Technology*	254,069	0.02	0.14
Within 2 Quarters of Competitor Failure in *Different Market, Same Technology*	254,069	0.13	0.34
After First Competitor Failure in *Same Market, Different Technology*	254,069	0.78	0.41
After First quarters of Competitor Failure in *Same Market, Same Technology*	254,069	0.07	0.25
After First 2 quarters of Competitor Failure in *Different Market, Same Technology*	254,069	0.31	0.46
Sponsor Firm's Number of Development Projects To-Date	251,077	164.32	304.26

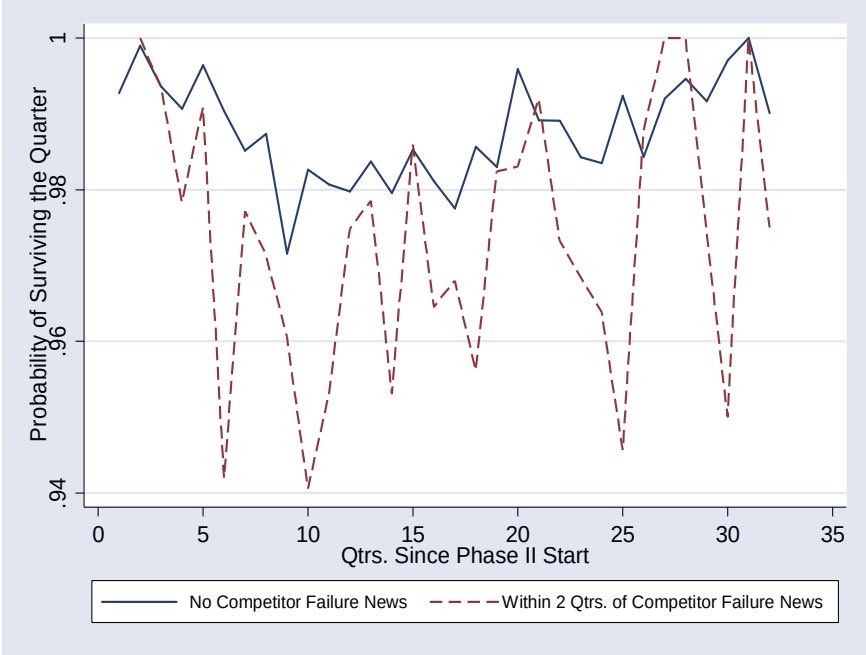
Note: The panel data of phase II projects consists of 254,069 project-quarters. The table displays the frequency that projects are within a two quarter window (i.e. same quarter, one quarter after, or two quarters after) from each type of failure event. The sponsor firm is assigned using the drug development history data by company. When multiple firms are involved in developing a drug during a given quarter, the larger of the companies, as determined by total development projects to-date, is assigned. In 1% of observations, the sponsor company was ambiguous and, therefore, not assigned.

Figure 2: Project Death Rates in Phase II

A. Cumulative Hazard Rate



B. Project Survival Rates with and without Same Market and Technology Competitor Failure News



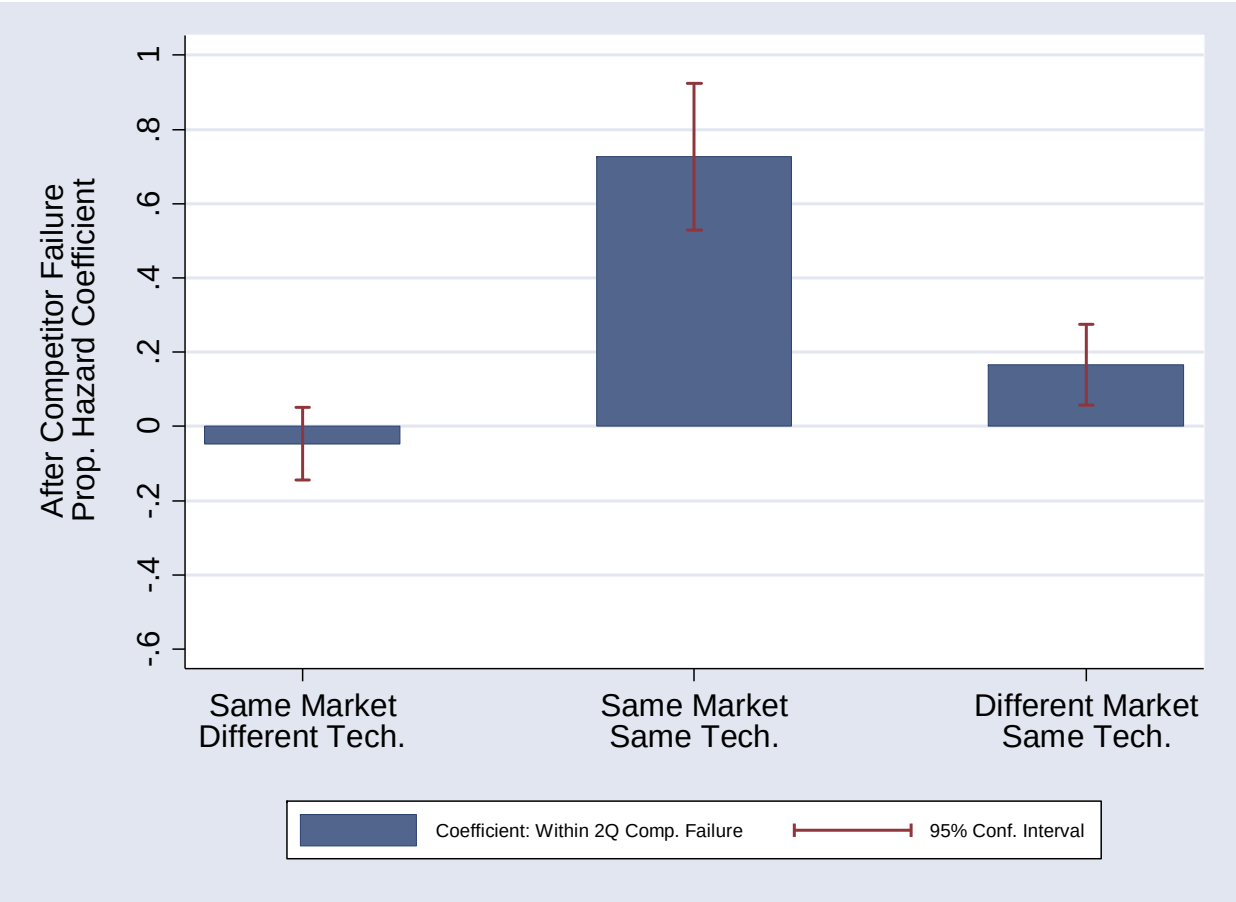
Note: Each panel represents a different way of tracking the overall rates of project exit throughout. Panel A graphs the cumulative hazard rate of project discontinuation by number of quarters since entering phase II. The intuition for the cumulative hazard rate is that it represents the project death rate for a given project age given that the project survived until that point or later. Panel B shows the probability of surviving a given quarter, conditional on entering that quarter (e.g. the likelihood that a project which enters its 8^{th} quarter of phase II clinical trials does not get officially discontinued during that period). The hashed line is the average survival rate for project-quarter observations that are within two quarters since a same market, same technology competitor disclosed project discontinuation. The solid line is the average survival rate for projects that are not within this half year window since the close competitor failure event.

Table 3: Competitor Failure News Impact on Hazard Rate of Exit

	(1)	(2)	(3)	**(4)**	(5)
After Any Competitor Failure News	-0.013				
	(0.077)				
After Competitor Failure News (Same Market, Different Tech.)		-0.063			
		(0.055)			
After Competitor Failure News (Same Market, Same Tech.)		0.414**			
		(0.077)			
After Competitor Failure News (Different Market, Same Tech.)		0.106*			
		(0.045)			
Nb. Competitor Failure Events (Same Market, Different Tech.)			0.002		
			(0.004)		
Nb. Competitor Failure Events (Same Market, Same Tech.)			0.154**		
			(0.039)		
Nb. Competitor Failure Events (Different Market, Same Tech.)			0.027**		
			(0.009)		
Within 2qtrs Since Competitor Failure News (Same Market, Different Tech.)				-0.037	-0.026
				(0.045)	(0.052)
Within 2qtrs Since Competitor Failure News (Same Market, Same Tech.)				0.677**	0.599**
				(0.098)	(0.126)
Within 2qtrs Since Competitor Failure News (Different Market, Same Tech.)				0.181**	0.180**
				(0.050)	(0.065)
3qtrs Prior to Competitor Failure News (Same Market, Different Tech.)					-0.062
					(0.051)
3qtrs Prior to Competitor Failure News (Same Market, Same Tech.)					0.064
					(0.146)
3qtrs Prior to Competitor Failure News (Different Market, Same Tech.)					-0.002
					(0.069)
Nb. Drug-Indications	10,637	10,637	10,637	10,637	10,637
Nb. of Observations	213,206	213,206	213,206	213,206	213,206
Log Likelihood	-10,525	-10,500	-10,511	-10,493	-8,020

Note: Estimates stem from Cox proportional hazard model specifications. All models include a full set of year indicator variables. The competitor failure news variables (treatment groups) in model 1 and 2 are all absorbing states, such that the indicator variable is equal to one starting with the first quarter where a competitor in the given category has disclosed discontinuation, and remains one until the end of that project's phase II data. In model 3, the intensity of competitor news may vary by the count of competitor failures experienced by the focal project as of a given quarter. Model 4 is the preferred specification, where the competitor failure news variables are indicators variables that take on the value of one when the focal project is within two financial quarters since the given type of competitor failure event. Coefficients may be interpreted as an increase in the log hazard rate. Standard errors in parentheses.† $p < 0.10$, * $p < 0.05$, ** $p < 0.01$

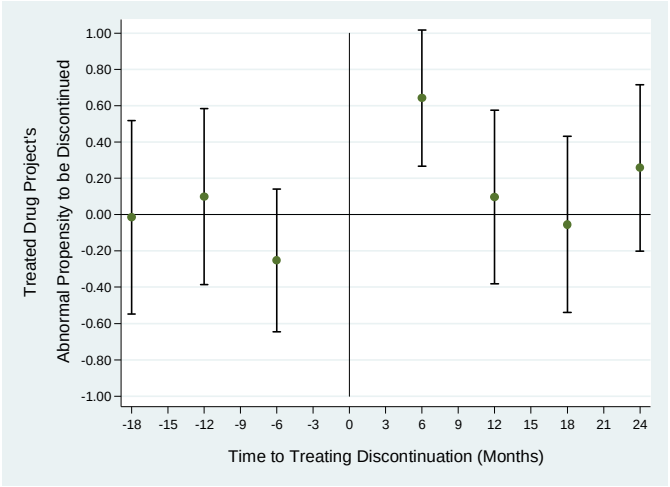
Figure 3: Competitor Failure News and Propensity to Exit



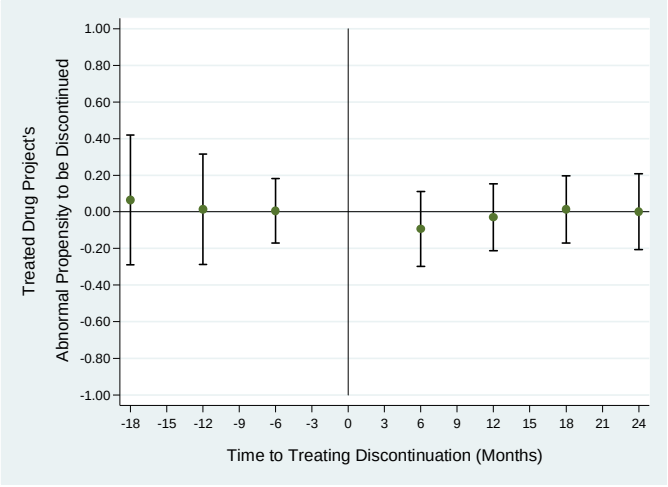
Note: The bars display the coefficients of interest from the main Cox proportional hazard model specification, which stratifies the sample by market and contains indicator variable for calendar time, and contains 215,142 project-quarter observations (discontinued projects are censored out after exit). The magnitude of each bar represent the change in hazard rate of project exit when a focal project is within a two quarter window after a competitor failure. The left bar displays this coefficient for same market, different technology competitor discontinuations, the middle bar shows the same market, same technology coefficient, and the right bar represents the different market, same technology effect. The red bars cover the 95% confidence intervals for each regression coefficient

Figure 4: Dynamics of Response to Competitor Failure

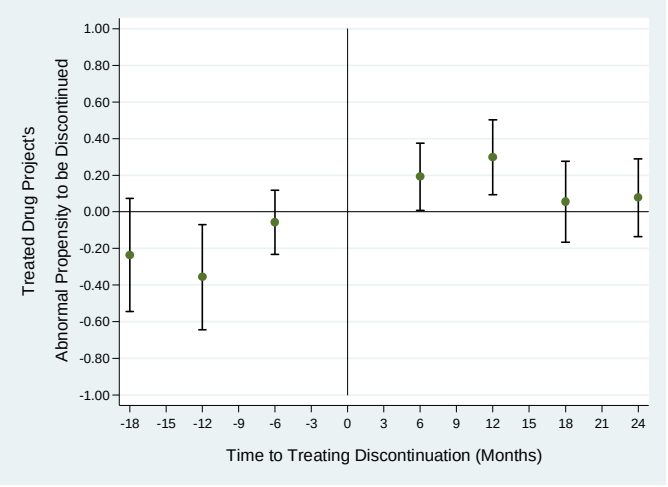
A. Same Market, Same Technology



B. Same Market, Different Technology

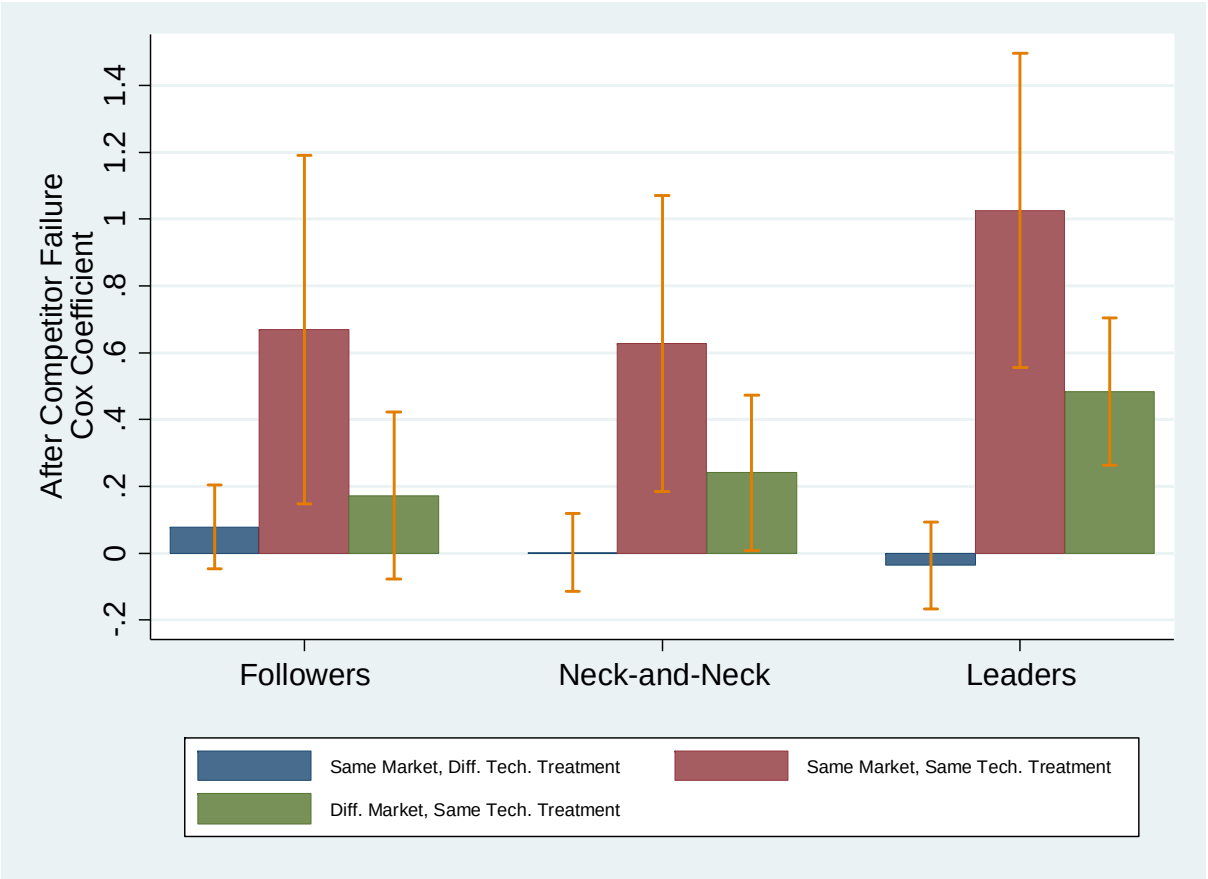


C. Different Market, Same Technology



Note: The green dots in the above plot correspond to coefficient estimates stemming from the cox proportional hazard model, where the variable for treatment status is interacted with the time (in six month increments) until the first competitor failure event (of each type). The six months prior to the first competitor termination event is the omitted variable. The 95% confidence intervals (corresponding to robust standard errors) are plotted with the help of capped spikes.

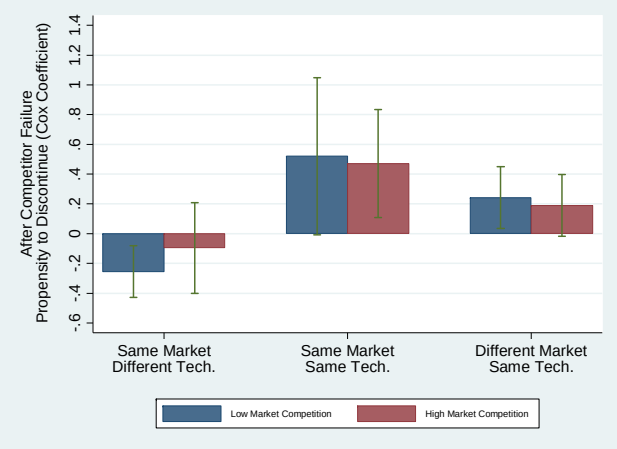
Figure 5: Entry Order and Response to Competitor Failure



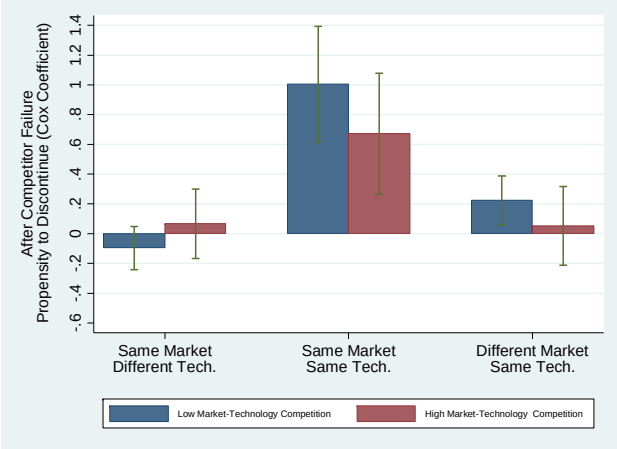
Note: The bars display the coefficients of interest from the main Cox proportional hazard model specification, which contains 215,142 project-quarter observations (discontinued projects are censored out after exit). Here, the coefficients of interest are the absorbing state of post-competitor failure news (as opposed the to the within two quarter window that may turn on and off). To capture the projects entry position relative to the first failed competitor (of each type), the regression includes interaction terms for each treatment effect type with the focal (treated) firm′s phase II entry position relative to their first treating project (follower, neck-and-neck, leader), and stratifies the baseline hazard by overall treatment groups (e.g. ever treated by same market, same technology) as well as therapeutic market. The orange lines cover the 95% confidence intervals for each regression coefficient.

Figure 6: Level of Competition and Response to Competitor Failure

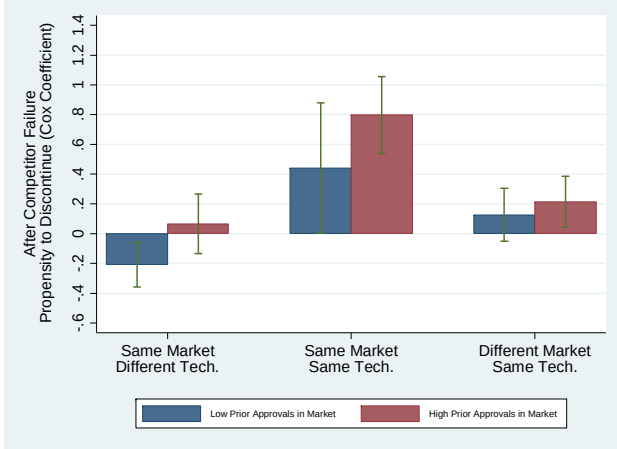
A. Level of Market Competition (in Development)



B. Level of Market-Technology Competition (in Development)

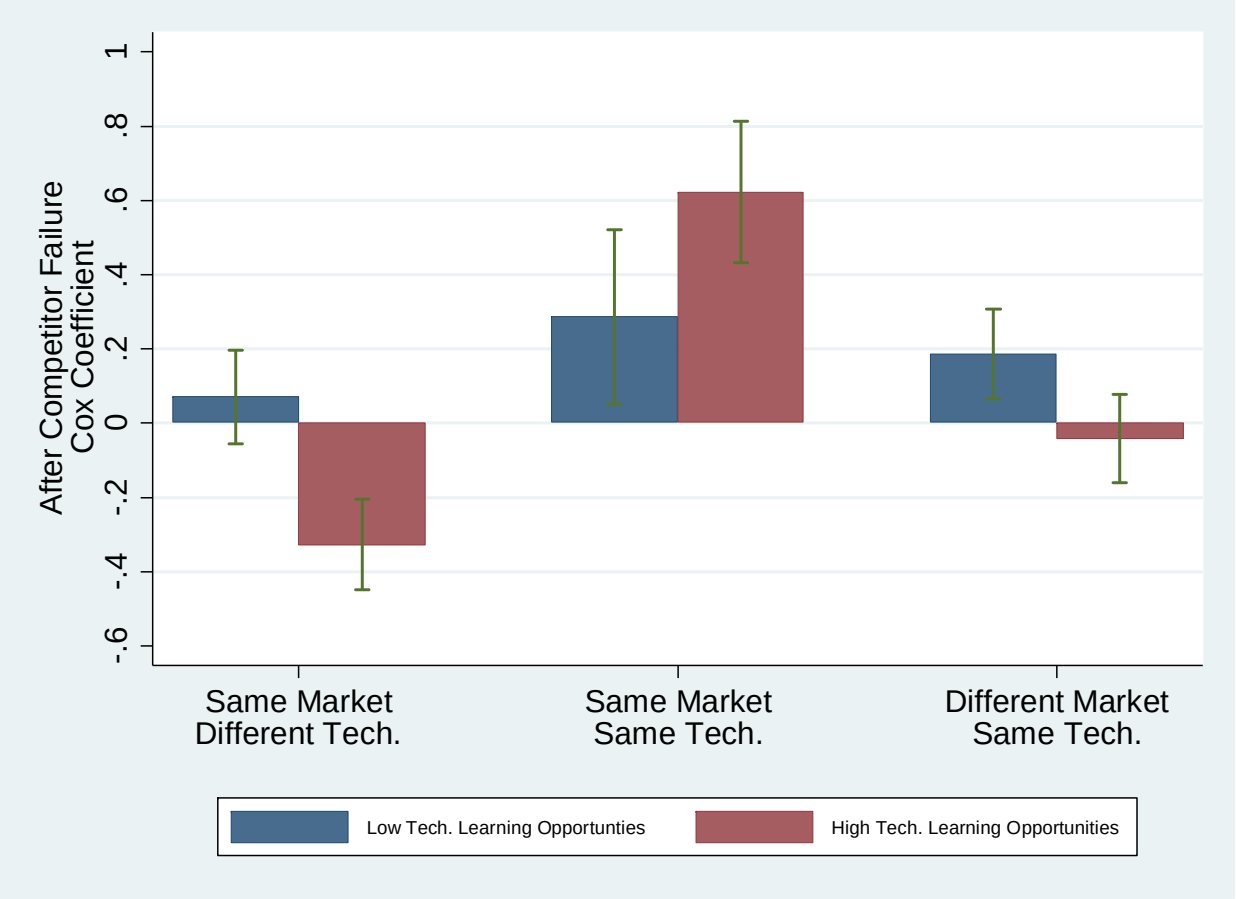


C. Level of Market Competition (Approved Drugs)



Note: The bars display the coefficients of interest from the main Cox proportional hazard model specification, split by bottom and top quartile of competition as defined in three different ways. In Panel A the level of competition is defined as the number of phase II development projects working on the same therapeutic indication. In Panel B, competition is the number of phase II development projects in the same therapeutic indication and same technology (target-action). In Panel C, the competition split is based off the number of previously approved drugs within the same therapeutic indication. The green lines cover the 95% confidence intervals for each regression coefficient.

Figure 7: Remaining Technological Learning Opportunities and Competitor Failure Response



Note: The bars display the coefficients of interest from the main Cox proportional hazard model specification, which contains 215,142 project-quarter observations (discontinued projects are censored out after exit). The magnitude of each bar represent the change in hazard rate of project exit when a focal project is within a two quarter window after a competitor failure. To capture the amount of remaining learning opportunities, the regression includes interaction terms for each treatment effect type with and indicator variable that takes on the value of one when the focal project has more than two remaining same technology competitors. The green lines cover the 95% confidence intervals for each regression coefficient

Table 4: Average Project Performance, by Technological Treatment Type (Logit)

	(1a) Graduation To Phase 3	(1b) Graduation To Phase 3	(1c) Graduation To Phase 3	(2a) Launched	(2b) Launched	(2c) Launched
Nb. Treatments (Same Mkt., Same Tech.)	-0.040	-0.004	-0.021	0.030	0.151†	0.168†
	(0.063)	(0.059)	(0.062)	(0.102)	(0.087)	(0.092)
Nb. Treatments (Different Mkt., Same Tech.)	-0.037**	-0.031**	-0.062**	-0.094**	-0.070**	-0.139**
	(0.012)	(0.012)	(0.013)	(0.026)	(0.025)	(0.034)
Predicted "Quality" (Prior)			0.464**			0.497**
			(0.066)			(0.093)
Predicted "Quality"—2nd Quartile		0.425**			0.557†	
		(0.114)			(0.298)	
Predicted "Quality"—3rd Quartile		0.764**			1.216**	
		(0.114)			(0.274)	
Predicted "Quality"—4th Quartile		0.880**			1.696**	
		(0.102)			(0.247)	
Predicted "Quality" Squared			-0.103**			-0.118**
			(0.029)			(0.039)
Predicted "Quality" Cubed			0.005			0.003
			(0.021)			(0.016)
Constant	-1.244**	-1.852**	-0.589**	-2.800**	-4.069**	-1.237**
	(0.119)	(0.142)	(0.148)	(0.211)	(0.309)	(0.235)
Nb. of Drug - Indications	10,375	10,375	7,888	10,366	10,366	7,881
Nb. Observations	10,375	10,375	7,888	10,366	10,366	7,881
Nb. Drugs	6,057	6,057	4,372	6,052	6,052	4,368
Nb. Indications	302	302	298	299	299	295

Note: Estimates stem from logistic regression specifications. The unit of analysis is drug-indication ("drug project"). The sample consists of the all drug projects that were ever treated by competitor failure news while in phase 2 development. Each model contains fixed effects for therapeutic areas (ATC2 codes), rather than specific indication fixed effects because the ATC2 codes are broader (some indications never had a drug approved). Predicted quality is assigned to each drug project based on the coefficients from a penalized logistic regression with a lasso penalty term, that predicts project success based on project characteristics (e.g. drug compound novelty) and historical development success rates within the indication, target, and indication-target, at the time that the drug project entered phase 2. These regressions include only drug projects which have an assigned drug target, and information about the drug compound's molecular structure. Treatment for competitor failures within the same market but different technology are excluded from this analysis, since 90% of observations are treated at least one time in this way, with a mean of 13.6 same-market, different technology competitor failure treatments. Due to this lack of variation, I focus this analysis on the two versions of same-technology competitor failure. Standard errors in parentheses. † $p < 0.10$, * $p < 0.05$, ** $p < 0.01$

Figure 8: Scoring Post-Treatment Decisions (Stylized Version)

	Remaining Tech. Competitors Leave	Remaining Tech. Competitors Stay-fail	Remaining Tech. Competitors Stay-Succeed
Leave	**N/A**	+	-
Stay-Fail	-	-	-
Stay-Succeed	+	+	+

Table 5: Decision Grading Descriptive Statistics

A. Sample Descriptive Statistics

	Count	Sum	Mean
Kill Project Within 2qtrs of Competitor News	35,545	1,141	0.03
Small Firm	35,194	7,293	0.21
Medium-size Firm	35,194	9,133	0.26
Big Firm	35,194	18,768	0.53
Novel Compound	35,545	23,425	0.66
Patent Expiration Window (1 year, pre/post)	35,545	11,719	0.33
Competitor Failure News from Same Tech, Same Market	35,545	3,658	0.10
Competitor Failure News from Same Tech, Diff. Market	35,545	34,236	0.96

B. "Leavers"	**Count**	**%**
Bad Decision	144	12.62
Neutral Decision	135	11.83
Good Decision	862	75.55
Total	**1,141**	**100**

C. "Stayers"	**Count**	**%**
Bad Decision	23,930	69.56
Neutral Decision	9,784	28.43
Good Decision	690	2.01
Total	**34,404**	**100**

Note: The decision grading analysis sample includes all "treatment events," where a phase two project experienced a *technology-related* competitor's project failure. I exclude events where the projects are only related by market because the main analyses revealed that these failure events do not lead to observable changes in competitor's project continuation. In total there are 35,545 instances where projects are "treated" by technological competitor's failure news. This set includes 2,346 unique drugs, 308 unique indications, 4,345 unique drug-indications, and 919 technology (target-action) areas.

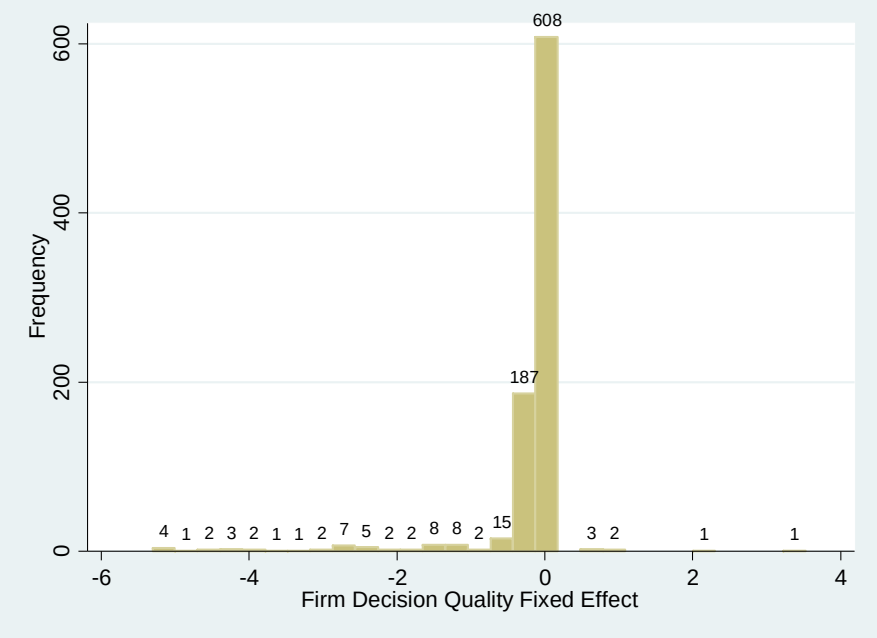
Table 6: Who Made the "Right Call"? Firm and Project Characteristics Correlations with Post-Treatment Decision Quality (Ordered Logit Regressions)

Dependent Variable: 1= "Bad Decision" 2= "Neutral Decision" 3= "Good Decision"	(1) Leavers	(2) Leavers	(3) Stayers	(4) Stayers	(5) Stayers Large Firms Only	(6) Stayers Large Firms Only
Log(# Patents Owned)	0.075†		-0.007		-0.144**	
	(0.045)		(0.008)		(0.032)	
Drug Compound Novelty	0.255	0.435	-0.127**	0.645**	0.518**	0.343*
	(0.165)	(0.368)	(0.029)	(0.147)	(0.103)	(0.162)
Approved Drug Patent Expiration Window	0.406†	1.977**	0.231**	-0.018	-0.167	0.056
	(0.222)	(0.442)	(0.035)	(0.130)	(0.121)	(0.146)
Concentration of Projects in Focal Market	-0.903	-0.998	0.221*	9.894**	2.184**	14.286**
	(0.849)	(2.355)	(0.104)	(1.105)	(0.461)	(1.571)
Concentration of Projects in Focal Technology	0.931*	9.824**	0.496**	-0.991	-0.663*	-1.030
	(0.394)	(2.950)	(0.077)	(0.810)	(0.335)	(1.179)
Homegrown Compound	-0.107	1.214**	-0.179**	1.767**	0.569**	1.235**
	(0.176)	(0.425)	(0.030)	(0.223)	(0.138)	(0.228)
Year Fixed Effects	✓	✓	✓	✓	✓	✓
Firm Fixed Effects		✓		✓		✓
Nb. of Drug - Indications	441	441	3,938	2,915	1,885	1,885
Nb. Observations	1,095	1,095	33,198	23,884	17,694	17,694
Nb. Drugs	298	298	2,137	1,709	1,072	1,072
Nb. Indications	125	125	301	272	226	226
Nb. Companies	158	158	981	837	269	269

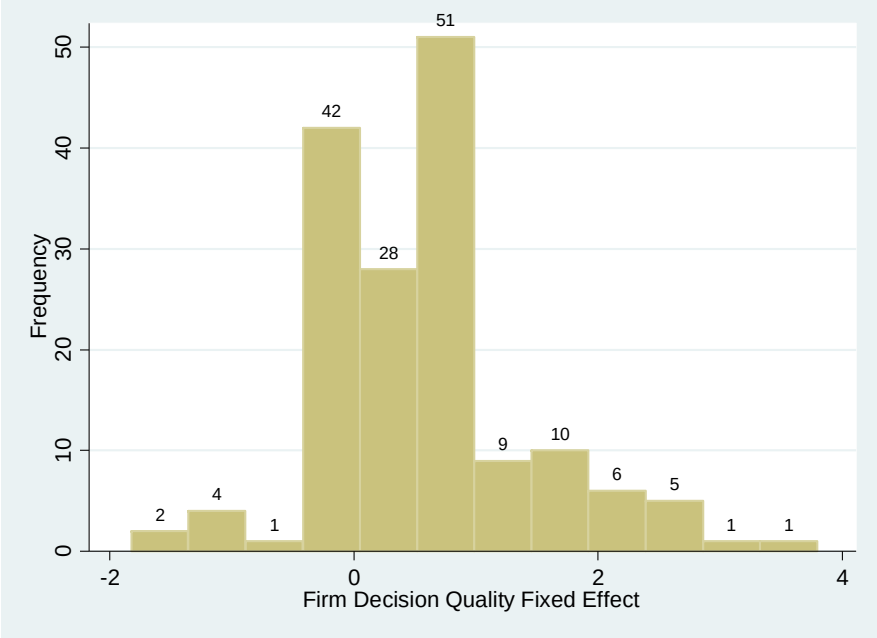
Note: Leavers are the cases where the project was terminated within two quarters of a competitor's failure within the same drug technology (target action). Within the leaver group, bad decisions (n=144) are when multiple firms with the same technology subsequently gain drug approval while none end up discontinued, or where the ratio of subsequent approvals to terminations is below the median. Leaver neutral decisions (n=135) are when the focal drugs discontinuation was followed by no subsequent technology competitor termination and less than two drug approvals. Leaver good decisions (n=862) are defined as the instances where there have been no subsequent drug approvals within the drug's technology area, and at least one other drug has been discontinued, or the overall ratio of subsequent approvals to failures is above the median. The stayer group is comprised of instances where a technology competitor failed and the focal drug project did not exit within two quarters of the competitor failure event. Bad decisions for the stayers (n=23,930) are when the drug project eventually went on to be officially discontinued. Stayer neutral decisions (n=9,784) consist of cases where the drug remains in development (either in active or inactive, but not officially terminated status). Good decisions for the stayers (n=690) are the instances where the project continued after technology competitor failure, and went on to win drug approval. Standard errors in parentheses. † $p < 0.10$, * $p < 0.05$, ** $p < 0.01$

Figure 9: Firm Decision-Making Performance

A. "Stay" Decision Quality

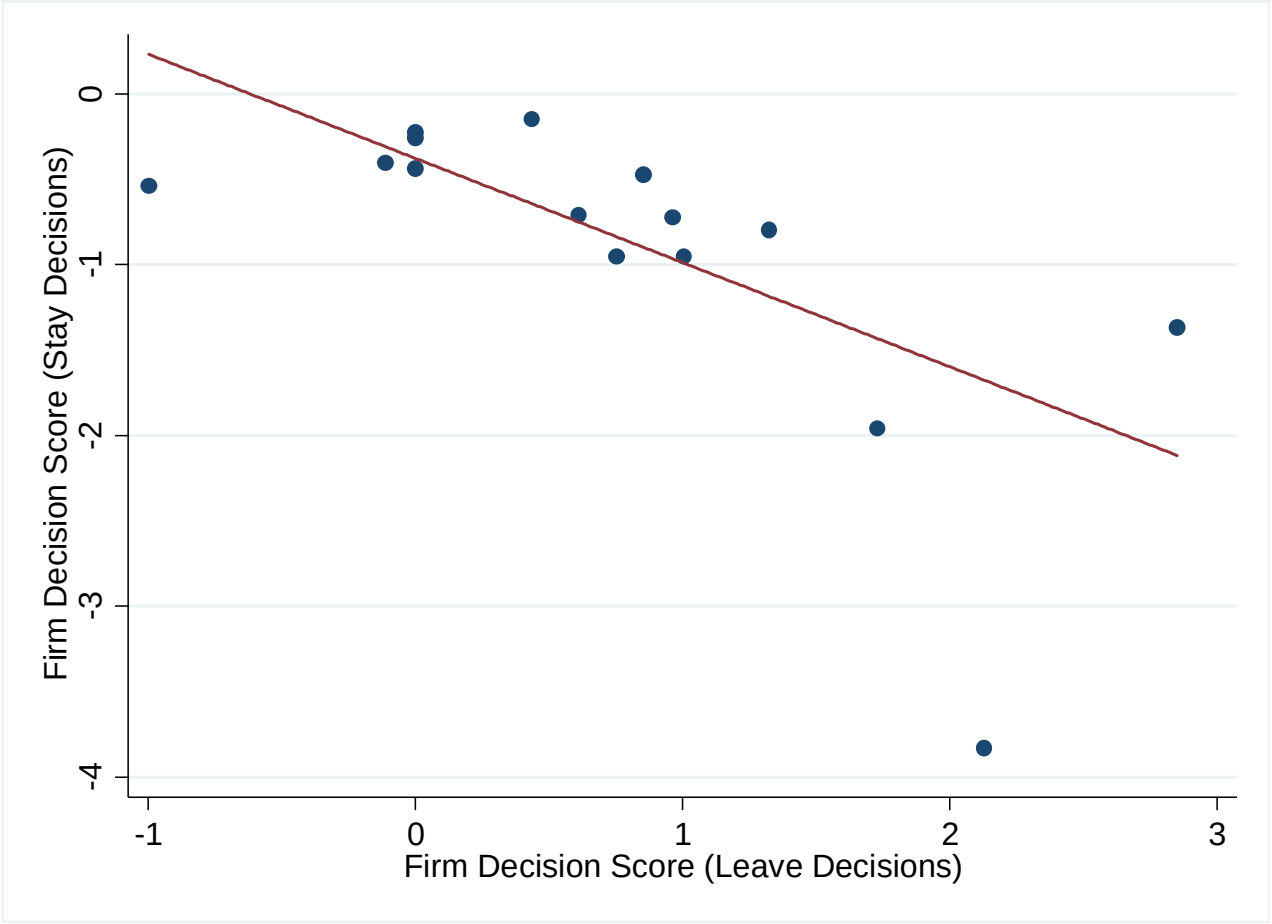


B. "Leave" Decision Quality



Note: Panels A and B display the distribution of the weighted decision-making firm fixed effects (after applying a Bayesian shrinkage estimator to control for signal-to-noise issues) for continuation and exit decisions, respectively. For clarity, each histogram bin is labeled with the number of fires represented in each score bin. The "stay" decision analysis involves more companies because many firms in the sample never choose to exit in the quarters immediately following a technological failure competitor news event.

Figure 10: Correlation between Stay and Leave Decision Scores (Binned Scatter Plot)



Note: The figure shows the average relationship between a firm's exit and continuation decisions, in equal sized bins of exit ("leave") decision scores. All decision scores are generated by estimating the fixed effects of ordered logit models for each type of decision (exit or continue) and then applying a Bayesian shrinkage estimator to control for signal-to-noise issues. The negative relationship displayed in the graph is statistically significant in a pairwise correlation test of the two decision scores.

Appendix A: Project Relatedness and Learning

The theoretical model evaluates how the value of project continuation changes after a competitor failure. If projects are technologically related, then a firm may update its belief about its own project after competitor failure news. The extent of this updating depends on the relatedness between the failed and focal projects. Here, I consider two different dimensions of relatedness: product market and technological distance.

I define w_{ij} as the true quality of a project using technology j for market i. The developer's initial belief about the prospects of succeeding with a given technology and market is $Pr[w_{ij} = 1] = p^0$. Failure signals may come from competitors in the same or different markets, and same or different technology areas. After a competitor failure, the developer updates its belief for a given project: $Pr[w^a_{11} = 1|w^b_{ij} = 0] = p$. The extent of this updating depends on the relatedness of projects in both market and technology space. The following table displays the potential values that p takes on depending on whether the failing project is in the same or different market (i, $-i$) and same or different technology (j,$-j$):

Indication=i tech=j	**Tech$_j$**	**Tech$_{-j}$**
Market$_i$	P_a	P_c
Market$_{-i}$	P_b	P^0

Failure signals from projects in a different market and different technology $(-i, -j)$ provide no useful information, so the posterior belief equals the prior, $p = p^0$. I impose the additional assumption that $p_c = p^0$. The intuition for this assumption is that two projects may be potential competitors in the product market, but if their underlying technologies are inherently different, then one's technical success (e.g. whether the method is possible) is independent of the other project's technical failure. While a signal from a different technology provides no additional information about the likelihood of success, signals from a same technology competitor may be informative, with varying informational value depending on whether the signal is from the same market as the focal project. The posterior belief after a same market and same technology failure event (p_a) and after a different market, same technology failure event (p_b), are both strictly smaller than the prior, p^0. However, the relative magnitudes of p_a and p_b depend on whether the technology has market-specific characteristics that influence the value of the failure news. For example, a drug with the biological target T may be very effective in inhibiting T, but cause major side effects. If inhibiting T is believed to be a useful approach to treating both a deadly disease (e.g. late stage colon cancer) and a non life-threatening condition (e.g. age-related macular degeneration), then the standards for for balancing safety and efficacy might be different, and the particular risks may diverge based on the nature of each problem. Here, the impact of same technology competitor failure news on own project continuation may or may not depend on market-specific factors.

The theory section in the main text of the paper provides an example for the valuing a project with the prospect of competitor learning. Equation (2) denotes p^- and p^+ as the updated beliefs, depending on whether the focal project experienced competitor failure news. The different values of p specified in the table above are essentially different options for the value of p^- following a competitor failure and depending on the relatedness of projects across the two key dimensions. An analogous table could provide the hypothetical updating values following no competitor news that one would substitute for p^+ in the valuation equation. Furthermore, a more complicated version of the model might treat competitors q are a vector with components $\{q_{i,j}, q_{i,-j}, q_{-}i, j\}$. In such an extension, the values of p^+ would depend on the distribution of competitor projects across the different types of competitor groups. For example, if no competitors shared the same technology ($q_{ij} = 0$) as a focal project, then the firm cannot infer anything about the project's probability of success if no competitor failures occur. In that case, $p^+ = p$.

Appendix B: Drug Similarity Data

Drug Similarity

While shared target-actions serve as my primary measure of technological similarity, some of my analyses also evaluate technological similarity and innovation novelty by using chemical informatics information. For roughly 20% of the drug records in the Cortellis database, we have detailed information on chemical structures.

Pairwise chemical similarity measures are quantitative measures for comparing the structural elements of compounds. Chemists and drug developers often uses drug similarity to predict chemical properties and to screen and compare drug candidates. Chemical structures may be represented graphically, or through standardized identification systems such as the simplified molecular-input line-entry system (SMILES) or the International Chemical Identifier (InChI) system. Basic chemical similarity calculations take a pair of these chemical structures as inputs, breaks them down in to their component fragments (known as the chemical "fingerprint"), and calculates the Jaccard coefficient (a.k.a "Tanimoto distance") between the two sets of fragments:[i]

$$J(A,B) = \frac{|A \cap B|}{|A \cup B|} = \frac{|A \cap B|}{|A| + |B| - |A \cap B|}$$

In practice, I took the full set of SMILES codes associated with Cortellis drugs and used the open source ChemmineR package[ii], to calculate all pairwise chemical similarity scores (where similarity score is greater than or equal to .1) for all drugs. I further calculate chemical "novelty" by using the similarity score of a focal drug to all previously developed drugs. Krieger, Li and Papanikolaou (2016) details the development of these novelty measures and summarizes the data.

[i] As a concrete example, chemical similarity can reveal that within the drug "class" of proton-pump inhibitors, Nexium is a direct copycat of the first-in-class Prilosec (similarity=0.94), while Prevacid is chemically quite different from Prilosec (similarity=0.39). Nexium is often mentioned as an example of a pure "me-too" drug, since AstraZeneca, developer of Prilosec, also patented, developed and marketed Nexium as a new drug, which effectively extended the patent life of the earlier innovation.

[ii] Full documentation: https://www.bioconductor.org/packages/release/bioc/vignettes/ChemmineR/inst/doc/ChemmineR.html

Appendix C: Disclosure of Discontinuation

Drug development firms disclose the discontinuation of a development project though different announcement mechanisms. The decision to shut down a project is often reported in a company press release (especially when the company is public and the discontinuation news may be considered material to the company's market valuation), in updated drug development pipeline documents (usually posted on the firm's website), and in financial filings. Cortellis for Competitive Intelligence tracks these disclosures and links them to drug development projects (drug-indications). To illustrate how these disclosures appear, I include two representative examples below.

It is common for firms to disclose that they are shuttering a drug development project via press release. For example, Evolutec Group announced it would discontinue development of their drug Votucalis on January 3, 2007. Evolutec had been developing the compound to treat conjunctivitis, lacrimal gland disease and ocular inflammation. The drug had entered phase II clinical trials in December 2003. At the time of discontinuation, they put out a press release:

> *Evolutec Group plc (AIM: EVC), the biopharmaceutical company developing novel products for the treatment of allergic, inflammatory and autoimmune diseases, announces that rEV131 did not meet its primary endpoint in the Phase II post-cataract inflammation trial.*
>
> *In the trial, rEV131, dosed twice-a-day, was compared to prednisolone, the standard of care, dosed four times-a-day, and placebo. The primary endpoint was inflammation 14 days after cataract surgery. There were no significant differences between rEV131 and placebo whereas prednisolone performed as anticipated.*
>
> *Evolutec will announce its preliminary results for 2006 on 27 February 2007 and expects to report cash and held-to-maturity investments as at 31 December 2006 of STG8.7 million. Mark Carnegie Brown, Chief Executive of Evolutec, said: "Following this disappointment, no more investment will be made by Evolutec in rEV131. Whilst we continue to explore partnering opportunities with rEV576, all strategic options to realise value for shareholders are under consideration. rEV576 has demonstrated exciting preclinical results in myasthenia gravis and Guillain-Barr Syndrome where there are currently no curative therapies."*
>
> *About Evolutec*
>
> *Evolutec, which is based in Reading, UK, is a clinical stage biopharmaceutical company with a focus on allergy, inflammation and auto-immune diseases.*
>
> *rEV576, the Company's second product development candidate is a complement inhibitor which has demonstrated preclinical activity against the autoimmune diseases myasthenia gravis and Guillain-Barr Syndrome, asthma and acute myocardial infarction ("AMI") (heart attack). Evolutec has established a research collaboration with Case Western Reserve University, Cleveland, Ohio, to undertake further preclinical work with rEV576 in myasthenia gravis. The Company expects to commence clinical trials with rEV576 in 2007.*
>
> *The rights to Evolutec's vaccine technology for animals are partnered with Merial. Merial is currently undertaking work in tick-borne diseases.*
>
> *Evolutec is listed on the AIM market of the London Stock Exchange and develops therapeutics originally isolated from the saliva of ticks. The tick remains undetected by its hosts, including humans, by injecting an array of molecules into the skin that suppresses host immunity. These stealth molecules have undergone millions of years of natural evolution to select a promising efficacy, potency and safety profile. Evolutec employs the tick's evolutionary stealth technology to offer the potential of treating human diseases.*

While some discontinuation disclosures are quite specific about the reasons for failure (like the above), others are more vague about the rationale for stoppage. In November 2010, QLT Inc. discontinued its development of compound QLT091568 for flaucoma and ocular hypertension. The drug had entered phase II trials in September 2008, but November 3, 2010, the company mentioned in its Q3 earnings announcement that development would halt, stating simply:

> *The Company has discontinued development of QLT091568, a prodrug of a beta adrenergic antagonist (a novel beta blocker), that was under investigation for its potential ability to lower intra-ocular pressure in glaucoma and ocular hypertension patients.*

Appendix D: Alternative Econometric Specifications

In this appendix, I describe the alternative econometric specifications employed to estimate the effect of competitor news on project exit decisions. In the main results, I present a survival model difference-in-differences approach to measuring firms' response to competitor project discontinuation news on a panel of development project-quarters. I favor this survival model framework because it accounts for the natural death rate of projects as they move through their development time line, and allows me to control for different life cycles across therapeutic areas. Some of these same analysis qualities can be applied through alternative regression specifications involving the same panel data, or a dyadic data structure. Below I describe three of these alternative specifications. First, an ordinary least squares (OLS) approach using the same project-level panel data described in the main body of the paper. Next, I describe the alternative dyadic data structure, and how I apply both hazard and OLS models to this data to estimate the average response to each type of competitor exit news. In summary, all the regressions point to the same qualitative patterns of firm response to each type of competitor project discontinuations. These results provide important robustness checks on the main survival model, and ensure that the paper's main findings are not artifacts of the analysis data structure or regression model choice.

OLS with Project-Level Panel

This specification uses the same drug-indication-quarter panel as the survival model specifications in the main body of the paper. The outcome variable is an indicator variable for whether or not the focal drug-indication ("project") i was discontinued in quarter t. Unlike the hazard model, which censors drugs out of the analysis sample after their discontinuation, I keep all projects in the analysis sample for their entire time in phase II (up to 32 quarters). To avoid right-censoring, I drop projects that had neither reached 32 quarters, exited, or graduated to phase III as of the end of 2014. While the hazard models contain a baseline hazard rate, h_0, in the OLS version, I control for natural death rates through time using indicator variables for each value of phase II age (quarters since entered phase II) as an independent variable. As with the hazard models, I include time (financial quarter) fixed effects and control for therapeutic area (market), k, and define "treatment" groups based on relationship to competitors' discontinued projects both in terms of market (k) and drug target-action (q). The resulting regression equation is as follows:

$$\begin{aligned} DISCONTINUED_{ikt} = \beta_0 &+ \beta_1(SAME\ MKT,\ DIFF\ TECH\ NEWS)_{k,-q,t} \\ &+ \beta_2(SAME\ MKT,\ SAME\ TECH\ NEWS)_{k,q,t} \\ &+ \beta_3(DIFF\ MKT,\ SAME\ TECH\ NEWS)_{-k,q,t} \\ &+ f(AGE_{ikt}) + \gamma_t + \delta_k + \epsilon \end{aligned}$$

As with the main hazard model specifications the different treatment groups can be defined as absorbing states ("turned on" after the first competitor project of a given type discloses an exit), counts of the associated event type, or as "treatment" windows ("turning on and off" depending on proximity in time to the competitor exit news).

At a high level, the results are qualitatively the same as the hazard model specifications: *same market, same technology* news leads to the biggest change in propensity to exit, *same market, different technology* news leads to a small and possibly negative impact on exit rates, and *different market, same technology* leads to a modest increase in pulling the plug. Column 3 in Table D1 reports the coefficients corresponding to $beta_1$, $beta_2$, and $beta_3$ in the two-period (before and after competitor news), absorbing state treatment version equation above.

Interacting the absorbing state "treatment" version with the time until first discontinuation news (of each type) provides the difference-in-differences event study graph that is comparable to Figure 4 in the main body of the paper. The one key difference in interpreting the OLS version instead of the hazard model version is that the "treatment effect" is cumulative in the OLS version. An positive coefficient the OLS model event study means that the probability of a project being discontinued in t quarters since treatment is higher than the probability of a same age and same indication untreated project being discontinued in that same time period; though the divergence in their exit rates may have occurred at an earlier point in time (e.g. $t-1$). The hazard model version, however only captures changes in relative propensity to exit for the given period t. Appendix D, Figure 2 shows the results of this OLS event study regression.

Unlike the survival model event studies, the OLS versions have slight pre-trends in the *same market, same technology* and *same market, different technology* groups. In the former, the pre-period has a slightly positive trend at the time until competitor discontinuation approaches zero. However the pre-period coefficients are not significantly different from one another and their slight upward trend is dwarfed in magnitude by the large increase post-competitor news. The *same market, different technology* has a small negative pre-trend, but its coefficients are also not significantly different from one another. The overall shape of this group's event study is hard to interpret with the pre-trend, combined with the small negative coefficient directly following competitor news and the gradual increase until the coefficients are positive five quarters after competitor news. But with precisely estimated coefficients (due to the high frequency of these types of events) and the relatively small (near zero) coefficients, I can rule out any any economically meaningful response to *same market, different technology* in this specification.

Dyadic Data Construction

An alternative way to evaluate the impact of competitor exit on project continuation decisions to analyze each event in project pairs. Under this approach, an unit of observation includes the relevant exiting drug-indication project i ("treating," or signal "sender"), a project j that experiences the discontinuation news as a market or technology competitor ("treated," or signal "receiver"), and the time period t (financial quarter). Within each dyad's panel data, their may be only one "treating" event, and the "treating" project must exit prior to the "treated" project's exit (if applicable). The resulting data set has 11,017,691 observations with 151,840 treating-treated pairs.

The advantage of the dyadic approach is that it captures the pairwise relationship between those sending and receiving the project exit news. For example, the data structure allows for the creation control variables such as the amount of time elapsed in between the two projects phase II start date, indicator variables for the "treating" project or firm, and distance measures at the firm

level (e.g. how often the pair of firms competes/collaborates with one another). These pairwise variables go away in the single-level data (drug-market level panel).[iii]

The disadvantages of the dyadic data are that each panel does not include the relevant discontinuation news outside of the focal pair, and some project-quarter observations are overrepresented in the analysis sample if that project experienced many rival failures. This duplication also increases the overall number of observations and shrinks the standard errors, which is perhaps, misleading. Limiting the dyadic data to pairs where the "treating" project i is the first competitor news event of its kind for "treated" project j creates a sample equivalent to the absorbing state version of the single-level analysis data, where the only competitor news events that matter are the first ones.

Dyadic OLS

The baseline OLS specification is

$$\begin{aligned} DISCONTINUED_{ijkt} = \alpha_0 &+ \alpha_1(SAME\ MKT,\ DIFF\ TECH\ NEWS)_{k,-q,t} \\ &+ \alpha_2(SAME\ MKT,\ SAME\ TECH\ NEWS)_{k,q,t} \\ &+ \alpha_3(DIFF\ MKT,\ SAME\ TECH\ NEWS)_{-k,q,t} \\ &+ f(AGE_{jkt}) + g(EntryLag_{ij}) + \gamma_t + \delta_k + \theta_{ik} + \epsilon \end{aligned}$$

The regression results corresponding to the equation above are reported in Table D1, Column 1. Again, we see the largest effect corresponds to the *same market, same technology* news, with a smaller increase (about one half the magnitude) associated with *different market, same technology* news. The major divergence from the single-level data set results is that the *same market, different technology* coefficient is positive and significant, though smaller than the coefficients from the other two groups.

Figure D2 shows the dynamic event study version of these results, splitting each coefficient out by number of quarters before and after the competitor news event. The overall patterns are similar to the single-level OLS dynamics (Figure D1), with the exception of the *same market, different technology* group. For this group, the coefficients are very precisely estimated due to the large number of observations in this specification. However, one can see an upward linear trend beginning in the pre-period and continuing through the quarters after competitor failure news. While I do not have a clear explanation for this subtle trend, it implies that one should put less weight on the positive coefficient for *same market, different technology* that I find in the two period model.

[iii] For example, in the comparison of follower, neck-in-neck and leader projects' responses to competitor news (Figure 5 in the main body of the paper), I define firms' relative entry positions based on their first competitors news event in each category. Characterizing each treatment event by the entry timing of the firms involved is straightforward in the dyadic data. However, in the single-level data these characterizations are trickier: multiple competitors may exit in the same period, and their entry relative to any one competitor project (follower, neck-in-neck, or leader) may be different for each project. As such, I simplify by relying on the first competitor exit event to characterizing a "treated" projects relative position.

Dyadic Hazard Models

The last version of the alternative regression specifications applies the cox proportional hazard model to the dyadic data. As in the main specification in the paper, I stratify the baseline hazard by therapeutic indication (market) and evaluate each type of competitor news' impact on the hazard rate of project discontinuation. As in the dyadic OLS specification, I add in control variables for the "treating" project ik and the time elapsed between the "treating" and "treated" project's entries into phase II development:

$$\begin{aligned} h_{i,j,k}(t,X) = h_{0k} \times exp[&\alpha_1(SAME\ MKT,\ DIFF\ TECH\ NEWS)_{k,-q,t} \\ &+\alpha_2(SAME\ MKT,\ SAME\ TECH\ NEWS)_{k,q,t} \\ &+\alpha_3(DIFF\ MKT,\ SAME\ TECH\ NEWS)_{-k,q,t} \\ &+g(EntryLag_{ij}) + \gamma_t + \theta_{ik}] \end{aligned}$$

Table D1, column 2 reports the results of the two-period version of this model. The results are in-line with the dyadic OLS results, except that the *same market, different technology* coefficient is only marginally significant (at the 10% level), and smaller in magnitude relative to the other two coefficients of interest. The event study version, depicted in Figure D2, shows large spikes in the hazard rate of own project discontinuation in the first quarter after the competitor exit for both the *same market, same technology* and *different market, same technology* groups. The *same market, different technology* coefficients are mainly flat, with a small increase right immediately following the competitor news, but are all not significantly different from zero.

Appendix E: Additional Analyses on The Impact of Failure News

Portfolio Characteristics. Organizational characteristics might also influence the response to competitor failure news. Drug developers can be characterized along numerous dimensions, but here I focus on factors that are likely to alter a firm's opportunity cost for continuing a given project, or moderate the firm's ability to accurately interpret and apply competitor failure signals.

One of the attractive features the analyzing drug pipeline data is the ability to assess a firm's entire portfolio of project investments. One might characterize these portfolios along a number of different dimensions, or combine different measures to create a portfolio score or desperation index (Higgins & Rodriguez, 2006). Rather than applying all types of portfolio measures to the companies in my analysis data set, I focus on two characteristics that are particularly relevant to firm agility, commitments and expertise. First, I evaluate how firms' overall concentration of projects, by market or technology, influences their continuation decisions following competitor news. Second, I test how firm experience in a given market or technology area impacts response to competitor failure news. Though a firm's level of portfolio diversity and expertise reflect strategic choices regarding organizational structure and value creation, these choices may also have systematic impact on a firm's agility and decision-making quality.

I measure portfolio concentration using a simple Herfindahl index of projects by company-quarter. Snapshots of different portfolios in time help to illustrate the variation in firm concentrations and commitments. On one extreme, the data includes small biotechnology firms like Discovery Genomics, who in 2003 had two active development projects for a blood disease (Hemophilia B) using two different targets. This portfolio yields a market Herfindahl index of 1, and technology Herfindahl index of 0.5. In contrast, Schering-Plough had a large and diverse set of over 100 active pipeline projects in 2000, resulting in a market index of 0.01 and a technology index of 0.02. Since small firms like Discovery Genomics do not have enough development drugs to allow for much variation in market and technological concentration, I limited the analysis to firms with more than 10 development projects.

On average, firms with higher market or technology portfolio concentrations are less likely to terminate their phase II projects (Figure E1B and E1C). Some of this difference between low and high portfolio concentrations is due to the mechanical relationship between firm size and portfolio characteristics. However, this propensity to move forward with development may also reflect higher levels of commitment to a particular therapeutic mission, sales channels, collaborations or scientific hypothesis. Since the relationship of interest is how competitor news alters project continuation decisions, I control for the different groups' baseline hazard rates of project exit by splitting the sample into low and high concentration firms using a median cutoff, and run the main specification on each group.

The results are displayed in Figure E5. The results for each group are quite similar to the overall average effects with one exception. For both the market and technology definitions of portfolio concentration, the low project concentration group exhibited no significant project updating following a *different market, same technology* competitor failure, with effect magnitudes right around zero. Meanwhile, the estimates for the high concentration groups indicate that following *different market, same technology*, their propensity to terminate their own project increased 27% for the high market concentration group and 52% for the high technology concentration group.

Since the *same market, same technology* coefficients did not differ by portfolio concentration groups, the no-response result for *different market, same technology* and low portfolio concentrations points to inattention as an explanation. One would typically imagine that firms highly committed to a particular technological area would be more hesitant to move away from that area due to structural factors like economies of scale, marketing advantages, and expertise, as well as behavioral biases like the sunk cost fallacy and optimism bias (Kahneman & Tversky, 1979; Sharot, 2011). However, the results imply that these focused firms are more likely to act on this type of competitor information, while the more diverse firms do not deem the news actionable. The most intuitive explanation for this difference is that focused firms monitor their technological rivals more studiously, since they have so much at stake in their main technology areas. Another explanation is that firms with less project concentration prefer to maintain diversified portfolios and do not mind fluctuations in the risk of any one part of their portfolio. Under this perspective, a focused firm cannot afford to see large (correlated) portions of its portfolio go down together, while the diversified firm can absorb new risk that is isolated from their other bets.

Exploring Treatment Intensity and Potential Cascading. The history of competitor failure within a particular market or technology area could potentially amplify or moderate the reaction to project discontinuation. In order to understand how the sequencing of failure events impacts the response to competitor failure, I used two separate subsample analyses. In the first, I address how firms response to the first competitor failure (of each type) that they experience while in phase II, as compared to subsequent failure events. Second, I separate cases of lone project failures ("singletons") from those where multiple projects within a given market and/or technological area exit within a short window of time ("clusters"). The goal of these analyses is to evaluate whether multiple signals catalyze information cascades and produce competitor responses that differ from the average effects summarized above.

To compare initial to subsequent treatment events, I interact the treatment variables from the preferred specification (two quarter window since the given type of competitor failure news) with indicator variables for whether the particular competitor failure window was the first of its kind experienced by the focal project. The results from this regression are reported in Figure E4A. The magnitude of each treatment effect is quite similar and not statistically distinguishable between first and subsequent treatments.

In the second analysis, I compare instances where a cluster of competitors abandon their project in a short period of time, to cases where the failure signal is from a sole competitor project. The intuition behind this analysis is that multiple failure events might represent a stronger or more salient signal to the remaining projects, and some exit decisions are influenced by watching other firm's responses to an initial event (e.g. "if they think it's bad news, then we should too"). The results (displayed in Appendix E, Figure E4B) show some differences between the two scenarios. Most notably, the *different market, same technology* coefficient for the clustered failure treatment scenario is relatively large (0.31) and statistically significant from zero ($p < 0.01$), and significantly larger than its solo treatment coefficient counterpart ($p < 0.05$). The magnitude of the solo *same market, same technology* coefficient appears larger than the clustered treatment version, however they are not statistically different since the rarity of the clustered *same market, same technology* treatments results in a very noisy estimate.

Within-Firm Expertise. While my analysis of portfolio diversity utilizes cross-sectional variation in firm focus (see Portfolio Characteristics above), my approach to firm expertise leverages within-

firm development histories to separate firms and their ability to interpret and act on competitor failure news. Here, I define expertise based on the number of total projects developed by the firm in the relevant technology space. The measure is related to portfolio concentration, because in general, one would expect highly concentrated firms to build more expertise in their chosen focus areas. However, portfolio focus might shift over time. For example, a firm might decide to move their cancer R&D efforts towards certain gene therapy technologies. But if the firm has lots of prior experience in other therapeutic approaches (e.g. hormone therapies or stem cell replacement), they might maintain some projects in those alternative areas and retain expertise.

To measure how experience in a particular technological area influences the response to competitor failure news, I split the sample into companies that were above and below the median of project experience (3 prior drugs developed) within the focal technology area at the time of competitor discontinuation news. The results are displayed in Figure E5. Here, we see that the response to *same market, different technology* and *same market, same technology* news is fairly similar for both groups. The response to *different market, same technology* news is quite different across levels of experience. The high experience group accounts for all the increased propensity to discontinue following *different market, same technology* competitor discontinuations, while the low experience group does not respond to this type of competitor news, on average. Again, inattention is a possible explanation if the low experience firms are less knowledgeable, or are not as tied to the network of scientists and doctors working in these target areas. Another interpretation is that the low experience areas tend to be more novel therapeutic approaches, so developers put less stock in their (equally inexperienced) competitors' project failures.

Firm's Commitment to Focal Drug. Another project feature that might influence the firm's response to competitor failure news is the firm's level of commitment to that project. Firms may be more committed to a particular uncertain project for a number of reasons. For example, senior leadership may have particularly strong beliefs in a given idea, project investments may not be fungible, or the firm may promise investors completion of particular projects. Here, I evaluate how project commitment influences the response to competitor failure news by using variation in the number of therapeutic indications (diseases) for which the firm is developing the focal drug. In my analysis of competitor reactions, my unit of analysis is the drug-indication level. However, a firm may develop a single drug for more than one indication. By doing so, the firm is committing more resources and effort to develop that particular drug.[iv]

Figure E7 displays the results of this analysis. I divide treatment events into events where the focal project had one or less additional indications in development (low commitment), and projects where the firm was also developing the drug for two or more additional indications (high commitment). I find that the *same market, different technology* and *same market, same technology* news types have no statistically significant differences in average response to the failure news. However, the low commitment group has a significantly higher response than the high commitment group to *different market, same technology* news (p¡0.01). In fact, the low commitment groups result accounts for all of the positive response that I find in the average full sample response to this type of news. Taken together, these splits imply that commitment does not completely mitigate learning effects, but it does correlate with firms willingness to alter investments in response to *different market, same technology* news.

[iv] Economies of scale are possible when developing a drug for different conditions. For example, some preclinical testing of toxicity in animals might be applicable for multiple human indications.

Type of Failure and Signal Strength. In addition to market and technology categories, the nature of a failure signal may vary along other dimensions. Ideally, one would want to characterize each competitor failure event into detailed reasons for failure and strength of signal. In practice, such characterization is difficult due to both the volume of failure events, and the limited and heterogeneous information that firms provide about their discontinuation events. That said, one can use features of the informational content as proxies for different types of failure signals. I investigate two of these informational features that might provide meaningful proxies for the type of failure event.

First, I use actions involving a drug's other development projects as a surrogate for the type of failure. As described above, firms may develop a single drug for multiple therapeutic indications. Whether a firm discontinues the development of a drug for multiple indications or just a single indication may reveal (or correlate with) the reason for the discontinuation decisions. For example, in July 2013, AstraZeneca stopped development of the drug Pasireotide for the indication of meningioma, but continued developing the drug for other indications. In contrast, Pfizer halted all development of Figitumaumab for seven different conditions in February 2011 after it had trials terminated early for safety concerns. While the former example may have also had safety concerns, they would appear to be indication-specific concerns given that the firm continued development for the other diseases. Furthermore, if AstraZeneca stopped the meningioma project due to efficacy concerns, then the efficacy signal was not strong enough for the firm to cancel related projects.

To test whether the single vs. multiple indication discontinuation does indeed reveal information about the nature of a failure event, I use a sub-sample of 300 project discontinuations for which I could positively determine the reason for failure (due to reasons given for early terminated trials) and examined the correlation between their reasons for failure and multiple indications discontinuations. I found a statistically significant positive correlation between multiple indication discontinuations and safety reasons for failure, but no such correlation with efficacy or strategic reasons for project termination.

The results of this analysis are displayed in Figure E8. Though none of the differences between the single indication and multiple indication failure news variables are statistically different (within each competitor failure news type), the reaction magnitude is greater for the multiple indication failure group in each case. The biggest difference is in the *different market, same technology* failure news type, where the single failure group does not yield a coefficient significantly different from zero, but the multiple indication failure group has a significantly positive response. One can interpret these results as weak evidence to support the notion that some types of failure signals elicit stronger competitor reactions.

The second measure for failure type I investigate is the proximity in time between discontinuation announcements and the end of the drug project's last trial. This study's main identification strategy relies on the idea that discontinuation announcements are non-anticipated and are directly tied to project R&D results. One potential threat to these assumptions is if project discontinuations are actually just results of shocks that are common to all projects within a market or technology group.[v] Another threat to this empirical approach is if discontinuation announcements are com-

[v]For example, if an FDA issued a regulatory decision or issued guidance that equally increased the riskiness of all projects in that group.

pletely decoupled from R&D results, and reveal strategic concerns rather than information about the discontinued project's quality.

To address these concerns, I compare the response to discontinuations announced close (in time) to the end of the project's last clinical trial to projects discontinued more than one year following the last trial outcome. The motivating idea for this analysis is that decisions more closely tied to the end of a trial are less likely to be timed with a common and non-failure-related information shock to the market or technology. When I interact the main treatment specifications with whether or not the failure news was within a year or the last trial date, I find no statistically significant differences between the two groups (within each of the three competitor news types). My primary interpretation of this (null) result is that firms are indeed responding to competitor failure new rather than other types of information, because the reaction is so similar for both the trial-linked news (whose timing is unlikely to coincide with other news types) and decisions made further away from trial end dates. In theory, both types of discontinuation could be influenced by R&D results because sometimes it takes the firm a while to fully analyze and digest a trial's data, or the firm needs to run additional lab experiments before deciding whether to move forward with the project.

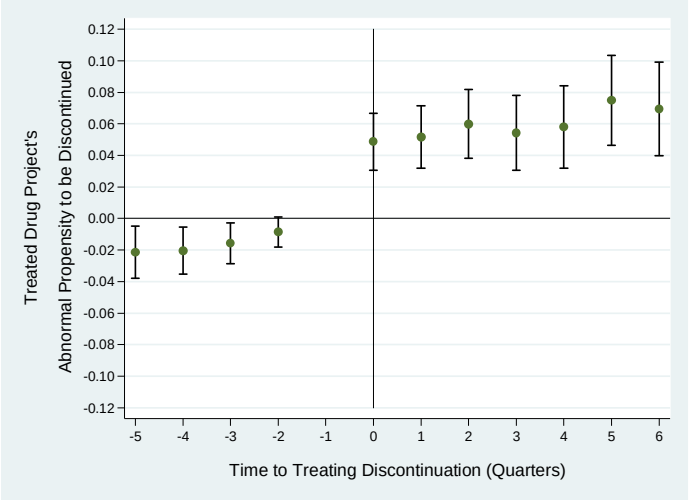
Table D1: Comparing Regression Specifications for Competitor News Effects

	(1)	(2)	(3)	(4)
	Dyadic OLS	Dyadic Cox	Single-Level OLS	Single-Level Cox
After Competitor Failure News (Same Market, Different Tech.)	0.041**	0.050†	-0.021**	-0.063
	(0.002)	(0.026)	(0.008)	(0.055)
After Competitor Failure News (Same Market, Same Tech.)	0.119**	0.531**	0.050**	0.414**
	(0.019)	(0.086)	(0.015)	(0.077)
After Competitor Failure News (Different Market, Same Tech.)	0.062**	0.228**	0.015†	0.106**
	(0.008)	(0.051)	(0.009)	(0.045)
Nb. Observations	5,069,504	7,725,658	223,249	215,142
Nb. Drug-Indications	8,436	11,145	8,217	10,637
Log-Likelihood		-1,313,324		-832,518

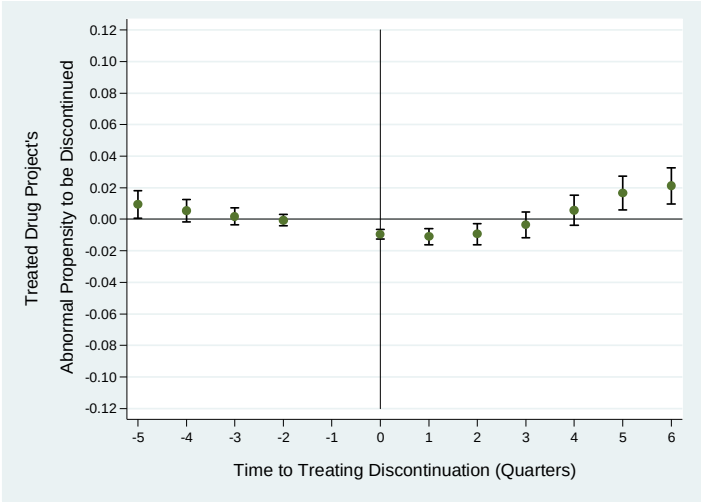
Note: Estimates in columns 1 and 3 stem from ordinary least squares regression specifications, while estimates in columns 2 and 4 are from cox proportional hazard models. The regression models in columns 1 and 2 analyze the dyadic data at the level of treating project-treated project-quarter. Column 2 contains more observations because I limited the OLS analysis to projects that had either exited or graduated to phase two by the end of 2014 (in order to avoid right-censoring issues). The regression models in columns 3 and 4 use the same single-level data described in the main body of the paper (project-quarter).The outcome variable is project discontinuation. In each model, the variables of interest are indicators with absorbing states, such that they take on the value of 1 after the first instance of the given type of competitor exit news experienced by the focal project. The Standard errors in parentheses. † $p < 0.10$, * $p < 0.05$, ** $p < 0.01$.

Figure D1: Dynamics of Response to Competitor Failure (Single-Level OLS Version)

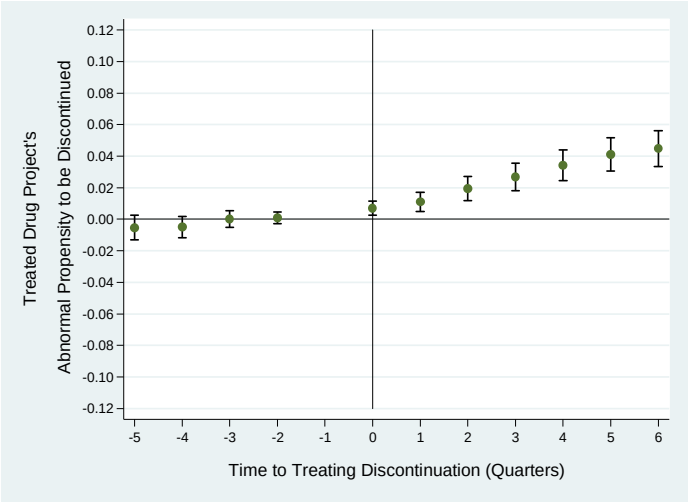
A. Same Market, Same Technology



B. Same Market, Different Technology



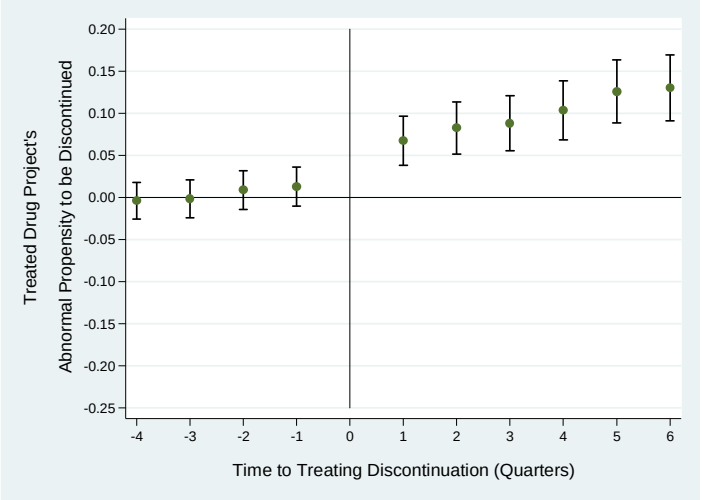
C. Different Market, Same Technology



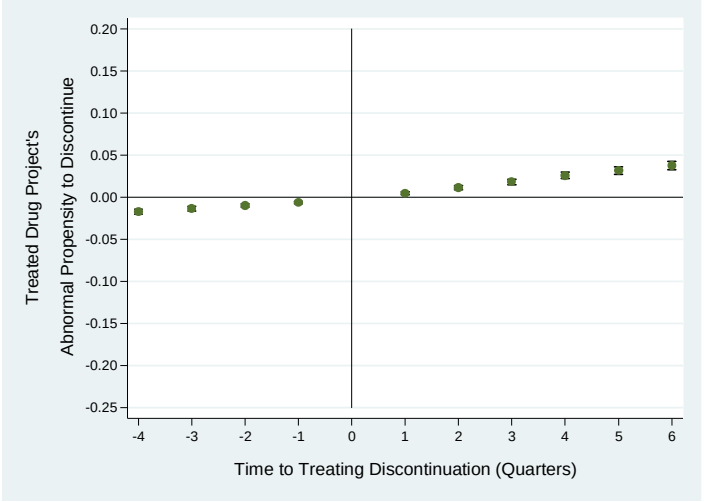
Note: The dots in the above plot correspond to coefficient estimates stemming from the ordinary least squares regression model, where the variable for treatment status is interacted with the time (in quarterly increments) until the first competitor failure event (of each type). The quarter prior to the first competitor termination event is the omitted variable. The analysis data is at the drug-market-quarter level. The 95% confidence intervals (corresponding to robust standard errors) are plotted with the help of capped spikes.

Figure D2: Dynamics of Response to Competitor Failure (Dyadic OLS Version)

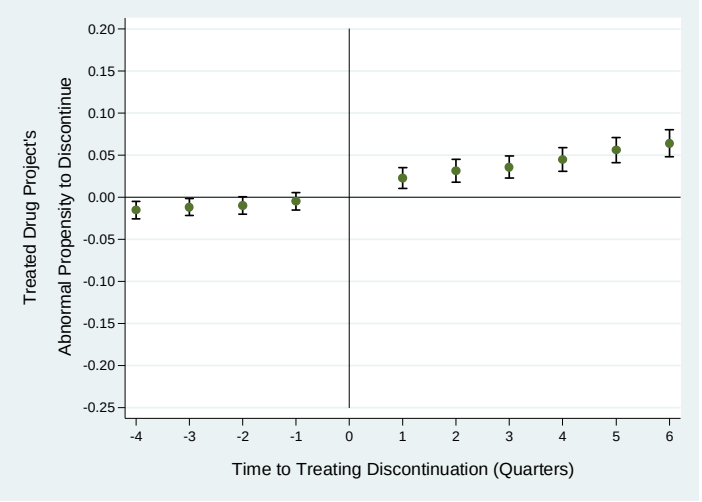
A. Same Market, Same Technology



B. Same Market, Different Technology



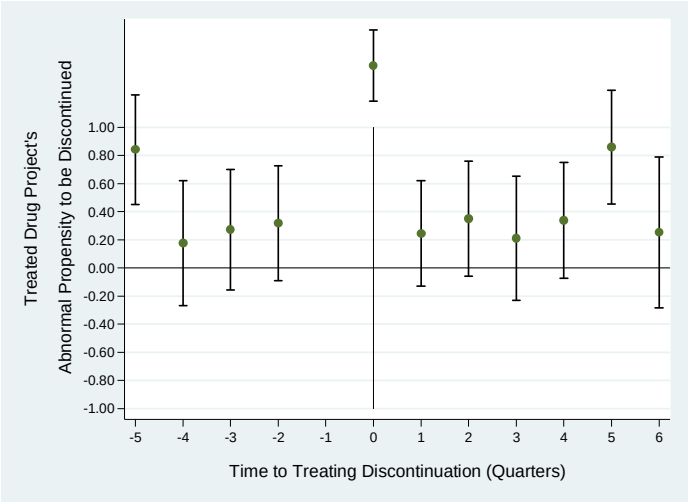
C. Different Market, Same Technology



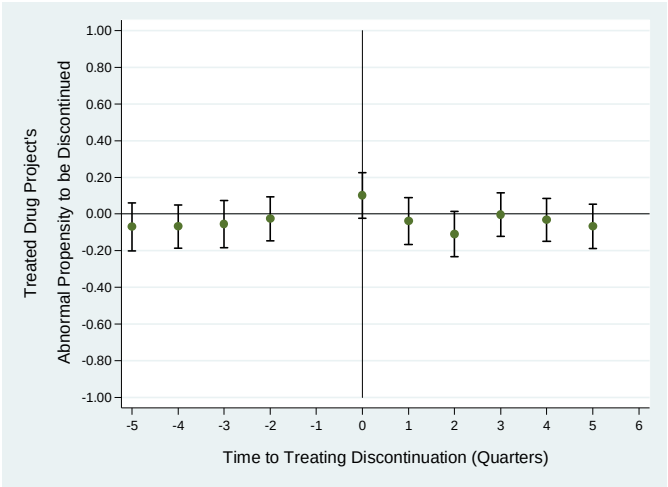
Note: The dots in the above plot correspond to coefficient estimates stemming from the ordinary least squares regression model, where the variables for treatment status are interacted with the time (in quarterly increments) until the first competitor failure event (of each type). The quarter prior to the first competitor termination event is the omitted variable. The analysis uses the dyadic version of the panel data (treating project-treated project-quarter level). The 95% confidence intervals (corresponding to robust standard errors) are plotted with the help of capped spikes.

Figure D3: Dynamics of Response to Competitor Failure (Dyadic Hazard Model Version)

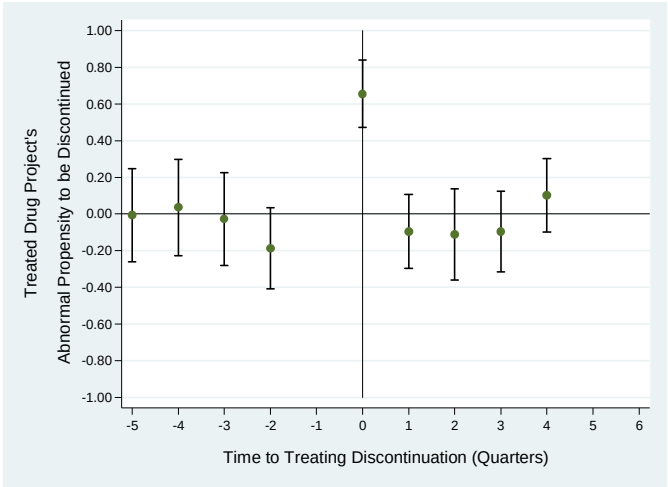
A. Same Market, Same Technology



B. Same Market, Different Technology



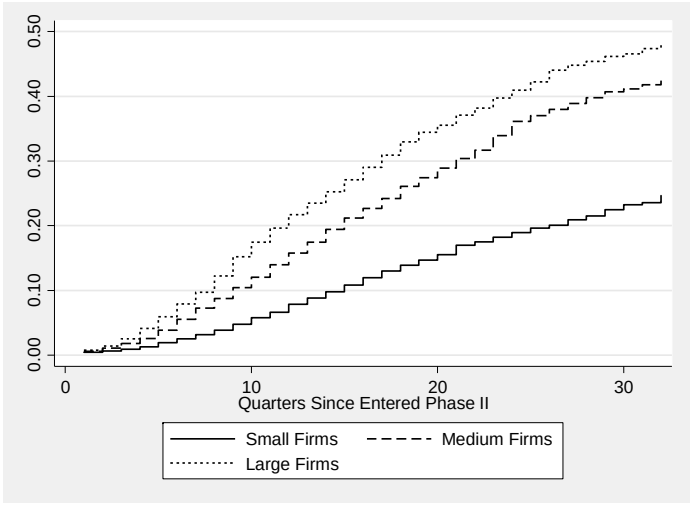
C. Different Market, Same Technology



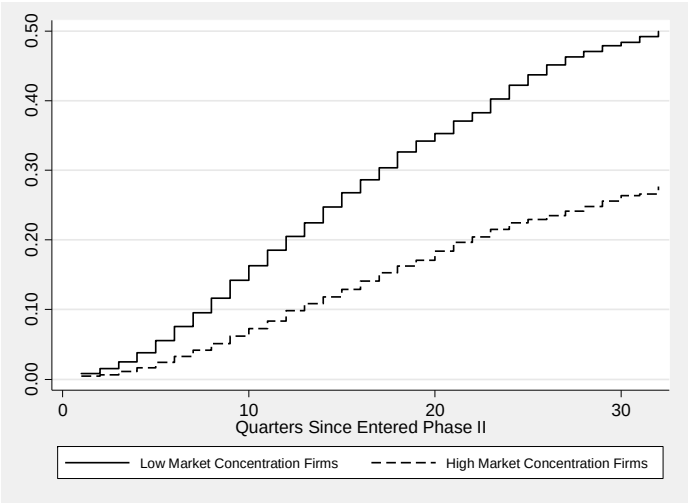
Note: The dots in the above plot correspond to coefficient estimates stemming from the cox proportional hazard model, where the variables for treatment status are interacted with the time (in quarterly increments) until the first competitor failure event (of each type). The quarter prior to the first competitor termination event is the omitted variable. The analysis uses the dyadic version of the panel data (treating project-treated project-quarter level). The 95% confidence intervals (corresponding to robust standard errors) are plotted with the help of capped spikes.

Figure E1: Cumulative Hazard of Project Exit, by Project Type

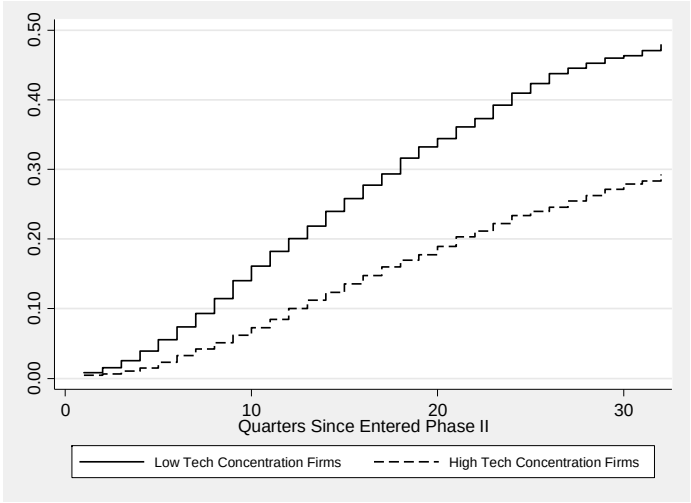
A. Firm Size



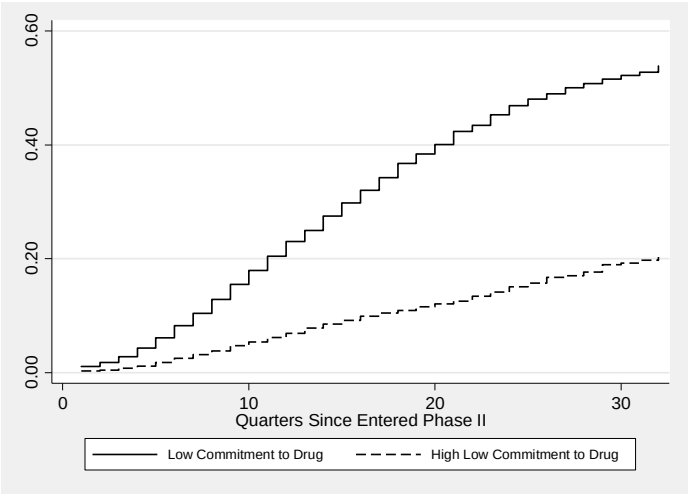
B. Pipeline Market Concentration



C. Pipeline Technology Concentration

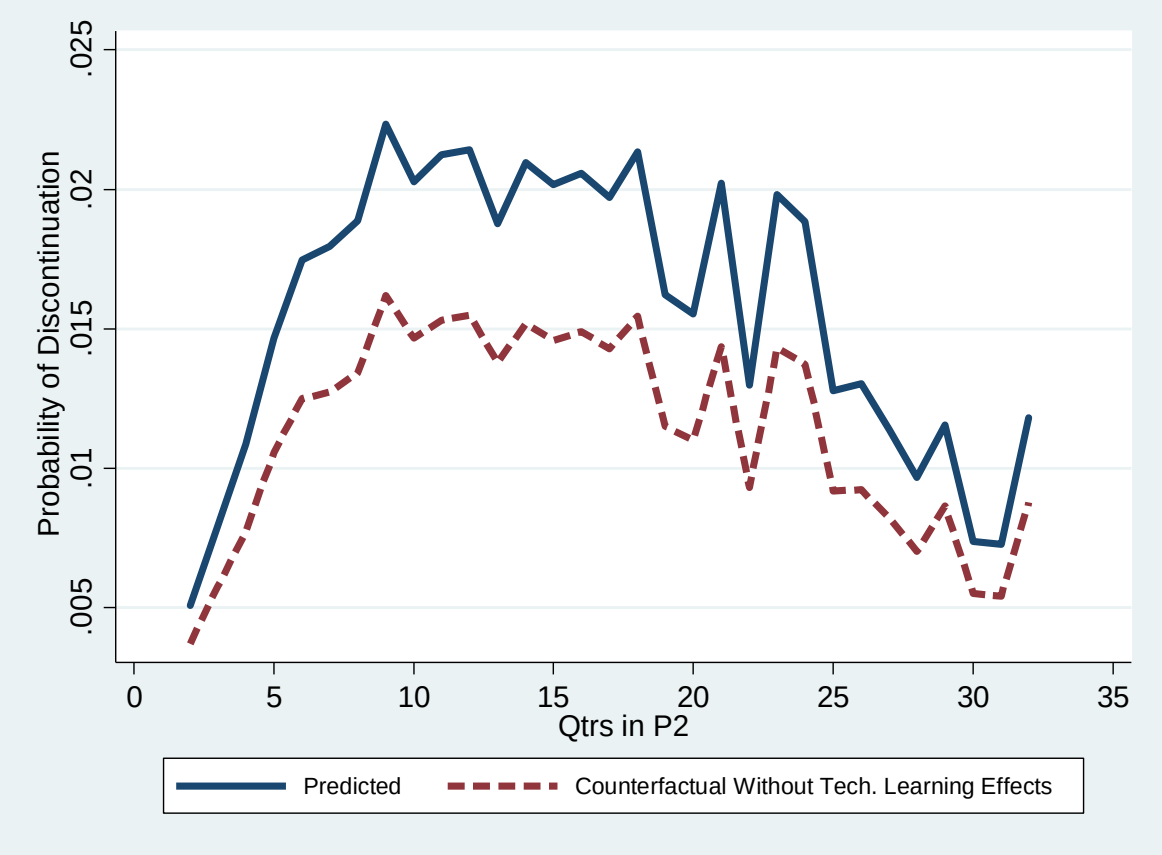


A. Additional R&D Commitments to Focal Drug



Note: The graphs plot the cumulative hazard estimate for project exit by time elapsed since the start of phase II trials. In Panel A, the hazard rate of exit is split by firm size—as proxied by the firms number of projects developed (low is the bottom quartile, medium is the middle two quartiles, and high is the top quartile). Panels B and C split the sample by level of therapeutic market or technological concentration of the focal firms projects as of the time period (median split). Panel D divide the analysis sample into drug projects for which the developing firm is concurrently developing the drug for zero or one other medical indication (low commitment) and drugs being developed for more than one other indication (high commitment).

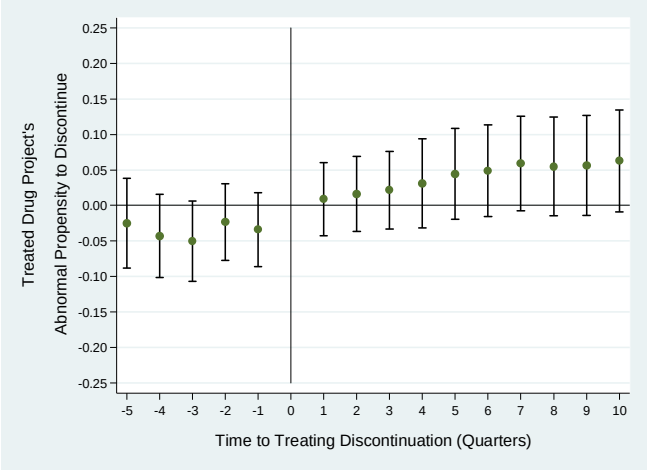
Figure E2: Discontinuation Rate by Quarter for Projects that Experience Technological Competitor Failure News



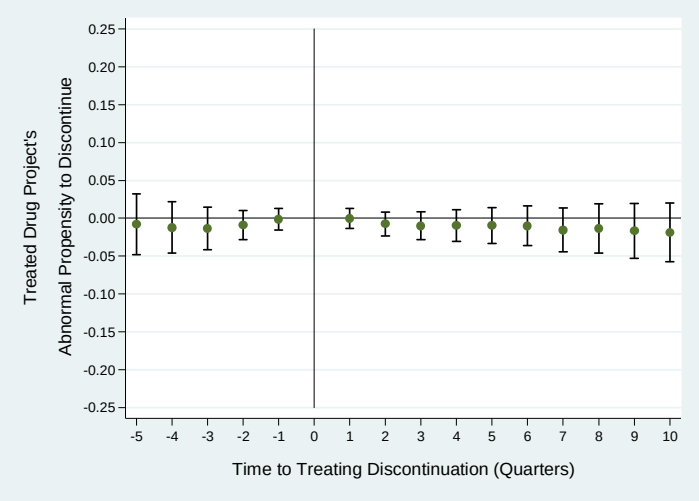
Note: The graph shows the average predicted probability that a phase II project is terminated, given that it survived until a given project age (quarters into phase II) and did not graduate to phase III. The solid blue line is the predicted values generated by the main econometric model (corresponding to Table 3, Column 4) for projects that experience technological competitor failure news at each project age. The dashed red line is the counterfactual prediction, which is calculated by removing the technological competitor learning effects from the predicted termination value.

Figure E3: Placebo Test, Phase III Projects and Phase II Failure News (Dyadic Data)

A. Same Market, Same Technology



B. Same Market, Different Technology



C. Different Market, Same Technology

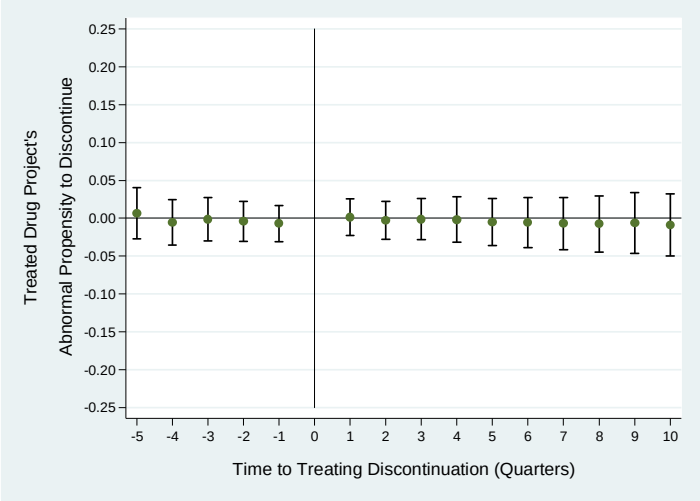
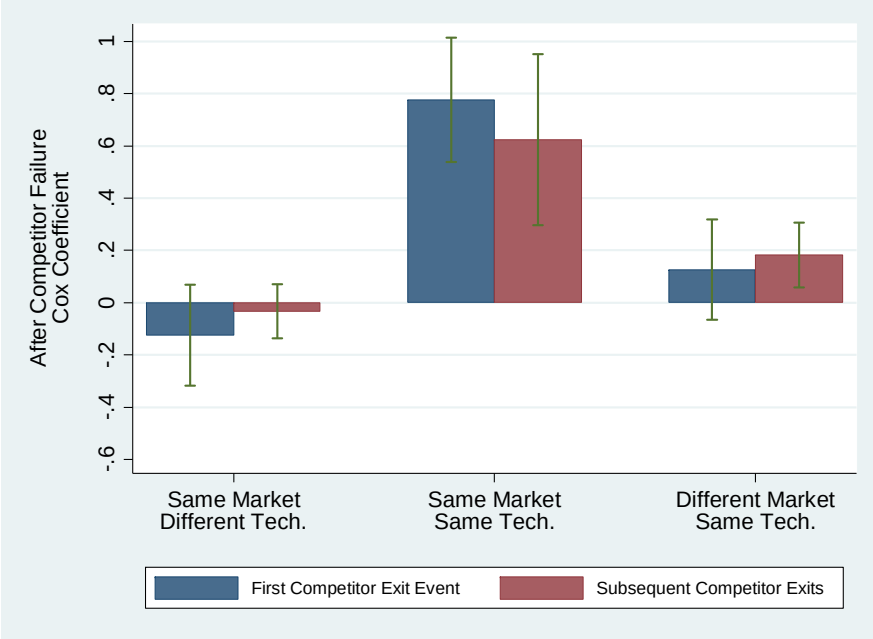
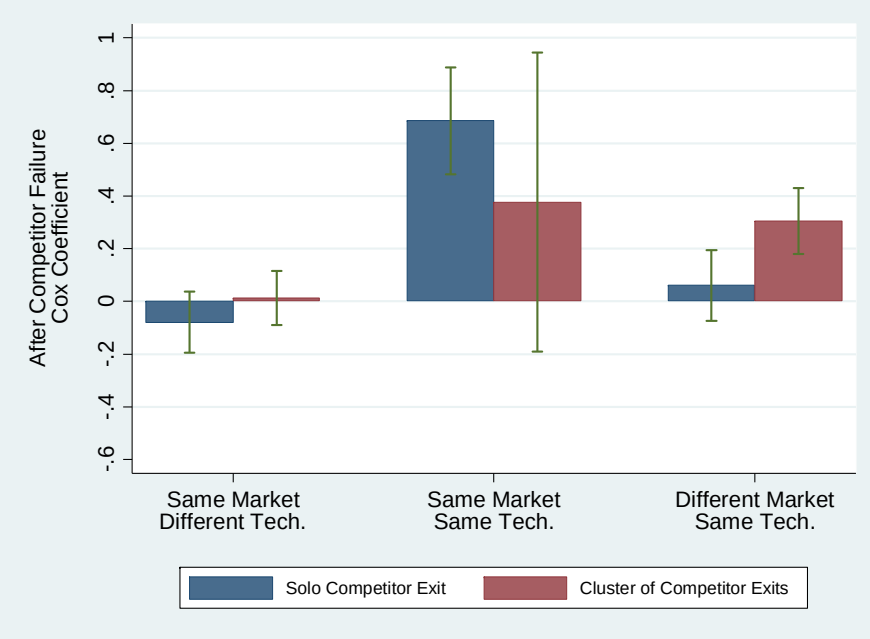


Figure E4: Treatment Order and Clustering

A. First vs. Subsequent Treatment Events



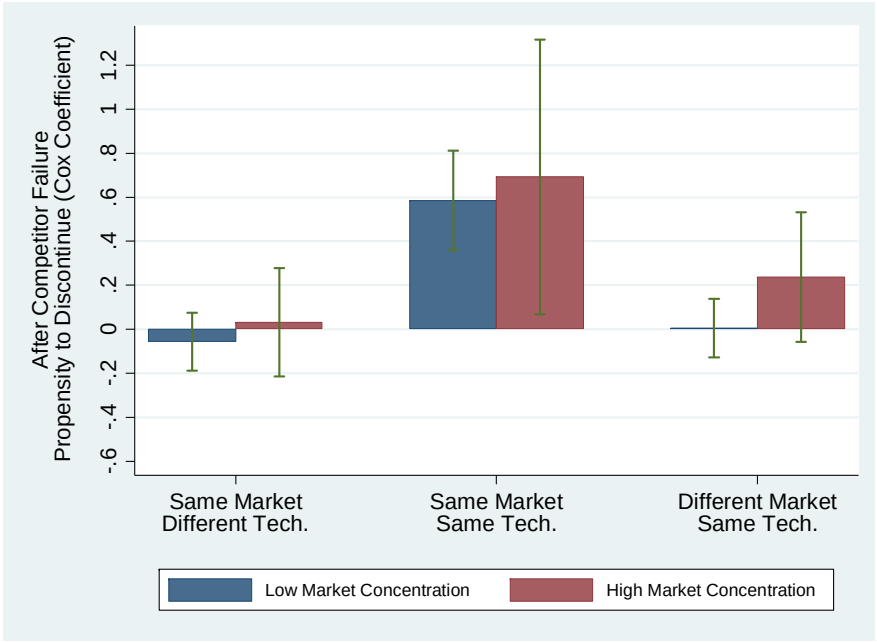
B. Solo vs. Clustered Treatment Events



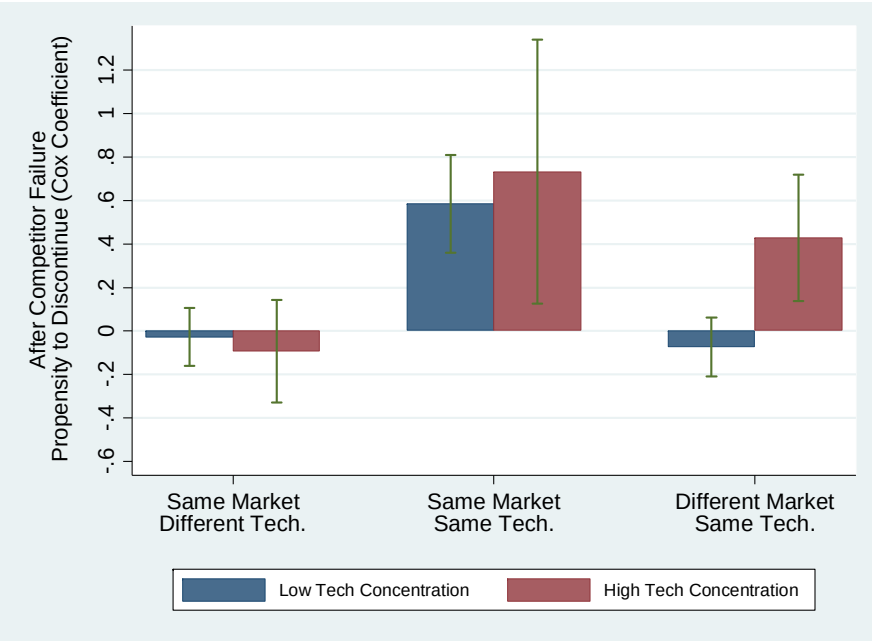
Note: The bars display the coefficients of interest from the main Cox proportional hazard model specification, where the type of competitor failure news event is interacted with whether the news event is the first of its kind or a subsequent event (Panel A), and whether the competitor failure news events involved a single competitor discontinuation or a cluster of multiple competitor discontinuations within three financial quarters (Panel B). The green lines cover the 95% confidence intervals for each regression coefficient

Figure E5: Pipeline Concentration and Propensity to Learn from Competitor Failures

A. Response to Competitor Failure, by Pipeline Market Commitment

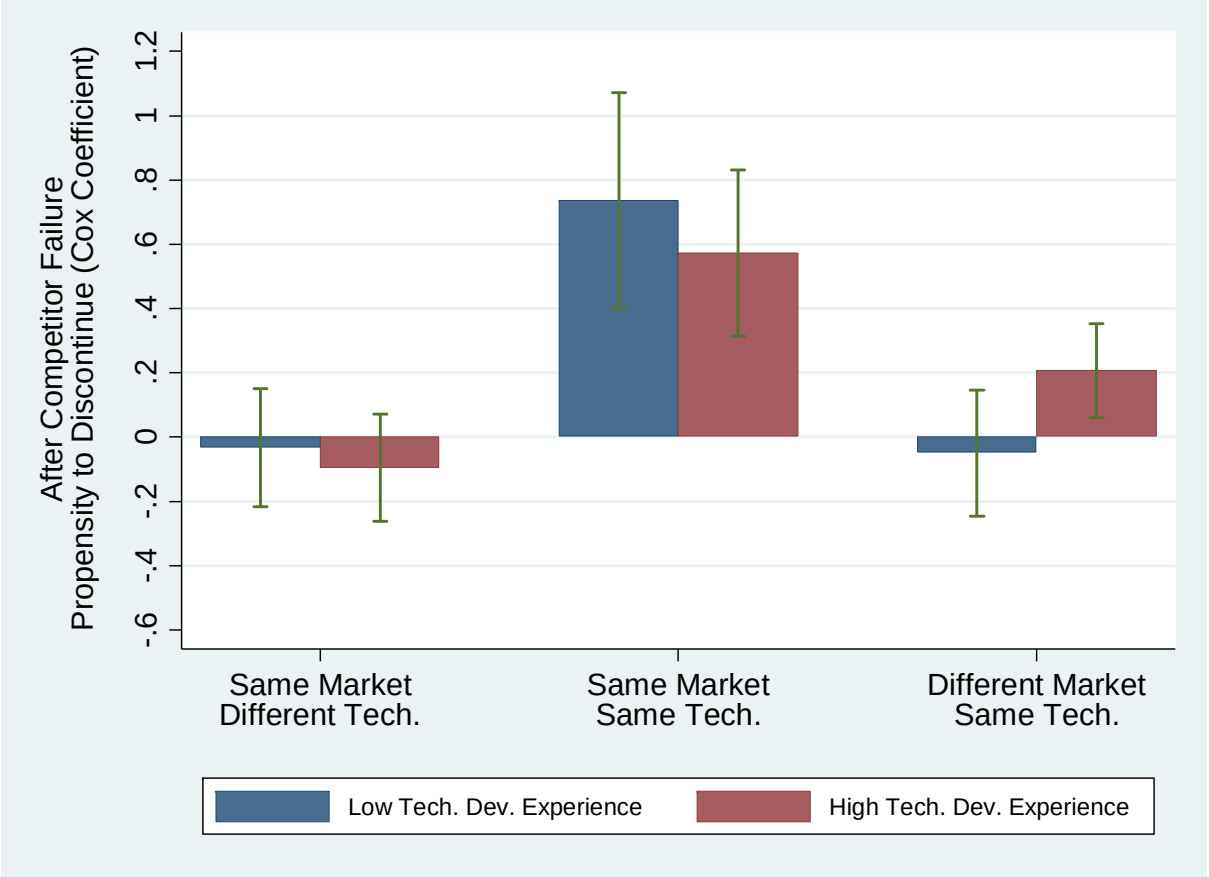


B. Response to Competitor Failure, by Pipeline Technology Commitment



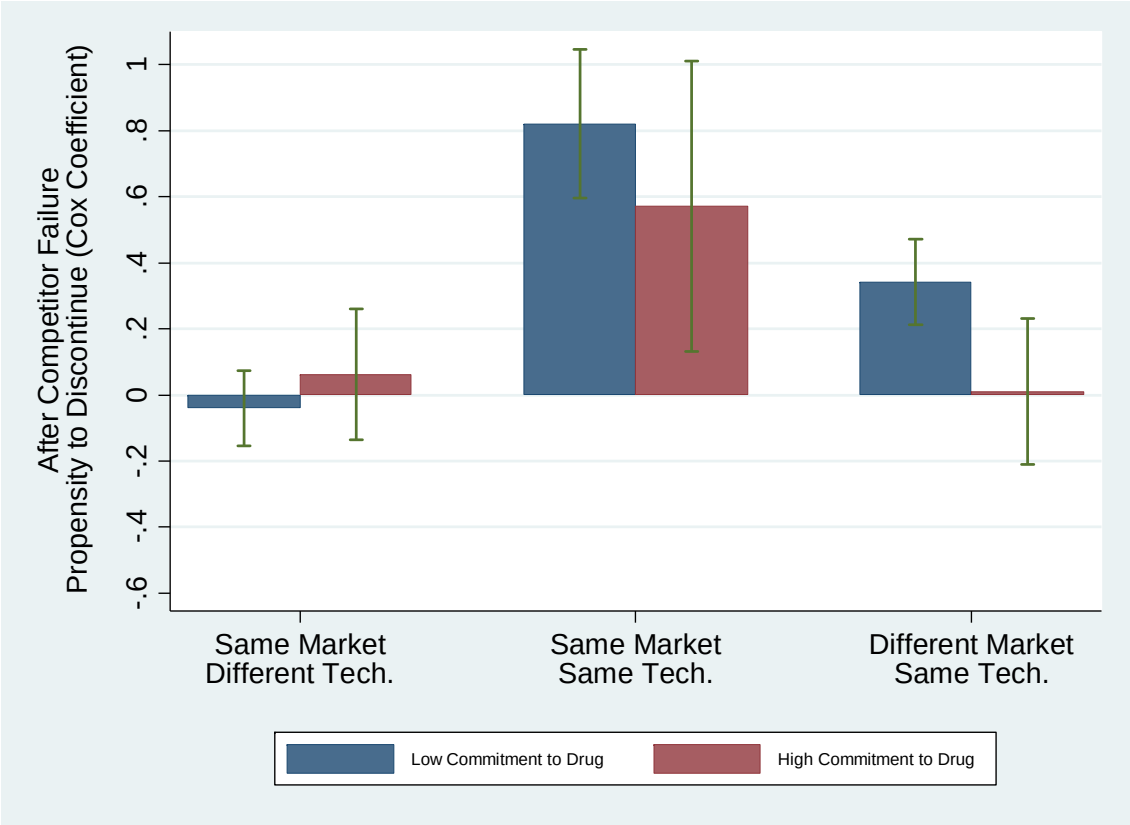
Note: The bars display the coefficients of interest from the main Cox proportional hazard model specification, split level of pipeline project concentration by therapeutic markets (Panel A) and technologies (Panel B). Concentration is measured by a Herfindahl index of a given firms projects across markets or technologies by company and time period (financial quarter). These analyses exclude firms with less than 10 projects in order to eliminate very small biotech firms that are unlikely to have a choice of pipeline market or technology diversity. The green lines cover the 95% confidence intervals for each regression coefficient. The difference in the coefficients' magnitude is not statistically significant for the first two types of news in each panel, but the different market, same technology group coefficients are significantly different across the two groups in both panels ($p<0.05$).

Figure E6: Technological Experience and Response to Competitor Exit News



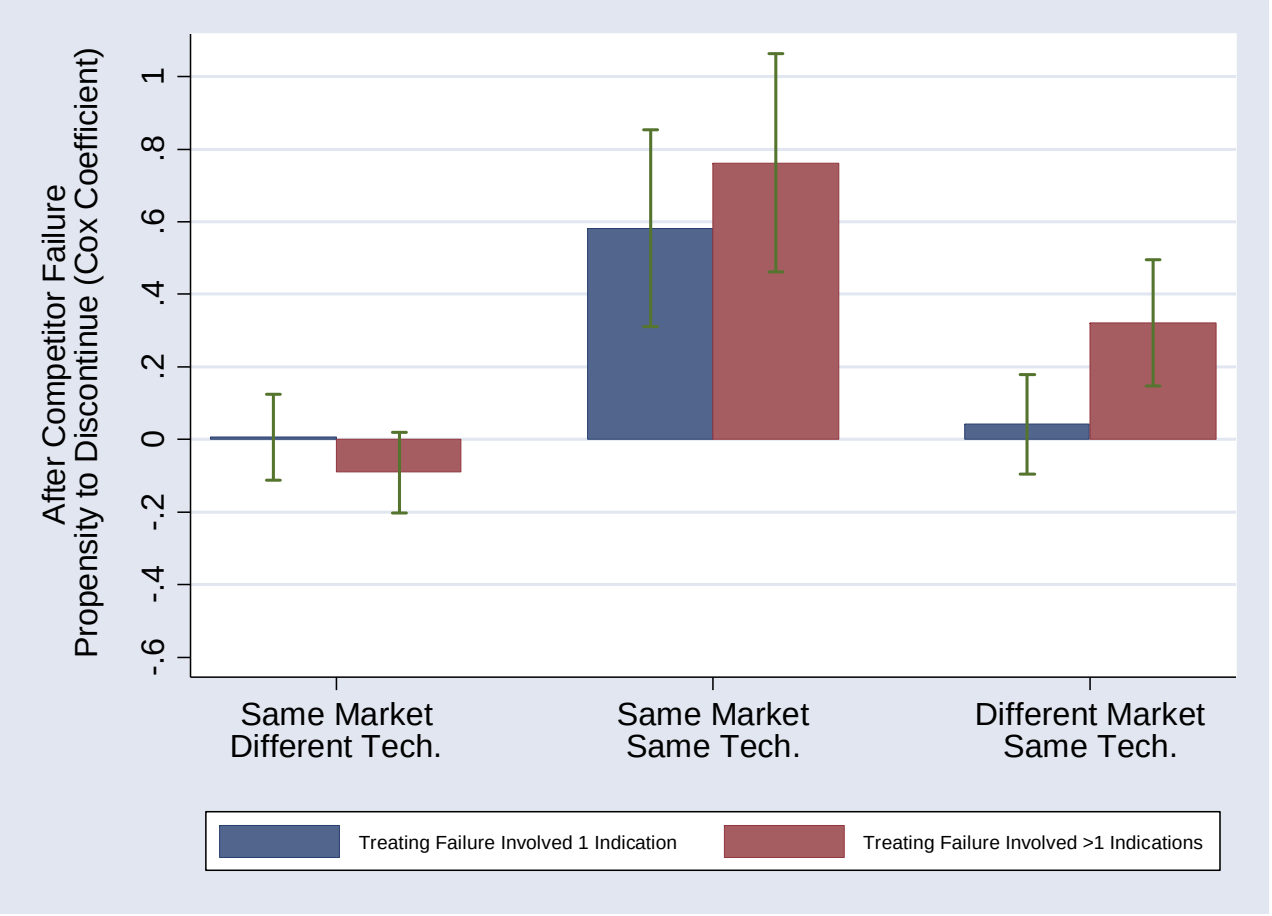
Note: The bars display the coefficients of interest from the main Cox proportional hazard model specification, split by the firm's level of experience with the focal technology. The magnitude of each bar represent the change in hazard rate of project exit when a focal project is within a two quarter window after a competitor failure. To capture the amount of technological experience, the sample is split between those below and above the median level of experience (number of development projects) within the technology area. The green lines cover the 95% confidence intervals for each regression coefficient

Figure E7: Additional R&D Commitments to Drug and Response to Competitor Exit News



Note: The bars display the coefficients of interest from the main Cox proportional hazard model specification, with interactions for the firm's level of additional R&D commitments to the focal drug. The magnitude of each bar represents the change in hazard rate of project exit when a focal project is within a two quarter window after a competitor failure. The sample is split between those below and above the median level of additional project commitments (number of active development projects) for a given drug. Low commitment is defined as having zero or one additional active development (for different therapeutic indications) projects for the focal drug, while high commitment is when the developers have more than one additional development project for the same focal drug. The regression controls for the underlying differences in project continuation rates, by stratifying the baseline hazard rate discontinuation by commitment level (in addition to therapeutic indications). The low and high commitment groups at not statistically different for the first two types of news, but are statistically different for the different market, same technology group ($p<0.05$). The green lines cover the 95% confidence intervals for each regression coefficient.

Figure E8: Treating Failure Type and Response to Competitor Exit News



Note: The bars display the coefficients of interest from the main Cox proportional hazard model specification, with interactions for whether the competitor drug's failure news involved only one indication discontinuation (blue) or multiple indications (red). The magnitude of each bar represents the change in hazard rate of project exit when a focal project is within a two quarter window after a competitor failure. The green lines cover the 95% confidence intervals for each regression coefficient.