

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

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June 25, 2020

Abstract

I analyze project continuation decisions where firms may resolve uncertainty through news about competitors' research and development (R&D) failures, as well as through their own results. I examine the trade-offs and interactions between product-market competition and technological learning from parallel R&D projects. Leveraging the biopharmaceutical industry's unique characteristics to overcome barriers to measuring project-level responses, 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 from within the same market and same technology area—more than doubling their propensity to terminate drug development projects in the wake of this type of information. Finally, I explore how levels of competition, uncertainty, and opportunities to learn moderate the response to competitor failure news.

*I am thankful to Pierre Azoulay, Alessandro Bonatti, Fiona Murray, and Scott Stern for their invaluable guidance and comments throughout this project. I am also grateful for insightful conversations with Michael Bikard, Daniel Fehder, Roberto Fernandez, Lee Fleming (discussant), Jeff Furman, Bob Gibbons, Matt Higgins, Brian Hubbard, Danielle Li, Manuel Hermosilla, Marvin Lieberman (discussant), Kyle Myers, Abhishek Nagaraj, Ramana Nanda, Tom Nicholas, Ray Reagans, Tim Simcoe, Chris Stanton, Ariel Stern, Carolin Haussler (discussant), Heidi Williams, and Yufei Wu. Many other colleagues and seminar participants at the NBER Summer Institute (Innovation; Aging), various MIT seminars, the Munich Summer Institute, the Roundtable for Engineering Entrepreneurship Research (REER), and the NBER Productivity Lunch also provided very helpful comments. Amanda Liu, Descartes Holland, and Matt D'Amico provided excellent research assistance. Research reported in this publication was supported by the Kauffman Foundation and the National Institute on Aging under Award Number R24AG048059 to the National Bureau of Economic Research. The content is solely the responsibility of the author and does not necessarily represent the official views of the National Institutes of Health or NBER.

1 Introduction

How should a firm respond to a competitor’s product development failure? On the one hand, the loss of a competitor is positive news, leaving greater potential market share for the remaining players. On the other hand, a rival’s failure might contain important, cautionary information about technological roadblocks that limit the likelihood of success. Interpreting these types of competitor outcomes is a key consideration for firms making capital-intensive investments in oligopolistic settings. Yet, empirical studies of research and development (R&D) spillovers have not addressed how competitive and technological pressures influence project investments in the wake of competitor failure.¹

In this paper, I examine project-level spillovers and tease apart the different types of information contained in a competitor’s project exit: (i) knowledge spillovers, (ii) product-market competition effects, and (iii) the combination of both. Empirically, I evaluate how biopharmaceutical firms alter their project investments following competitors’ clinical trial failures. I measure how different types of competitor news (same vs. different *market*, same vs. different *technology*) influence the likelihood that a firm “pulls the plug” on its own drug development project. To overcome barriers to measuring the project-level response to competitor discontinuation news, I use unique features of the pharmaceutical R&D setting, including the observability of development milestones, the staggered timing of entry and outcomes, and the separability of product markets and technologies. I find that, on average, firms are more responsive to the negative signal of a failed *same technology* competitor than to the (positive) signal of one less *same market* competitor.

I develop a theoretical framework that adds learning from competitors’ R&D exits to the investment decision. To do so, I evaluate R&D investments as real options, combined with the possibility of both payoff and knowledge externalities. In this framework, the extent to which firms update their beliefs following competitor exits depends on how the “focal” project relates to the failed competitor project: *same market, different technology* (SM-DT); *same market, same technology* (SM-ST); or *different market, same technology* (DM-ST). I describe a belief updating process in which the interaction of these two effects need not equal the sum of the separate market and technology responses. Furthermore, the framework suggests that the project’s level of competition and uncertainty should moderate how firms respond to competitor exits. Last, the model reveals how competition can make a project *more* attractive when the focal and competitor projects share the same technology. Such competitors provide additional signals about the technology’s underlying quality—effectively lowering the cost of experimentation.

¹See Griliches (1991), Bloom et al. (2013), Schnitzer & Watzinger (2015), Manresa (2016), Colino (2017), and Lucking et al., (2018) for examples of how R&D successes create spillovers at the *firm*-level.

The choice of an empirical setting is crucial for R&D spillover analyses. While innovation scholars have argued that disclosure and the ability to assimilate external information have positive effects on the rate of innovation (Henderson & Cockburn, 1994; Cockburn & Henderson, 1994; Ederer, 2013; Bloom et al., 2013; Boudreau & Lakhani, 2015), we have little evidence of whether and when competitors respond directly to each other’s R&D project outcomes.² One reason for the scant empirical work is that making valid inferences about competitor spillovers requires a special type of setting. The analyst must be able to observe the market structure and a given competitor’s entire set of projects, track the timing of project development and failure events, and follow the developers’ subsequent choices. Further, a suitable setting must involve project continuation decisions with large capital expenditures, so that the corresponding investments have the potential to shift firm performance. The timing of failure news must be surprising and disclosed promptly and publicly, generating well-defined decision points and learning opportunities (i.e., signals from competing projects). Perhaps most importantly, the setting must provide metrics to assess technological and product market relatedness between competing projects. Without these ingredients, one cannot isolate knowledge spillovers and competition effects.

The pharmaceutical drug development setting is uniquely well-suited to fulfill these requirements because its regulatory structure and disclosure environment generate observable project-level data in the context of high-stakes decisions. Project selection and termination decisions are central to firm performance in drug development. Failure is a frequent occurrence and interpreting competitor outcomes is a game played by executives, scientists, journalists and investors alike.³ 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 R&D spillovers because human trials are typically the last stop in resolving scientific uncertainty about a compound or therapeutic hypothesis. Outside of trial results, common shocks are rare due to the slow-moving nature of disease markets and translational science. Finally, strong intellectual property protection, long development timelines, and the high cost of trials creates a racing environment with substantial capital commitments and very little incentive to “wait and see” how competitors fare (Schulze & Ringel, 2013).

I use this structured and highly competitive setting to evaluate how different types of competitor failure news influence project termination decisions. I construct a dataset that comprises all clinical development projects over the period of 1997-2014, along with each project’s development

²Economists have studied how events like bankruptcies and product recalls influence stock market valuations of competitor firms (Lang & Stultz, 1990; Ahmed et al., 2002), or sales performance of related products (Freedman et al., 2010). However, these studies focus on third-party valuations and market demand, rather than competitors’ own investment decisions. Closer to the setting of this study, Magazzini et al. (2012) evaluate how subsequent drug developers build off the knowledge generated by previously failed vs. successful drug candidates, by comparing citations to patents associated with those drug candidates.

³Tracking rival projects has grown into its own profitable business with considerable resources and time spent on external competitive intelligence databases and pipeline consultants.

milestones. I focus on projects undergoing phase II clinical trials, which are typically the first major test of a drug’s effectiveness and safety (vs. a placebo or standard of care). I estimate the effect of competitor news on project termination patterns by linking each focal project to its competitors’ project exit events, and by using a difference-in-differences survival model approach to control for the typical life cycle of development projects. I distinguish between product-market and technological competitors, and take advantage of variation in the (plausibly exogenous) timing of entry and failure to identify the effect of competitor failure news on project exit rates.

Using this setup, I show how the relationship between competitors across both market and technology categories dictates how competitor failure news affects the focal firm’s decision to abandon R&D projects. While the average effect of any type of competitor failure news is negligible, same technology competitor failure news results in a 23% jump in focal projects’ exit rates. More specifically, the combination of same market and same technology (SM-ST) competitor failures leads to the largest increase (more than doubling) in project exit rates, while DM-ST competitor discontinuations results in a smaller (18%) increase in exit rate. This difference between the two same technology groups suggests that disease-specific knowledge spillovers dominate the positive effects of reduced competition. On average, news of SM-DT competitor failure does not impact project survival rates.

I test the additional theoretical predictions by evaluating key subgroups of competing projects. I find that only when the level of competition is low does SM-DT failure decrease other companies’ propensity to exit. Using focal projects in the final stage of trials, I show that more advanced projects are less sensitive to all types of competitor news. Finally, I explore how having greater technological learning opportunities (i.e., more ST competitors) influences project investments and reactions to competitor news. The results are consistent with firms being more willing to test more risky (likely to fail) projects when projects have more same technology competitors. Furthermore, firms that have more competitor learning opportunities are more likely to continue following SM-DT news, and less likely to exit following DM-ST news. Overall, the evidence supports a model in which more ST competitors *increase* continuation value at the margin, and firms gain in option value when they herd into SM-ST R&D races.

To ensure that the main empirical strategy captures responses to competitor news, rather than the independent failure of competing projects with a “shared fate,” I employ a variety of robustness checks. Using subsamples and alternative variable definitions, these analyses further isolate competitor information effects by focusing on projects less likely to have “died of natural causes.” Section ?? describes these robustness checks, which together suggest that the results are not driven by simultaneous and independent competitor exits.

The main results highlight the importance of both separating and interacting the different dimensions of R&D competition when evaluating spillovers. Moreover, a simple back of the envelope

calculation shows that “turning off” the competitor learning channel might have resulted in 1,683 (3.7%) additional quarters of active phase II clinical trials—suggesting that the reallocation of more than two billion dollars in R&D investments is attributable to competitor learning.

Both the theoretical and empirical analyses focus on *project*-level spillovers of competitor exit. By measuring firm-level performance outcomes and cumulative failure experience, prior studies are not able to capture when rivals’ outcomes directly enter project investment decisions.⁴ My approach uses a crucial distinction between product-market competitors and technology competitors first applied by Bloom et al. (2013), who separate the countervailing knowledge and competition effects at the *firm* level. This paper makes a distinct contribution to the R&D spillovers literature by applying these market and technological competitor distinctions at the project level, and adds one additional layer: their interaction effect. By allowing technological spillovers to vary depending on the particular product-market application, the econometric results illuminate whether different types of project spillovers are equally informative.

This paper also contributes to the literature studying real options. Prior work highlights how real options provides flexibility to experiment and explore more uncertain paths (Dixit & Pindyck, 1994; McGrath, 1997; Grenadier, 1999; Miller & Folta, 2002; McGrath & Nerkar, 2003; Adner & Levinthal, 2004; Manso, 2011; Nanda & Rhodes-Kropf, 2016), but does not capture cross-competitor learning and spillovers. This paper shows how competitor news can be an essential component of real options valuation because competitor failures resolve both market and technological uncertainty.

The paper proceeds as follows. I begin with the theoretical predictions that combine insights from real options theory with competition and knowledge spillovers. Next I discuss the drug development setting and how learning from failure plays out in the pharmaceutical industry. Third, I describe the main empirical approach and results. By comparing the competitor responses across projects in different competitive and technological contexts, I test additional predictions from the theoretical framework and validate robustness. Finally, I discuss the implications of the results and conclude.

⁴Bennett & Snyder (2017) demonstrate how focusing on cumulative success and cumulative failure leads to biased estimates of learning. Two recent working papers apply variants of measuring cumulative (failure and success) experience within the context of drug development (Garzon-Vico, 2012; Rao, 2018). However, their focus is not on the temporal dynamics of failure entering competitors’ decisions, or separating market and technological forces. This paper focuses on how the most recent failure events impact organizational actions, rather than probability of success.

2 Theoretical Framework

2.1 R&D Projects as Real Options

How should firms update R&D investment decisions in response to changing information about competitors? I analyze these decisions by adding competitor learning into a real options framework. This framework builds on prior work that describes option value of experimentation in entrepreneurship (e.g., Nelson, 1961; Kerr et al., 2014; Nanda & Rhodes-Kropf, 2016; Manso, 2016), while adding the prospect of both payoff and information externalities.⁵ Unlike these prior approaches, here firms must evaluate uncertainty regarding if and when competitor information will be revealed, as well as the relevance of technological or market signals. While existing real options models (e.g., Dixit & Pindyck, 1994; Grenadier, 1999; Kellogg & Charnes, 2000; Kellogg, 2014, Décaire et al., 2019) recognize that flexibility is a major source of investment value, they do not allow competitor outcomes to separately change beliefs about “technical risk” (probability of moving on to the next stage) and expected payoffs (conditional on technical success).

In addition to drug development, the analysis below is relevant for other industries with high project uncertainty, large capital commitments, correlated technological outcomes (i.e., competitors testing related hypotheses), publicly observable actions and outcomes, and potential payoff externalities. These production settings will also have well-established demand.⁶ Outside of life science-based businesses, applicable settings might include the automotive industry, mineral exploration, energy production, aerospace technology, venture capital investing, and medical devices.

2.2 Structure of the Game

Traditional real options models represent decision points as pre-specified opportunities to reevaluate an investment that occur at some regular interval (i.e., monthly valuation, annual planning meeting, etc.). An option is more valuable when the investment has more opportunities to be reevaluated (more flexibility), and more volatility between those intervals. I add to this general framework by considering competitor news as leading to belief updating *in-between* those traditional stages—making all stages (potentially) more valuable.

⁵This approach also relates to models of strategic experimentation (Malweg & Tsutsui, 1997; Keller et al., 2004; Akcigit & Liu, 2016; Bryan & Lemus, 2017; Bonatti & Horner, 2017; Awaya & Krishna, 2019) and the analysis of static auctions with correlated signals (Dasgupta & Maskin, 1987; Kagel et al., 1987; Hendricks & Porter, 1988). In contrast to prior work, I do not assume that no news (about a rival’s project) is bad news. In the clinical trials setting, no news might actually be a positive sign (about the underlying technologies), because failures are hard to hide.

⁶If 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 conveyed as much about consumer preferences and marketing as the technology itself.

I define investments as a single experiment or “stage” of an R&D project (e.g., phase II clinical trial), and consider a firm’s choice to stop or continue any given “focal” project. A simple way to view this choice would be as the expected value of a gamble involving probability of success (p), cost (c), and payoff conditional on success (V^0), versus a fixed outside option (\bar{V}). The firm will then choose to invest if the expected value is greater than the reservation value:

$$p(V^0 - c) - (1 - p)c > \bar{V}. \quad (1)$$

This simple approach is attractive since the firm only has to generate predictions for its own projects (based on historical averages and/or extant experimental and market data), and wait for the next round of experiments to finish.

Next, I incorporate the possibility of vicarious learning into the model. The timing in this alternative setup is as follows. Rather than committing the entire investment amount c at the start, the focal firm invests c_1 to enter the stage, where $c_1 + c_2 = c$. The focal firm expects to get a failure signal (“bad news”) from the competitor with probability $g(p^0)$, which is decreasing in p^0 because the competitor failure probability is negatively correlated with the focal project’s success. If competitor failure occurs, then the focal project reaches a new intermediate decision point where the firm can stop and recover \bar{V} , or continue at cost c_2 and face an updated gamble, with a lower probability of success ($p^L < p^0$) and a monopoly payoff (V^H).

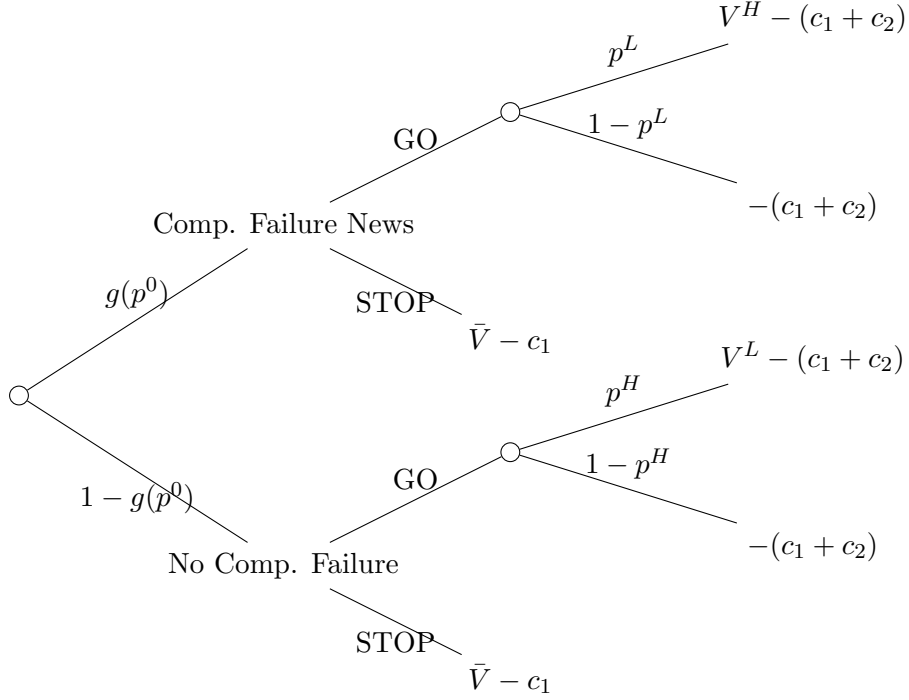
If competitor failure signals do not arrive, the focal firm retains the option to stop the project and recover its opportunity cost of continuation. However, no signs of competitor failure also result in updating of a different type, where beliefs about the likelihood of the success increase ($p^H > p^0$) and beliefs about the level of competition increase, such that expected payoffs decrease to V^L (where $V^L < V^0 < V^H$). It is due to this decreased payoff expectation (conditional on technical success) that the firm may decide to drop out after no competitor news.

In a standard model, more (expected) competitors would have a strictly negative effect on project value (lower V^0). Here, competitor signals introduce a countervailing force: more competitors increase the likelihood of receiving competitor news and resolving uncertainty earlier. In particular, competitor failures create new decision points—allowing firms to abandon their project early and recover \bar{V} , rather than continuing to spend on a project that was unlikely to be profitable. For illustration in Figure 1, I consider a scenario with only two projects competing for the same market, both of which share the same underlying technology (i.e., SM-ST competitors).

In order to compare this decision tree to the simple valuation in Equation (1), the continuation paths (“GO”) must yield an expected value equivalent to the gamble in Equation (1):

$$\begin{aligned} E_{GO}[V] &= g(p^0) \times p^L(V^H) + [1 - g(p^0)] \times p^H(V^L) - c \\ &= p^0(V^0) - c \end{aligned} \quad (2)$$

Figure 1: Single R&D Stage with Competitor Learning



By allowing the termination option (“STOP”) under this alternative game structure, the overall investment’s valuation is given by:

$$\begin{aligned}
 E[V] = & g(p^0) \times \underbrace{\max\{(p^L V^H - c) - (1 - p^L)c, \bar{V} - c_1\}}_{\text{Updated Payoff Post Comp. Failure}} \\
 & + [1 - g(p^0)] \times \underbrace{\max\{(p^H V^L - c) - (1 - p^H)c, \bar{V} - c_1\}}_{\text{Updated Payoff w/o Comp. Failure}}
 \end{aligned} \tag{3}$$

The project is weakly more attractive in Equation (3) than in Equation (1) because of the option value generated by competitor learning. Either of the two scenarios (competitor fails, or no competitor fails) has the potential to be a more attractive bet than the version with no competitor learning. Meanwhile, if either scenario generates a less attractive gamble, the firm can abandon the project early—saving both direct costs (c_2) and opportunity costs (\bar{V}). The updating opportunity from competitors effectively creates an additional stage of the game and adds flexibility due to the abandonment option.⁷

⁷All else equal, firms prefer cheaper experimentation and more information about their technology’s potential—all of which they effectively get from technologically similar competitor news. That preference also implies more entry (“herding”) into more crowded technological areas, on the margin. Such entry would be privately optimal for the firm, but might not be socially optimal if it reduces the diversity of technological experimentation.

This logic extends to cases with more than one competitor. Multiple potential competitor failures create additional intermediate branches in the decision tree (e.g., Competitor A fails then Competitor B fails; Competitor A fails, but no news from Competitor B; no competitor failure news from Competitor A or Competitor B). More ST competitors increase option value while potentially limiting expected payoffs (if they also target the same market). When the number of ST competitors is greater than one, the probability of competitor failure news becomes $g(p^0, n_{ST})$, which is decreasing in p^0 but increasing in n_{ST} —i.e., the more ST competitors with risky technological hypotheses, the higher the likelihood that one fails. In Sections 2.3 and 2.4 below, I explore for how additional competitors of each type influences the change in continuation value following competitor news.

2.3 Updating Process

A firm’s expectations about an R&D project’s technical success (p) reflects its belief that the technology will succeed in a given product-market application (“the hypothesis”). That belief is formed by three components: 1) a common (shared) belief based on public knowledge about the performance of the project’s technology for its intended application,⁸ 2) common beliefs about the general usefulness of the technology for *any* application, and 3) project-specific information gained through proprietary experiments with one’s own intellectual property. The first two components combine to form the “public signal,” while the third represents the “private signal.”

Competitor failure news (or lack thereof) leads the firm to update p if the focal and competitor project share a technology (ST), but more so if the projects share both a market application and technology (SM-ST). In either case, the extent of the updating also depends on the focal project’s maturity, which I represent as the baseline level of uncertainty u , where $u \in (0, 1)$.⁹ The level of project uncertainty matters because the firm puts more weight on its internal signals as it completes more of its own project-specific tests. Without any of its own experimental data, the firm will rely solely on public information to form its beliefs, but that reliance erodes as experiments help resolve project-specific uncertainty. The firm’s belief is represented as a function of the u , as well as the public and private signals:

$$p = u(\textit{Public Signal}) + (1 - u)(\textit{Private Signal}) \tag{4}$$

The updating response to competitor news acts through the public components of the belief. After a DM-ST competitor failure, the *Public Signal* value decreases by b and everything else stays the same. The decrease in the *Public Signal* value is $b^1 > b$ if the competitor was also targeting the

⁸For example, scientific publications on the role of pathway X for causing disease Y; or consensus beliefs about the strength of material Z at high temperatures.

⁹One might approximate u as $1 - (\%$ of a project’s experiments that are complete). Project uncertainty is highest before the first experiment, and decreases as the firm gathers more proprietary data.

same market (SM-ST). Therefore, the change in probability of success after a single competitor's failure (or lack thereof) becomes:

$$p^H - p^0 = p^0 - p^L = \begin{cases} u \times b & \text{if Competitor Type: } \textit{Diff. Market- Same Tech. (DM-ST)} \\ u \times b^1 & \text{if Competitor Type: } \textit{Same Market - Same Tech. (SM-ST)} \end{cases}$$

Superscripts H and L correspond to good news and bad news (high and low), respectively. $b^1 u > bu$, where both are greater than 0 and less than p^0 .

Similarly, the firm's initial belief about payoffs (conditional on success) is based on information about demand and baseline competition, $V^0(n)$, where n is the number of expected market competitors. V is unaffected by news about competitor projects aimed at different market applications (DM). However, when a competitor project that was targeting the same market drops out, the expected number of competitors decreases (e.g., $n - 1$) and the potential payoff belief increases to V^H . Likewise, lack of failure news from SM competitors leads to decreased payoff expectations V^L .

The magnitude of payoff updating ΔV (i.e., $V^H - V^0$, or $V^0 - V^L$) is represented as a decreasing and convex function $d(n)$. Since the impact of less competition on profits is greater as the market approaches monopoly (Bresnahan & Reiss, 1991), the increase in expected rewards will be greater when the focal project has fewer competitors at baseline, and the effect may be negligible if competitors are numerous.

Generalizing to scenarios with multiple competitors (of different types), baseline payoff expectations are a function of both the number of R&D competitors targeting the same market (i.e., n_{SMST} and n_{SMST}) and priors about the probability of success for those projects (e.g., p_{SMST} , $p_{SMST'}$, $p_{SMST''}$, etc.). Regardless of whether the failed competitor shares the same technology as the focal project, the payoff updating should be the same: increased expected payoff following competitor failure news, $V^H(n^-)$, and gradually decreasing expected rewards in the absence of failure news, $V^L(n^+)$, where the extent of updating, $d(n)$, depends on the baseline number of competitors.

The updating process following a single competitor failure can be summarized in the below 2×2 's for the scenarios with and without a competitor failure:

Figure 2: Updating

		<i>Competitor Failure News</i>				<i>No Failure News</i>	
		Product Market				Product Market	
		<i>SameMkt</i>	<i>DiffMkt</i>			<i>SameMkt</i>	<i>DiffMkt</i>
Tech.	<i>SameTech</i>	p^{--}, V^+	p^-, V^0	Tech.	<i>SameTech</i>	p^{++}, V^-	p^+, V^0
	<i>DiffTech</i>	p^0, V^+	p^0, V^0		<i>DiffTech</i>	p^0, V^-	p^0, V^0

2.4 Model Predictions

Applying this framework to the empirical setting of drug development yields four main propositions. Proofs are presented in Appendix A.

Proposition 1. *The two opposing effects, the technological learning and market competition effects, can each be the dominant effect for some initial beliefs p^0 and V^0 , updating parameters b and u , and payoff function $d(n)$.*

Corollary: *Though unobservable to the outside analyst, the continuation value underlies the decision to continue or terminate a project. Therefore, one can empirically measure the relative magnitudes of these two effects by comparing how each type of competitor failure news changes the likelihood of project discontinuation.*

The (pure) market effect—the change in continuation value induced by a SM-DT competitor failure—increases a project’s continuation value due to higher payoffs under reduced competition. The learning effect—the change in continuation value following a DM-ST competitor’s failure—decreases the probability of success and the continuation value. While the direction of each effect is clear (by definition), the relative magnitude of these opposing effects is not fixed in the model (i.e., either could dominate). As a result, the relative size of the two effects is an empirical matter.

Proposition 2. *Simultaneous market and technology news (SM-ST) leads to the largest downwards updating on the likelihood of success, with an effect on the continuation value that is lower than the sum of the two opposing independent effects.*

For technological learning, SM-ST news is more informative than DM-ST news: $b^1u > bu$. SM-ST news should elicit relatively greater changes in probability of (focal project) exit than the sum of the separate (and opposite signed) SM-DT and DM-ST effects.

The intuition for this prediction is that differences in product-market applications should moderate the relevance of competitor technology signals. For example, doctors might be willing to accept nasty side effects for some, but not other, diseases and patient populations (e.g., children vs. adults, slow vs. fast progressing diseases). Both safety and efficacy standards may vary across diseases. Therefore, failure in one market application (disease) does not necessarily rule out the drug for other conditions.¹⁰ Empirically, the change in likelihood of project termination following SM-ST news should be greater than the sum of the (negative) SM-DT and (positive) DM-ST independent effects.

Proposition 3. *Continuation values change more in response to (same market) competitor failures when the baseline number of same market competitors (n_0) is smaller.*

High levels of market competition can greatly diminish the payoff externalities of competitor failure. In markets with many existing products and/or intense R&D competition for the next generation products, losing a single pipeline competitor does little to the expected rewards of success. This prediction follows from the assumption that payoffs are a decreasing convex of competition.

Proposition 4. *The impact of a same technology competitor dropping out on project value is increasing in the level of uncertainty (u).*

Competitor signals are most useful for belief updating when firms still have a fair amount of uncertainty about their own project’s quality. After many stages of testing and data gathering, firms’ will weight their internal information about their own projects more than any public signals about the hypothesis. If the firm holds strong positive beliefs in these late stages, then it will likely view DM-ST competitor failures as idiosyncratic to the failed competitor’s approach, rather than as a signal about the true quality of its own technology.

Proposition 5. *Continuation value is increasing in the number of technological learning opportunities (same technology competitors).*

Learning opportunities effectively speed up experimentation by resolving some uncertainty *earlier*. ST competitor failures provide new decision points where firms can cut losses and abandon projects. Due to the increased expectation of competitor news, the relative amount of belief updating on p (following competitor ST failure news) increases in n_{ST} for “no news” and decreases in n_{ST} for competitor failure news.

The higher expected frequency of decision points increases the value of the project abandonment option. With no change to the level of market competition, more DM-ST competitors increase

¹⁰The same could be true in other contexts. For example, the reliability and stress tolerance needs of materials is different for aerospace than it is in bicycle manufacturing. So failure of a new material to meet the standards in one area does not preclude the introduction of this technology for other uses.

the likelihood of those additional decision points without changing the expected payoffs. For the marginal project, the propensity to exit decreases with more learning opportunities because firms expect that more decision-relevant information (competitor failures or no news) is coming soon. Thus, continuing is a smaller commitment with more updating opportunities: more competition increases the value of the stopping option since the direct costs incurred are lower the earlier one drops out (i.e., $\frac{c_1}{c_2}$ becomes smaller).¹¹

3 Setting

3.1 The Drug Development Process

Drug development is a multi-stage journey with a regulatory process consisting of preclinical experimentation and clinical trials. Trials are designed to test a drug for a particular disease (indication) in humans, and developers may initiate trials for different indications (either sequentially or in parallel).¹² I study both small molecule drugs and large molecule drugs (biologics) but exclude vaccines, which undergo a different regulatory and clinical testing process. Drug development typically begins with lab (*in-vitro*) and animal testing before drugs reach three sequential phases of human clinical trials. Appendix B provides more detail about these development phases.

The focus of this study is the firm’s decision to stop development for drugs that have progressed into phase II trials, which serve as a drug’s first real test of both safety and efficacy in humans. These trials may last months or years,¹³ may involve several hundred people who have the condition (disease) of interest, and typically require randomized and blinded assignment into a control group “treated” by a placebo or the existing standard of care. Data safety monitoring boards—made up of independent scientific, medical, and statistical experts—are assigned to review intermediate results and stop trials early when they deem it unsafe and/or unethical to continue. A great deal of uncertainty remains when starting phase II trials: about 32% of phase II projects will progress to phase III, and only 16% will make it to FDA approval (Hay et al., 2014).

The competitor signals are rival project failures in either phase II or phase III trials. In principle, information about projects in earlier stages of development is not relevant for rival projects that have already cleared earlier safety and efficacy hurdles. The analysis focuses on competitor failure events that happen prior to FDA review. This limitation ensures that the information conveyed

¹¹Similar to an American put option on a stock, the investor gets more option value when volatility is higher, and the investor can sell early when the expected value of the asset decreases.

¹²I refer to the development of a compound for a given indication as a drug “project.”

¹³The length of a trial depends on the disease and endpoint (e.g., mortality, blood pressure, tumor growth, etc.) of interest. Some diseases might take longer to progress and require years of monitoring to infer a therapy’s efficacy. The median time spent in phase II trials is two and a half years.

in the discontinuations does not include any direct signals about the regulator’s level of scrutiny (Blankshain et al., 2013).

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 study found that about half of the 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 statistical signals from a project’s own phase II trial may be noisy and the tradeoffs between safety and efficacy are not easy to balance. Therefore, even after a project’s own trial finishes and the results are un-blinded for review, the decision to continue or halt development can be complicated. Information about rival projects may be particularly relevant for such marginal projects.

3.2 Disclosure

Due to disclosure requirements, firms are well-aware of competing projects’ progress. Early entry is disclosed through a combination of patent filings, scientific publications and company documents. These disclosures usually reveal a drug compound’s key features, including its molecular mechanism of action (if known) and its potential therapeutic uses. Once the company has completed preclinical investigations of a drug compound, it must file an investigational new drug application (IND) with the FDA before starting human clinical trials. Various policies also require firms to disclose clinical trial information, including the drug compound and disease application, by pre-registering in public trial registries like the National Library of Medicine’s clinicaltrials.gov.

The decision to halt a drug development project is one that affects potential consumers, employees, investors, and competitors. Firms reveal discontinuation news through a variety of mechanisms and with different 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. Competitive intelligence services monitor progress and these discontinuation disclosures—alerting subscribers to new disclosure events.¹⁴ These announcements contain statements about the events leading up to the decision, and only a small fraction of the discontinuation announcements are preceded by premature clinical trial terminations. When the rationale for discontinuation is disclosed, the most commonly cited reasons for stoppage are (disappointing) efficacy and safety issues. On a few occasions, termination announcements cite disappointing results from competitors’ projects as a reason for stoppage (see IDO example below). Appendix B presents examples of discontinuation disclosure statements that have different levels of transparency.

¹⁴This paper’s primary data source, Cortellis, tracks these disclosures and links them to drug development projects (drug-indications) identifiers and company information.

One empirical concern is that firms of different sizes or experience have different incentives to publicly report their trial failures (see Appendix B for a discussion of materiality and Regulation Fair Disclosure). However, I find that official discontinuation rates are similar for relatively large and small firms alike. In the analysis sample, large firms that had ever developed 10 or more projects officially terminate 33% of phase II projects, vs. 29% for smaller firms. I also do not find much of a difference in firm experience/size for how often phase II drugs turn into “zombie” projects (those never officially discontinued but also never advanced).

3.3 The Ripple Effects of Trial Failures

Trial failures may have repercussions throughout the industry. With great uncertainty surrounding cutting-edge drug trials, competitors anxiously await news about relevant rival projects. For example, in the long quest to find an effective Alzheimer’s treatment, a number of firms have pursued β -secretase (BACE) inhibitors, aimed at reducing the production of amyloid plaques in the brain. In October 2016, leading up to Eli Lilly’s expected announcement of their BACE inhibitor (solanuzemab) phase III trial, *STAT News* described how 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 [class of drugs].” However, the article also noted that poor results 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). In the end, when Lilly reported that the solanuzemab trial failed, its stock price dropped 10.5% in a single day. At the time, the solanuzemab failure was widely regarded as a negative blow to the BACE inhibitor approach and bad news for similar efforts at other firms, yet some research teams held out hope. Most recently, Biogen’s elenbecestat joined the list of failed BACE inhibitors in Fall 2019.

A recent high-profile failure in the burgeoning field of immuno-oncology had a very public influence over rivals’ investments. In the Spring of 2018, pharmaceutical company Incyte announced the failure of its cancer drug, epacadostat, an indoleamine-pyrrole 2,3-dioxygenase (IDO) inhibitor. To map the epacadostat example onto the terminology of this paper: IDO is the drug’s primary “technology” and Incyte was developing it for a variety of therapeutic markets (melanoma, glioblastoma, ovarian cancer, and others). Following the epacadostat failure news, NewLink Genetics stopped a melanoma trial of their own IDO inhibitor (i.e., a SM-ST project), explaining that the decision was made “in the context of the failure of a competitor’s trial of its enzymatic IDO inhibitor in a similar clinical setting.” Bristol-Myers followed suit, pulling the plug on three different trials it was sponsoring using its own IDO inhibitor, which the company had acquired in a \$1.25 billion

acquisition. Bristol-Myers changed the status of its trials on clinicaltrials.gov and credited the “emerging data on the IDO pathway” as its motivation for closing trial registration early.¹⁵

Yet, the signal from competitor exits is not always clear. Interpreting trial results can take months or years, and rival firms might not have much information to work with after the initial disclosure. Scientific publications with the detailed results can provide more guidance. For example, after a safety failure, analyzing the trial data might reveal if the drug was unable to properly interact with a molecular target, or if the safety issues were the result of collateral damage (“off-target” effects). However, firms need not publish their findings (reporting requirements are scant), and if they do, the publication may not emerge until years later. In the empirical analyses below, I use the drug pipeline data to measure when failure news has ripple effects.

4 Data and Sample Construction

The main goal of the empirical portion of this paper is to identify whether and when R&D failure news influences competitors’ project continuation decisions. Measuring project-level spillovers requires a different level of granularity than classic studies of R&D spillovers.¹⁶ For this study, I assemble a comprehensive dataset with project development histories.

4.1 Drug Pipeline Data

The starting point for my sample construction is the drug development records in Cortellis, which contains development information for 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 curators. Cortellis links each milestone event to its applicable disclosure information (e.g., press release, company investor literature or pipeline documentation, financial filings, etc.). Most records also have detailed data summarizing the drug’s development history and milestones.

This paper’s analyses use those 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, and product withdrawal announcements.

¹⁵See <https://endpts.com/bristol-myers-dumps-late-stage-ido-studies-in-wake-of-incytes-pivotal-implosion-in-yet-another-setback> and <https://www.fiercebiotech.com/biotech/bristol-myers-drops-phase-3-trials-800m-ido-drug>.

¹⁶Patent data are most commonly used to study innovation spillovers and measure the relatedness of R&D projects (see Griliches, 1991; Lerner & Seru, 2017). However, their effectiveness in capturing project spillovers is limited because patents are not matched one-to-one with development projects, their scope and citations often reflect legal or patent office idiosyncracies, and their snapshot-like content lacks information about project investments or progress.

4.2 Market and Technology Groups

In my analysis of competitor reactions, I separate drugs according to two different dimensions of relatedness: therapeutic indication (“market”) and molecular target-actions (“technology”).¹⁷ Characterizing drug development projects along these two distinct and non-mutually exclusive dimensions is aligned with how researchers at major drug developers categorize projects (Cook et al., 2014; Shih et al., 2017).

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 one is usually the “lead” indication. Approximately 28% of all drugs in the Cortellis data have more than one development indication. Of the drugs that reached phase II clinical trials, 34% of started phase II trials for more than one indication. Sharing an indication does not mean that two drug compounds are similar in structure or share molecular mechanisms. Appendix Figure A.1 shows that merely sharing an indication tells us very little about any two drugs’ structure.¹⁸ Furthermore, drug development for the median indication spans more than 10 molecular mechanisms (target-actions).

Cortellis indication names are usually quite specific (e.g., “dry age related macular degeneration”), but also include some more vague categories (e.g., “joint pain,” “stomach pain”). In some cases, two or more distinct Cortellis indication categories actually refer 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.¹⁹

Target-Actions (Technology). A biological target is a molecule in the body upon which a drug acts and influences its function. For example, a drug may bind to and inhibit the function of a specific receptor (e.g., tropomyosin kinase receptor inhibitors), or a drug might function as an “agonist” by activating and increasing function in a protein (e.g., adrenoreceptor agonists). In these cases the target is defined by the biological pathway, and the action is determined by the functional change (e.g., “inhibitor,” “agonist,” “antagonist” etc.). Roughly 65% of Cortellis drug candidate records (70% of projects in this paper’s analysis sample) contain information about the

¹⁷Bloom et al. (2013) looks at market and technology at the *firm*-level, using industry codes for product markets and patent classes for technologies.

¹⁸The drug similarity measure is detailed in Appendix C.

¹⁹Assigning ICD-9 codes to the Cortellis indication names is a challenge that requires knowledge about both the medical conditions and how health care providers classify those 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 condition 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). I’m grateful to Manuel Hermosilla for providing the mapping from Cortellis indication names to ICD-9 codes.

drug’s primary (and secondary, if applicable) biological mechanisms of action. Though two drugs may differ in their compounds’ molecular structures or delivery mechanism, by attempting to treat a condition through the same target-action, the drugs are essentially testing the same hypothesis about how altering a biological process influences a clinically desirable outcome. 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 the intended target. Often, these off-target effects are the source of drug safety/toxicity issues.

Many target-actions are useful for more than one medical condition. Sometimes, those medical conditions are naturally related through overlapping biological causes and symptoms. For example, the drug Humira (adalimumab) is a tumor necrosis factor-alpha inhibitor used to treat a range of inflammatory and autoimmune conditions such as rheumatoid arthritis, psoriasis, Crohn’s disease, and ulcerative colitis. In other cases, experimentation (or serendipity) reveals that a biological target-action may have multiple, seemingly unrelated disease applications. Angiogenesis inhibitors such as Genetech’s drug Avastin (bevacizumab) were originally explored as cancer drugs, but scientists realized (and later proved) that by blocking the formation of new blood vessels, the target-action was also promising for treating age-related macular degeneration. 59% percent of target-actions in Cortellis have development activity for more than one medical condition, with a mean of 4.2 indications per target-action (median=2). A single drug compound may also act on multiple known targets. In the set of Cortellis drug records that have at least one target, approximately one out of five has more than one primary target-actions (with a maximum of 13).

Same “technology” (target-action) drugs are not only similar in their therapeutic pathways, they are also more likely to be similar in their chemical structure. Using chemical informatics techniques, Krieger, Li, and Papanikolaou (2019) show that small-molecule drug candidates within the same target-action group are more likely to be structurally similar. Similar compounds will, on average, behave similarly in the human body (see Appendix C for more detail); however, small differences can lead to drastically different efficacy or adverse effects. Furthermore, the failure to effectively treat one disease does not necessarily rule that drug (or similar drugs) out for different diseases. A failure within a certain market and technology is certainly not good news for other disease applications, but the extent of any competitor learning is not (*ex-ante*) obvious: different patient populations might respond better to a drug or tolerate certain side effects better.

I apply the chemical similarity techniques to the competitor pairs in my analysis sample, and report the results in Appendix C. Drugs that share a target-action have greater average similarity than drugs that merely share a therapeutic market. However, the distributions show that ST pairs are rarely clones and that ST compounds still have plenty of chemical diversity. So while trial outcomes signal the validity of the target-action’s treatment hypothesis, competing drugs’ idiosyncratic features make their signals imperfect substitutes for any drug’s own trial results.

4.3 Sample Inclusion Criteria

To estimate the project-level response to competitor failure news, one needs data that captures 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-dates for all drugs. Drug projects are eligible for inclusion in the final analysis data set starting with the earliest date after entering phase II clinical trials, until they exit or 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.” Frontier project discontinuations are those occurring after phase II trials began, and before any drug projects within the given indication and target-action combination have reached approval and market launch.²² This frontier 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 failure if it meets the following three conditions: it shares either a market or technology with the failing frontier competitor, the focal project was active in phase II for at least one quarter at the time of the competitor news, and the focal and competitor projects entered phase II within 10 years of one another.²³ A frontier discontinuation event may only “treat” competitor projects if its discontinuation date was prior to the discontinuation of the competitor project.²⁴

The analysis data is 1997-2014. 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 II. 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

²⁰Cost estimates vary, with average Phase II trial cost reported as anywhere from \$13 million to \$80 million, while phase I cost estimates range from \$4 to \$8 million (Adams & Brantner, 2006; <https://aspe.hhs.gov/report/examination-clinical-trial-costs-and-barriers-drug-development>; <https://lifescienc.com/2014/11/a-billion-here-a-billion-there-the-cost-of-making-a-drug-revisited/>).

²¹16% of phase II and 50% of phase III projects eventually reach approval, according to Hay et al. (2014).

²²The main findings are robust to further excluding observations where the treating and treated drugs share at least one known target-action (even if not an indication) with a previously launched (i.e., FDA approved) drug. See Appendix Table A.3.

²³While 10 years may seem like a long window, the median time in phase II is two and a half years, and the 90th percentile is over six years. The median length of a phase III trial is four years (90th percentile over 10 years). Therefore, a relevant frontier competitor project may still be under development 10 years after starting its own phase II trials.

²⁴Since 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.

projects” account for many of projects that persist in the panel for 32 quarters before I censor out their subsequent project-quarters. Section ?? summarizes the analyses using this more liberal definition of project discontinuation, and reports similar overall results.

4.4 Analysis Data

The final analysis data set contains 6,183 drugs and 325 ICD9 indications (markets), which combine to form 10,639 drug-indications (projects). Projects may experience relevant competitor failure events in three different ways: 1) SM-DT, 2) SM-ST, and 3) DM-ST. Ninety-five percent of the projects eventually experience at least one competitor failure within the same market, 11% experience a competitor failure within the same market and same technology, and 43% experience a competitor failure within a different market but same technology.

I generate a set of variables for the number of times a given phase II project has experienced a competitor failure within each category, as of any given date. Next, 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. Tables 1 and 2 summarize the descriptive statistics for the analysis sample.

[Tables 1 & 2 Here]

The average likelihood of a project being discontinued in a given quarter is 1.2% (conditional on surviving up until that point). Thirty-seven percent of the projects which were not right-censored by the end of the analysis period (i.e., had the opportunity to complete 32 quarters in phase II, exit, or graduate to phase III before the third quarter of 2014) are actively discontinued during the sample period, while 20% of those projects graduated to phase III development.

5 Results

This section evaluates how competitors’ failures impact project exit decisions in clinical trials. I first describe the overall project exit patterns in Section ?. Section ? explains the econometric strategy to identify the responses to competitor failure news. Section ? then reports the results of the main regressions, which correspond to Propositions 1 and 2 from the model. Section ? analyzes heterogeneous effects as they relate to Propositions 3, 4, and 5.

Next, I test the robustness of the empirical results with a number of alternative specifications and sample splits (Section ?), as well as different project “death” definitions (Section ?). Finally, Section ? describes a series of “back-the-envelope” calculations to quantify the magnitude of the overall competitor learning effects.

5.1 Overall Exit Rates

The econometric approach that follows isolates the impact of competitor failure news on firms’ continuation decisions. But as a first step, I establish the “typical life cycle” for projects in phase II. Figure 3A shows the cumulative hazard rate of projects by the number of quarters spent in phase II (up to 32 quarters). Intuitively, this figure represents the average 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.

Figure 3B shows the average quarterly project survival rate in phase II. This figure distinguishes between projects that are proximate (in time) to SM-ST competitor failure news, and projects that have not recently experienced such news. The figure shows that the survival is almost always lower for projects in the time window after a SM-ST failure news events.

[Figure 3 Here]

5.2 Empirical Strategy: Measuring Project Updating After Competitor Failure

The main analyses evaluate project-level response to a competitor’s project termination. Other studies address how *cumulative failures* within the firm or industry affect the likelihood of a project or firm’s success.²⁵ However, these prior analyses either do not leverage the timing of disclosure announcements, assert strong assumptions about the decaying value of competitor news over time, or they 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.²⁶

The baseline specification is a panel difference-in-differences proportional hazard model. The dependent variable is an indicator for whether or not the focal project was terminated as of a given period. Using hazard models on panel data helps account for natural death rates at different project ages.²⁷ 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.

²⁵For example, Ingram & Baum, 1998; Haunschild & Sullivan, 2002; Baum & Dahlin, 2007; Kim & Miner, 2007; Madsen & Desai, 2010; Rao, 2018.

²⁶Overall 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 my econometric framework accounts to timing of exogenous (surprising) events, as well as the changing market environment.

²⁷The hazard models here are similar to a discrete time logistic regression specification. Running the equivalent logit model (with controls for therapeutic indication and project age) yields nearly identical results.

Furthermore, by stratifying the baseline hazard rate by therapeutic market, I estimate treatment effects relative to the most relevant counterfactual exit rates. In other words, the survival model framework allows one to ask, “how does recently learning of a competitor failure influence the propensity to exit, when compared to ‘untreated’ projects of the same stage, age, and market?”

This approach requires three identification assumptions. The first 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. Any public (or insider) information about disappointing trial outcomes that circulates before discontinuation announcements should bias the treatment coefficients towards zero. To the extent that any such leakage occurs, one might consider the information effects in this approach as conservative estimates of competitor response to failure news. I also test this assumption empirically, by assessing the extent of any pre-trends leading up to competitor discontinuation events (see Column 4 of Table 3, and Figure 5).

The second identification assumption is that firms do not delay their trials in order to free-ride on competitors’ results. As previously mentioned, these types of “wait and see” strategies are costly due to wasting patent protection time. Nonetheless, I empirically test for differential responses for competing projects that entered later (“follower” projects; see Appendix Figure A.6).

Third, this approach assumes no unobserved common opportunity shocks. Other studies of R&D spillovers (e.g., Bloom et al., 2013; Schnitzer & Watzinger, 2015; Lucking et al., 2018) instrument for R&D spending (using state tax credits) to address a classic “reflection problem” (Manski, 1993). In measuring continuous flows of R&D activity (at the firm level), those studies aim to measure how rivals’ patent production influences the focal firm’s output and performance. Ideally, an instrument provides an exogenous change in the level of rivals’ R&D activity, so that the analyst can distinguish true firm spillovers from outcomes driven by common external shocks.

An important feature of this study’s analysis sample is that such common opportunity shocks are highly unlikely. By the time a project reaches clinical trials, typically many years have passed since the pioneering scientific work that led to the drug (e.g., drug target identified by an academic lab). In order to reach phase II clinical trials, the compounds have already gone through rigorous preclinical lab (*in-vitro*) and animal studies, as well as phase I testing in humans. At that point, remaining scientific uncertainty will be determined after relevant trial results are unblinded. Moreover, by limiting the project sample to “frontier” drug development projects (in trials), I minimize the risk of unobserved common signals coming from regulators and marketed drugs.²⁸ It is unlikely that regulators send any common signals that would kill a new drug class before trial results play

²⁸See Appendix Table A.3 for robustness checks using more restricted analysis samples, in which no drugs that share the same technology have reached the market.

out. Any general macroeconomic shocks should impact different drug development areas equally, and are captured in the calendar time fixed effects in the regressions.

Unlike other product development areas with trends in consumer preferences (e.g., software, self-driving cars, food and beverage, etc.), disease markets stay relatively stable and predictable over time. One exception is infectious diseases, where the market for vaccines can skyrocket with an outbreak (e.g., Ebola, Zika, etc.). Outbreaks should not impact the analyses because I remove vaccines from the analysis sample. Moreover, pharmaceutical demand shocks are quite rare, and negative demand shocks even rarer.²⁹ In contrast to other R&D activities, clinical trial outcomes are distinct and discontinuous events (i.e., failure disclosures) at the *product* level. Firms have little control over the timing of their trial outcome news, and the information content does not depend on the previous stock of R&D activity.

My main specification is analogous to hazard models in Gans et al. (2008), Rao & Dutta (2012), and Aral & Walker (2012), where the timing of both treatment and response is of central importance in interpreting the results. In practice, I employ a Cox proportional hazard model specification, using drug-market-quarter level data:

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

In this specification h_{0k} is the baseline hazard rate of project exit, stratified by therapeutic market, and γ_t represents calendar time (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) SM-DT, 2) SM-ST, and 3) DM-ST.

In the main specifications (Table 3), 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). Appendix Table A.1 displays those modified specifications. In addition, I evaluate a dynamic version, where each competitor failure event type is interacted with indicator variables for number of quarters until the competitor news event (see Figure 5).

²⁹Prescription drug spending in the US (as a % of GDP) has risen consistently since the late 1970s, with only a slight dip following the 2008 recession (see <https://www.brookings.edu/blog/up-front/2017/04/26/the-hutchins-center-explains-prescription-drug-spending/>). Policies expanding insurance coverage for prescription drugs have created occasional positive demand shocks (e.g., the 2006 enactment of Medicare Part D).

Appendix D also outlines alternative regression approaches. The alternative models and data structures produce the same overall patterns of response to competitor exit news.

5.3 Impact of Failure News Results

Below I describe the paper’s main empirical results on responses to competitor failure of each type. Using the survival model approach described above, these results speak directly to Propositions 1 and 2 from Section 2.4. The primary goal of these analyses is to compare the magnitude of responses to each type of failure news (SM-DT, SM-ST, DM-ST).

Table 3 presents the estimates from the main regression specifications for project exit rates—all using the “treatment window” that takes on a value of one within two quarters after each type of competitor failure news. Column 1 reports the results of a naive specification, grouping competitor discontinuation news events into a single type. Under this grouped competitor news variable, the results show no significant change in the propensity of project exit following competitor discontinuation. However, the story shifts once I separate different types of competitor discontinuation news.

Separating competitor news into the (not mutually exclusive) SM and ST groups reveals that recent competitor failures do, in fact, significantly increase exit rates when the competitors share a technology (Column 2). The coefficient (0.274) implies a 23% increase in the likelihood of exit in the window following a ST competitor failure. This effect was hidden in the Column 1 version because the number of SM competitor failure news events far outweighs the effect of ST failure events (see Table 1). The two category version is the (binary) analog to the similarity measures used in Bloom et al. (2013) and Lucking et al. (2018). However, this two-way split still does not capture the full picture of competitor responses.

Columns 3 through 6 in Table 3 further divide the competitor news into the three competitor news types: SM-DT, SM-ST, and DM-ST. Column 4 additionally tests the “no-anticipation” assumption by including indicator variables for the window before each type of treatment, and shows that no competitor failure news has any significant impact on discontinuation rates before the announcement period. Columns 5 and 6 add control variables for the number of each type of competitor and firm characteristics.

[Table 3 Here]

The impact of each type of failure news is quite similar across these preferred models (Columns 3-6).³⁰ On average, competitor news from the SM-DT group yields no significant change in hazard rate of project exit, with magnitudes close to zero.

³⁰Testing the proportional-hazards assumption yields non-significant results (i.e., the proportionality assumption holds.)

SM-ST competitor discontinuations lead to large and highly significant ($p < 0.01$) increases in the hazard rate of project exit, while DM-ST discontinuation news leads to a smaller but still statistically significant increase in the probability of project exit. Wald tests confirm that the SM-ST coefficient is significantly larger than the DM-ST coefficient in each model ($p < 0.01$). Focusing on column 3, the SM-ST coefficient represents a 0.739 increase in the log hazard (109% increase in probability) of project exit following a closely related competitor’s project discontinuation, and the DM-ST coefficient implies a 0.158 increase in the log hazard (17% increase in probability) of project exit following a technological competitor’s discontinuation disclosure in a different therapeutic area. The coefficients from Column 3 are also depicted as bars in Figure 4.

[Figure 4 Here]

Figure 5 shows the event study of experiencing a competitor discontinuation event, by interacting the treatment event status with indicator variables for time before (or after) the project’s earliest treatment event using six-month increments. 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. The SM-ST effect seems to occur exclusively in the six-month window after the competitor news, while the DM-ST effect lingers a bit longer, despite being smaller.

[Figure 5 Here]

Even though the DM-ST effect lasts longer, one cannot simply add up the significant six-month coefficients in Figure 5 and compare them to the first post-treatment SM-ST coefficient. Since the coefficients relate to the exit rate, earlier increases to the hazard rate of exit have more of an impact than later increases—because a compounding effect kicks in over time and the base of active projects is smaller in later periods.³¹

At first look, the different magnitudes of the the two ST coefficients may seem surprising. How can the SM-ST news have a greater impact on exit rates if it also triggers the benefits from reduced competition? The first explanation is consistent with Proposition 2 from the theoretical model. Market-specific factors (e.g., side effects) produce greater belief updating following SM-ST news than after DM-ST news ($b^1 > b$). That greater belief updating translates to a downward shift in

³¹Using a two-period difference-in-differences model, where treatment is binary for post-competitor news (absorbing state version), I still find that the SM-ST coefficient is significantly larger than the DM-ST effect (see Appendix Table A.1). In general, as more time elapses after the initial competitor news “treatment” event, the more likely other news or own project results are to confound the competitor effects. Concerns of “shared fate” for similar technologies also come into play when one extends the treatment window. Therefore, the comparison of information effects across news types is best identified when the treatment window is smallest. For that reason, the main specification focuses on the first few quarters after competitor news.

continuation value and a higher propensity to exit. Furthermore, when SM-DT effects are weak (on average), then reduced competition does not produce a formidable “opposing force.”

A related explanation is that SM-ST news is more salient, even if not more valuable, than DM-ST news. The additional time it takes for DM-ST news to affect decisions (Figure 5) suggests that salience might play a role in the differential responses. Both stories highlight the importance of identifying the separate forces and the interaction effects of market and technological similarity.

5.4 Heterogeneous Effects and Testing Theoretical Predictions

The average response to competitor failure news in the main results (Table 3) substantiates that competitors indeed learn from one another, as well as the importance of separating the three different types of spillovers. In the clinical trials setting, the technological learning effects (on average) dominate market competition effects (Proposition 1), and firms appear to update more on SM-ST news than on DM-ST news (i.e., $b^1 > b$ as in Proposition 2). The theoretical framework also highlights key moderating factors: competition, uncertainty, and remaining learning opportunities. Below I explore each of these areas using project-level variation in the phase II project analysis data.

5.4.1 Level of Competition

Grouping projects by the level of competition and evaluating each group’s response to competitor failure puts Proposition 3 to the test. If competitor failure responses depend on the number of competitors, then the “treatment” effects will differ across competition groups. First, I compare the bottom half (low) vs. top half (high) of projects in terms of the number of potential market competitors in active development. This split reveals that the SM-DT effect is negative and significant when the level of market competition is low (first bar in Figure 6, Panel A).³² In other words, when potential competition is low, firms are significantly more likely to *continue* after a SM-DT competitor failure. For the high-competition group, the SM-DT negative effect is statistically insignificant (despite a similar number of observations), with a much smaller and noisier coefficient.

Next, I evaluate the subset of phase II projects in therapeutic markets with low vs. high levels of previously approved drugs. Similar to the result for development market competitors, the projects below the median in the number of on-the-market competitors are significantly less likely to terminate following a SM-DT competitor failure event. Appendix Figures A.3 and A.4 show the event study versions of these regressions for the low and high competition subgroups, respectively.

[Figure 6 Here]

³²Appendix Figure A.2 shows the bottom vs. top quartile split. The patterns are similar but with an even greater negative effect for the low competition SM-DT response.

The competition findings confirm the theoretical intuition (Proposition 3) that facing fewer competitors will influence decision-making under certain market structures. The magnitude of the negative SM-DT coefficient is greater when the baseline level of market competition is smaller (across both 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 more likely with few product development or market competitors. That said, low levels of competition do not seem to matter as much in moderating the technological learning effects in the ST news scenarios.

5.4.2 Project Stage, Uncertainty, and Relevance of Signal

Proposition 4 highlights the role that project uncertainty might play in continuation choices and updating after competitor failures. Using alternative definitions of which failures provide relevant news (and to whom), I evaluate this hypothesis in the trials setting. I operationalize project uncertainty as maturity in the development process (phase of development). In drug development, those uncertainty milestones are discrete phase transitions, rather than continuous changes; nevertheless, they are useful approximations for different levels of internal knowledge of the focal project’s feasibility.

An implicit assumption of the main empirical approach is that competitor outcomes are only relevant when the competing project is in the same or a more advanced stage of development. According to this approach, projects that significantly lag in development are irrelevant to the decision-making process. Furthermore, more advanced focal projects should have already resolved enough uncertainty on their own, and can ignore earlier stage competitors (Proposition 4 in the theoretical model). To test this prediction, I evaluate whether phase III projects are more or less likely to exit following news of a phase II competitor’s failure. This analysis sample contains 3,195 phase III projects that are ever “treated” by phase II failure news. The breakdown across competitor news types is quite similar to the main analysis: 92% experience SM-DT news, 9% SM-ST news, and 43% DM-ST news.

In Appendix Figure A.5, I present the event studies. For each competitor news type, the trends are fairly flat and none of the coefficients are significantly different from zero. Phase III project investments do not appear to respond to phase II competitor failures, regardless of the market and technology relationships.³³ The lack of response seen in Figure A.5 implies that developers only update their expectations about R&D success when their own project uncertainty is high. These

³³The 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 only phase III competitor had a different effect than the same type of news stemming from a phase II competitor. This comparison produced no statistically significant differences.

results are in-line with Proposition 4: when developers have already cleared certain development hurdles, they do not update beliefs based on earlier stage projects.

5.4.3 Learning Opportunities and Response to Competitor Failure

To explore whether competitor responses are smaller with more remaining learning opportunities (Proposition 5), I interact each of the three treatment types with an indicator for whether the focal project had relatively low or high ST learning opportunities. I define low vs. high learning opportunities as below or above the median number of ST competitors (five projects).

When the information environment is relatively rich with competitor learning opportunities, firms advance weaker projects into phase II testing. Table 4 reports the coefficients from the survival models. The correlation between high learning opportunities and the hazard rate of exit is positive and significant—implying that having above-the-median ST competitors is associated with a 24% higher (Column 2) relative probability of termination at any point in phase II.³⁴ The presence of competitors that have correlated technology signals may initially strengthen the firm’s belief in their own project through stronger public signals about the technology, while also effectively reducing the cost of exploration through the promise of additional relevant trial outcomes.

Table 4 also reports coefficients for each type of competitor failure news interacted with the remaining ST learning opportunities. The SM-DT coefficients show that having more ST competitors corresponds with being more likely to forge ahead following a “pure” market competitor failure. I find no significant differences between the high and low learning opportunity groups following SM-ST competitor news. The DM-ST effect almost disappears for projects with high remaining technology competitor learning opportunities. Essentially, the exits driving the overall DM-ST effect (Table 3) disproportionately involve low remaining learning opportunities. Projects with more learning opportunities were more likely to continue following DM-ST competitor news.

[Table 4 Here]

These findings are consistent with the updating process and Proposition 5 in the theoretical framework. Firms are more likely to advance risky projects when similar competitors will provide learning opportunities in the form of correlated (public) signals. Those learning opportunities increase the attractiveness of continuing with the focal project. A developer’s belief about a project’s probability of success is likely unchanged after a SM-DT failure. So if the project has zero or very few same technology competitors remaining, then the forward-looking developer does not expect to gain any more relevant technology insight from rivals. However, a larger number of remaining

³⁴By comparison, Budish et al. (2015) find that a 10 percentage point decrease in trial length (five-year survival rate) is associated with a 8.7 percent increase in trial entry. Both Budish et al. (2015) and the results here suggest that decreases in the cost of experimentation allow for project investments that otherwise might not happen.

technology competitors means extra information as competitors’ experiments complete over time. After a SM-DT competitor failure, the combination of a more attractive competitive environment (one less potential *market* rival) and many potential learning opportunities remaining makes the continuation option even more attractive than before .

A similar logic helps explain the DM-ST results, where the existence of more remaining competitors using the same target-action diminishes the exit response to DM-ST failures news. Here, developers might be more hesitant to pull the plug quickly if they believe more competitor signals may arrive in the near future—down-weighting any one given competitor failure while other peers remain. Observing that other ST competitors remain committed to their projects might also lead to positive feedback loops, such that developers believe their investment or clinical hypothesis is validated by others (i.e., the *public signal* remains quite high). Notably, I did not find any significant difference across learning opportunity levels following SM-ST competitor news. The information shock of these most similar competitor failures appears to overpower any secondary effects of remaining competitor outcomes (i.e., downward updating on p the outweighs remaining option value).

5.5 Robustness Checks

Appendix D details alternative regression specifications. The same qualitative patterns persist in the alternative specifications, though the magnitudes differ depending on the level of analysis and treatment definition. Below, I summarize key checks of the main identification strategy and the informational content of “failure news” events. Appendix E provides additional details on these robustness checks.

Identification Assumptions. First, one might be concerned about how entry order affects the results. In drug development, the looming patent expirations create a sense of urgency for development. “Wait and see” strategies may be too slow, given that development periods are long and expensive. However, firms might still choose particular entry timing in order to capitalize on information, 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).

To test whether entry order influences the results, I interact each competitor failure type with the focal (treated) firm’s phase II entry position relative to its first treating project: follower, neck-and-neck, leader. Appendix Figure A.6 displays the results of this regression as a bar graph. The relative magnitudes of the competitor failure news coefficients are quite similar for followers, leaders, and projects that are neck-and-neck (entering phase II within a year of one another). The magnitudes of the SM-ST and DM-ST coefficients are actually greatest among the leader group.

A related concern is that independent simultaneous failure might be driving the main effects for SM-ST and DM-ST news. Under this logic, ST projects have a “shared fate” and may learn about their own disappointing results around the same time. To address this concern, I limit the analysis sample to smaller project age ranges (e.g., the first 6/8/10/12/16 quarters in phase II, 4-12 quarters into phase II, etc.) and apply the primary regression specification. These regressions yield competitor news coefficients with magnitudes very similar to the primary regression specifications.³⁵ The median phase II trial in Cortellis lasts for more than two years (10 quarters), so the “treated” projects in these age-limited samples were unlikely to have completed their first phase II trials, let alone completed their entire battery of phase II investigations (usually involving multiple trials)—implying that simultaneous “bad news” is not likely to be driving the results.

I further restrict the analysis sample to ensure that the competitor responses are not driven by common shocks to related approved drugs. Appendix Table A.3 reports the results of the main specification applied to more limited samples that remove projects which share target-actions with any previously approved drugs. The restricted sample results are very similar to the main analysis—confirming that ST common signals from post-approval drugs are not influencing the results.

Additionally, the results do not significantly differ when I compare discontinuation signals accompanied by a press release to those without press releases, and when I exclude the set of “treated” projects that were proximate in time to their own trial end dates. These analyses help to rule out the possibility that competitors are independently failing within a few quarters of each other, and that more-publicized events drive competitor response.

Competitor Signal Strength. I employ three different tests of how the strength of the competitor failure signals moderate the focal projects’ responses. These regressions help test issues of network interference, and confirm the intuition that firms pay greater attention to “stronger” DM-ST signals. First, I find no significant differences when comparing the focal project’s response to the first treatment vs. subsequent failure news (Appendix Figure A.7A).

Similarly, I compare “solo” treatment events (a single competitor exit) to “clusters” of treatment for each type of failure news (Appendix Figure A.7B), and events wherein the competitor drug’s failure news involved only one discontinued indication vs. multiple discontinued indications (Appendix Figure A.8). In both of those additional splits, DM-ST responses are significantly stronger ($p < 0.01$) following the “stronger” competitor signals. Together, these results suggest that firms have a higher bar for reacting to DM-ST news. Developing their drug for different conditions, these

³⁵For brevity, results not shown. In the smaller samples limited to the first 6, 8, 10 or 12 quarters of phase II, the DM-ST coefficients were not significant, despite having magnitudes quite similar to the main specification (0.17, 0.10, 0.12, and 0.15, respectively). The SM-ST coefficient remains significant in all these samples, with a magnitude between 0.7–0.8.

rival projects appear less sensitive to any one project termination. In contrast, a single SM-ST competitive failure may be enough reason to reconsider one’s own related investments.

5.6 Alternative Definitions of Project “Death” and Technological Similarity

More Inclusive Project “Death.” The main survival models use a conservative definition of project exit: when firms *officially* announce project stoppage or when Cortellis codes a discontinuation event.³⁶ That definition does not account for obviously stagnant projects that continue on paper even though the firm does not commit any further resources to the project (e.g., no additional trials). One might call such cases “zombie” projects. If firms use competitor events as an excuse to officially cancel such already-defunct projects, the mis-characterization of stoppage would threaten this paper’s empirical results. To evaluate this possibility, I construct an alternative project “death” variable that includes projects that never report any additional development (e.g., no new trials and no progression) as “discontinued” observations. 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). Appendix Table A.2 presents these regression results. These hazard models yield results very similar to the main results in Table 3.

Chemical Similarity as Technological Distance Appendix C uses the same discontinuation definition as the main analyses, but uses compounds’ structural overlap as an alternative measure of technological similarity. I use the similarity measure developed in Krieger, Li and Papanikolaou (2019) to quantify chemical distance between project pairs. I interact compound similarity with different types of competitor discontinuation news.

Appendix Table A.4 shows that project exit rates are significantly increasing in the structural similarity to discontinuing competitors (Column 1). However, when comparing the compound similarity effect across different types of competitor news (Columns 2 and 3), that relationship partially breaks down because sharing a biological target-actions is correlated with the pair having higher chemical structure similarity. Overall, structurally similar compounds have greater exit responses; but those relationships are secondary to sharing the same target-action technology. Thus, in addition to adding a layer of granularity, these results supply further justification for using the same/different technology categories as the primary groupings for knowledge spillovers.

³⁶In addition to official announcements triggering the change to “discontinued” status, Cortellis also records exits based on the removal of a project from the firm’s active pipeline information on its website or in investor documents.

5.7 Overall Impact of Competitor Learning

A series of “back-of-the-envelope” calculations help illustrate the overall magnitude of the competitor learning effects. I use the regression results to predict the overall rate of project terminations, with and without the two significant learning channels (SM-ST and DM-ST). Since entry behavior would also change in a regime with no competitor disclosure, this exercise can only represent a crude characterization of a counterfactual zero disclosure regime.

Appendix Figure A.9 displays the learning channel’s magnitude. The figure graphs the predicted probability of project discontinuation by project age (quarters in phase II), compared to the hypothetical discontinuation rate—if one were to “turn off” the ability to learn from competitors (e.g., if firms were not required to disclose trial starts and project terminations). The “predicted” discontinuation is based off the main econometric specification’s average predicted discontinuation value (corresponding to Table 3, Column 3) for observations “treated” by SM-ST or DM-ST news. This exercise 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.

Another way to think about the magnitude of learning is to ask the following question: how many terminations might have occurred without learning from competitor disclosures? In the analysis sample of 10,637 projects, 2,550 projects exited in the first 32 quarters of phase II, 1,658 project terminations occurred within two quarters of any type of competitor exit, and 463 discontinuations happened after a ST competitor exit. Assuming the same level of entry, I use the regression results to generate a “back-of-the-envelope” prediction of the exit rate, but *without* competitor learning. Many projects would eventually exit in both scenarios, but might be terminated sooner with competitor learning. Without a full structural model, one cannot estimate a true counterfactual here. Again, the no-learning scenario ignores how entry and continuation decisions might also change in a regime without competitor failure disclosures. For the sake of illustrating the role of learning on exit decisions, the “back-of-the-envelope” estimates hold entry and the number of competitors constant.

I find that turning off the learning channel results in 5.1% (129) fewer overall project exits. Simulating the predicted timing of project exits yielded 1,683 (3.7%) additional active project-quarters in the version without competitor learning. This estimate is from the average results of 1000 iterations of a Monte Carlo simulation, in which the main regression estimates predict the timing of each project termination, both with and after “shutting off” the competitor learning coefficients. While these estimates cannot reveal whether additional terminations are wise choices, they illustrate how the disclosure channel has a potentially large impact on R&D investment decisions and the fate of

R&D project teams. Even with a conservative estimate of trial costs, they suggest that competitor learning accounts for more than \$2 billion in reallocated R&D funds.³⁷

6 Conclusion

The ability to assimilate external knowledge and update effectively is of central importance to R&D managers (Cohen & Levinthal, 1990; Cockburn et al., 2000). Developing new technologies is an inherently uncertain process and requires judgments about both the expected value of the innovation and the potential of a given R&D investment to reduce uncertainty. This paper analyzes R&D project investments through the lens of real options with competitor learning. This framework highlights how competitor news provides additional decision points for reevaluating project investments. Competitor failure news can have payoff externalities, knowledge spillovers, or both. Furthermore, having more same technology competitors might actually increase a risky project’s attractiveness, by serving as an additional signals of technology quality.

The empirical results demonstrate that competitor outcomes directly enter project selection decisions. I exploit the unique features of pharmaceutical R&D, where competing projects are developed in-parallel and have distinct market and technology categories. I find that competitor discontinuations influence the probability of focal project exit, but the nature of this response depends on project relatedness. This response to competitor failure is also sensitive to the competitive environment and project characteristics. I find that market competition effects are stronger when competition is low. However, market competition considerations are subordinate to technological learning effects from highly similar competitors. Additionally, I find that project-specific uncertainty and the potential for future competitor learning both influence the magnitude of responses to competitor failure news.

The findings contribute to the literatures on real options and R&D spillovers. Failure disclosures are distinct learning opportunities and may function as additional experimental stages. To value real options with competitor learning, the analyst can include the possibility of these extra game tree “branches,” and quantify the additional option value from competitor information. On the spillovers side, the analysis reveals that the interaction of product market and knowledge externalities is not simply the sum of the two component effects. Managers and innovation scholars should account for this interaction, in addition to the two separate effects. Finally, the results suggest that learning spillovers might encourage (rational) herding both into and away from an R&D sub-field. This type of herding may be privately optimal but result in an overall lack of diversity in R&D (Dixit, 1989;

³⁷The US Department of Health & Human Services has estimated an average Phase II trial cost of \$10-\$16 million. See <https://aspe.hhs.gov/report/examination-clinical-trial-costs-and-barriers-drug-development>. Using the average of these cost approximations (\$13 million), an average trial length of 10 quarters, and the estimate of 1,683 additional active project-quarters, yields a total of \$2.2 billion in investments reallocated (or canceled) due to competitor learning.

Acemoglu, 2011) as firms prioritize information opportunities and industry trends over society's optimal mix of experiments. Policymakers can counteract such clustering by offering subsidies aimed specifically at differentiated or novel research lines. And contrary to traditional competitive strategy, firms and policy-makers might even want to encourage rivals to join in entering such new technology areas in parallel—enabling the industry to explore more uncertain frontiers in a richer information environment.

While drug development lends itself well to the study of R&D failure, the findings here are not limited to the life sciences. Any R&D setting where competitors test related technologies and target the same markets might use the same theoretical and empirical frameworks to value competitor information. However, other industries pose more difficulties for tracking R&D efforts, as well as pinpointing and decoding failure events. Future studies might address how variation in observability of competitor projects, disclosure regimes, and product complexity impacts competitor learning. When R&D failures are less public, might alternative signals (e.g., patent filings, hiring, rumors etc.) substitute as effective sources of competitor learning? How informative are R&D failures when products involve complex combinations of numerous technologies (e.g., smart phones, self-driving cars, satellites, supersonic jets, etc.)? And how do different R&D portfolio strategies improve or hinder firms' ability to interpret and act on competitor failures?

Furthermore, future analyses need not be limited to failure events, as firms also learn from their rivals' successes. The challenge in studying R&D successes is that firms may not disclose good outcomes in a single news event, but rather over the course of multiple announcements. And while this paper's analysis is limited to publicly available knowledge, R&D organizations have finer-grained information about their own projects and competitors. The flow of information about competitor projects combined with the deluge of internal data (e.g., experimental results and forecasts) should allow the modern R&D organization to continuously update the valuation of its portfolio projects.

While the nature of the information and disclosure may vary, reacting to competitor outcomes is of principal importance in industries where firms are juggling uncertain projects and information externalities. In these settings, novel information may drastically change the direction of investments. How firms vary in their response to external signals continues to be an exciting question for scholars examining firm performance and the supply of new technologies.

References

- Awaya Y, Krishna V (2019) Startup and Upstarts. SSRN Scholarly Paper No. ID 3380351.
- Abbring JH, Berg G (2003) The Nonparametric Identification of Treatment Effects in Duration Models. *Econometrica*, 71(5): 1491–1517.
- Acemoglu D (2011) Diversity and Technological Progress. Working paper, National Bureau of Economic Research, Boston.
- Adams CP, Brantner VV (2006) Estimating the Cost of New Drug Development: Is It Really \$802 Million? *Health Affairs* 25(2): 420–428.
- Adner, Ron, and Daniel A. Levinthal (2004). What Is Not A Real Option: Considering Boundaries for the Application of Real Options to Business Strategy. *Academy of Management Review* 29(1): 74–85.
- Ahmed P, Gardella, J, Nanda, S (2002) Wealth Effect of Drug Withdrawals on Firms and Their Competitors. *Financial Management* 31(3): 21–41.
- Akcigit U, Liu Q (2016) The Role of Information in Innovation and Competition. *Journal of the European Economic Association* 14(4):828–870.
- Aral S, Walker D (2012) Identifying influential and susceptible members of social networks. *Science* 337(6092): 337–341.
- Azoulay, Pierre(2004). Capturing Knowledge within and across Firm Boundaries: Evidence from Clinical Development. *American Economic Review* 94(5): 1591–1612.
- Baum JA, Dahlin, KB (2007) Aspiration Performance and Railroads’ Patterns of Learning from Train Wrecks and Crashes. *Organization Science* 18(3): 368–385.
- Bennett VM, Snyder J (2017) The Empirics of Learning from Failure. *Strategy Science* 2(1): 1–12.
- Blankshain J, Carpenter D, Moffitt S (2013) R&D Abandonment in Regulatory Equilibrium: Evidence from Asset Price Shocks Induced by FDA Decisions. Working paper.
- Bloom N, Schankerman M., Reenen, JV (2013) Identifying Technology Spillovers and Product Market Rivalry. *Econometrica* 81(4): 1347–1393.
- Bonatti A, Hörner J (2017) Learning to disagree in a game of experimentation. *Journal of Economic Theory* 169(May): 234-269.
- Boudreau KJ, Lakhani KR (2015) “Open” disclosure of innovations, incentives and follow-on reuse: Theory on processes of cumulative innovation and a field experiment in computational biology. *Research Policy* 44(1): 4–19.
- Bresnahan TF, Reiss PC (1991) Entry and Competition in Concentrated Markets. *Journal of Political Economy* 99(5): 977–1009.

- Bryan K, Lemus J (2017) The direction of innovation. *Journal of Economic Theory* 172(November): 247-272.
- Budish E, Roin BN, Williams H (2015) Do Firms Underinvest in Long-Term Research? Evidence from Cancer Clinical Trials. *American Economic Review* 105(7): 2044–2085.
- Cockburn I, Henderson R (1994) Racing to Invest? The Dynamics of Competition in Ethical Drug Discovery. *Journal of Economics & Management Strategy* 3(3): 481-519.
- Cockburn I M, Henderson RM, Stern, S (2000), Untangling the origins of competitive advantage. *Strategic Management Journal* 21: 1123-1145.
- Cohen WM, Levinthal DA (1990) Absorptive Capacity: A New Perspective on Learning and Innovation. *Administrative Science Quarterly* 35(1): 128–152.
- Colino D (2017) Cumulative Innovation and Dynamic R&D Spillovers. Working paper, Massachusetts Institute of Technology, Boston.
- Cook D, Brown D, Alexander R, March R, Morgan P, Satterthwaite G, Pangalos MN (2014) Lessons learned from the fate of AstraZeneca’s drug pipeline: a five dimensional framework. *Nature Reviews Drug Discovery* 13 (May): 419-431.
- Dasgupta, Partha, and Eric Maskin (1987). The Simple Economics of Research Portfolios. *The Economic Journal* 97(387): 581–95.
- Décaire P, Gilje EP, Taillard JP (2019) Real Option Exercise: Empirical Evidence. NBER Working Paper No. 25624.
- Dixit, A (1989) Entry and Exit Decisions under Uncertainty. *Journal of Political Economy* 97(3): 620–638.
- Dixit AK, Pindyck RS (1994) Investment under uncertainty (Princeton University Press, Princeton, NJ).
- Ederer F (2013) Incentives for Parallel Innovation (SSRN Scholarly Paper No. ID 2309664) Rochester, NY: Social Science Research Network.
- Freedman S, Kearney M, Lederman M (2010) Product Recalls, Imperfect Information, and Spillover Effects: Lessons from the Consumer Response to the 2007 Toy Recalls. *The Review of Economics and Statistics* 94(2): 499–516.
- Gans JS, Hsu DH., Stern S (2008). The Impact of Uncertain Intellectual Property Rights on the Market for Ideas: Evidence from Patent Grant Delays. *Management Science* 54(5): 982–997.
- Garde D (2016) A big Alzheimer’s drug trial now wrapping up could offer real hope — or crush it. STAT News (October 13).
- Garzon-Vico A (2012) Learning from Failure and Learning from Success in the Pharmaceutical and Biotech Industry. Working paper.

- Gill, Christopher J (2012). How Often Do US-Based Human Subjects Research Studies Register on Time, and How Often Do They Post Their Results? A Statistical Analysis of the Clinicaltrials.Gov Database. *BMJ Open* 2(4): e001186.
- Girotra K, Terwiesch C, Ulrich KT (2007) Valuing R&D Projects in a Portfolio: Evidence from the Pharmaceutical Industry. *Management Science* 53(9): 1452–1466.
- Grenadier SR (1999) Information Revelation Through Option Exercise. *Review of Financial Studies* 12(1): 95-129.
- Griliches Z (1991) The Search for R&D Spillovers. Working paper, National Bureau of Economic Research, Boston.
- Guedj I, Scharfstein D (2004) Organizational Scope and Investment: Evidence from the Drug Development Strategies and Performance of Biopharmaceutical Firms. Working paper, National Bureau of Economic Research, Boston
- Guedj I (2005) Ownership vs. Contract: How Vertical Integration Affects Investment Decisions in Pharmaceutical R&D. *McCombs Research Paper Series 2006* (Red McCombs School of Business, Austin, TX)
- Haunschild PR, Sullivan BN (2002) Learning from Complexity: Effects of Prior Accidents and Incidents on Airlines' Learning. *Administrative Science Quarterly* 47(4): 609–643.
- Hay M, Thomas DW, Craighead JL, Economides C, Rosenthal J (2014) Clinical development success rates for investigational drugs. *Nature Biotechnology* 32: 40–51.
- Henderson R, Cockburn I (1994) Measuring Competence? Exploring Firm Effects in Pharmaceutical Research. *Strategic Management Journal* 15(S1):63-84.
- Henderson R, Cockburn I (1996) Scale, Scope, and Spillovers: The Determinants of Research Productivity in Drug Discovery. *The RAND Journal of Economics* 27(1): 32–59.
- Hendricks K, Porter RH (1988) An Empirical Study of an Auction with Asymmetric Information. *The American Economic Review* 78(5): 865–883.
- Hermosilla MI. (2015) Imperfect Outsourcing of Technological Innovations. *Social Science Research Network*.
- Ingram P, Baum J (1998). Opportunity and Constraint: Organizations' Learning From the Operating and Competitive Experience of Industries. *Strategic Management Journal* 18(S1): 75-98.
- Kagel JH, Harstad RM, Levin D (1987) Information Impact and Allocation Rules in Auctions with Affiliated Private Values: A Laboratory Study. *Econometrica* 55(6): 1275-1304.
- Keller G, Rady S, Cripps M (2004) Strategic Experimentation with Exponential Bandits. *Econometrica* 73(1): 39-68.

- Kellogg D, Charnes JM (2000) Real-Options Valuation for a Biotechnology Company. *Financial Analysts Journal* 56(3): 76-84.
- Kellogg R (2014) The Effect of Uncertainty on Investment: Evidence from Texas Oil Drilling. *American Economic Review* 104(6): 1698-1734.
- Kerr WR, Nanda R, Rhodes-Kropf M (2014) Entrepreneurship as Experimentation. *Journal of Economic Perspectives* 28(3):25-48.
- Kim J, Miner A (2007) Vicarious Learning from the Failures and Near-Failures of Others: Evidence from the U.S. Commercial Banking Industry. *Academy of Management Journal* 50(3).
- Krieger J, Li D, Papanikolaou D (2019) Financing Novel Drugs. NBER Working Paper No. 24595.
- Lang L, Stulz R (1992) Contagion and competitive intra-industry effects of bankruptcy announcements: An empirical analysis. *Journal of Financial Economics* 32(1): 45-60.
- Lerner J, Seru A (2017) The Use and Misuse of Patent Data: Issues for Corporate Finance and Beyond. Working paper, National Bureau of Economic Research, Boston.
- Lowe RA, Ziedonis AA (2006) Overoptimism and the Performance of Entrepreneurial Firms. *Management Science* 52(2): 173-186.
- Lucking B, Bloom N, Van Reenen J (2018) Have R&D Spillovers Changed? NBER Working Paper No. 24622.
- Madsen PM, Desai V (2010). Failing to Learn? The Effects of Failure and Success on Organizational Learning in the Global Orbital Launch Vehicle Industry. *Academy of Management Journal* 53(3): 451-476.
- Magazzini L, Pammolli F, Riccaboni M (2012) Learning from Failures or Failing to Learn? Lessons from Pharmaceutical R&D. *European Management Review* 9(1): 45-58.
- Malueg DA, Tsutsui SO (1997) Dynamic R&D Competition with Learning. *The RAND Journal of Economics* 28(4): 751-772.
- Manhattan Institute (2012) Stifling New Cures: The True Cost of Lengthy Clinical Drug Trials. Report, Project FDA, Manhattan Institute for Policy Research.
- Manresa E (2016) Estimating the Structure of Social Interactions Using Panel Data. Working Paper.
- Manso G (2011) Motivating Innovation. *The Journal of Finance*. 66(5):1823-1860.
- Manso G (2016) Experimentation and the Returns to Entrepreneurship. *The Review of Financial Studies* 29(9): 2319-40.
- McGrath RG (1997) A Real Options Logic for Initiating Technology Positioning Investments. *Academy of Management Review* 22(4): 974-996.

- McGrath RG, Nerkar A (2003) Real options reasoning and a new look at the R&D investment strategies of pharmaceutical firms. *Strategic Management Journal* 25(1): 1–21.
- Miller, Kent D., and Timothy B. Folta (2002). Option Value and Entry Timing. *Strategic Management Journal* 23(7): 655–65.
- Nanda R, Rhodes-Kropf M (2016) Financing Risk and Innovation. *Management Science* 63(4): 901–918.
- Nelson RR (1961) Uncertainty, Learning, and the Economics of Parallel Research and Development Efforts. *The Review of Economics and Statistics* 43(4): 351–364.
- Pérez-Rodríguez JV, Valcarcel BGL (2012) Do product innovation and news about the R&D process produce large price changes and overreaction? The case of pharmaceutical stock prices. *Applied Economics* 44(17): 2217–2229
- Rao A (2018) *Strategic R&D Investment Decisions in the Pharmaceutical Industry* (SSRN Scholarly Paper No. ID 2652755). Rochester, NY: Social Science Research Network. <https://papers.ssrn.com/abstract=2652755>
- Rao H, Dutta S (2012) Free Spaces as Organizational Weapons of the Weak: Religious Festivals and Regimental Mutinies in the 1857 Bengal Native Army. *Administrative Science Quarterly* 57(4): 625–668.
- Schnitzer M, Watzinger M. (2017) Measuring the Spillovers of Venture Capital. Centre for Economic Policy Research Discussion Paper.
- Schulze U, Ringel M (2013) What matters most in commercial success: first-in-class or best-in-class? *Nature Reviews Drug Discovery* 12: 419–420.
- Sharma A, Lacey N (2004) Linking Product Development Outcomes to Market Valuation of the Firm: The Case of the U.S. Pharmaceutical Industry. *The Journal of Product Innovation Management*. 21(5): 297-308.
- Shih HP, Zhang X, Aronov AM (2018) Drug discovery effectiveness from the standpoint of therapeutic mechanisms and indications. *Nature Reviews Drug Discovery* 17(1): 19–33.
- Stern A (2016) Innovation under regulatory uncertainty: Evidence from medical technology. *Journal of Public Economics* 145(January): 181-200.

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
Ever Experience Competitor Failure in the...			
... <i>Same Market, Different Technology</i>	10,637	0.95	0.21
... <i>Same Market, Same Technology</i>	10,637	0.10	0.31
... <i>Different Market, Same Technology</i>	10,637	0.43	0.49
Active Quarters in Phase II	10,637	21.91	9.01

Note: The analysis data set contains 10,637 phase II drug-indications (projects) that entered phase II between 1997 and 2014. The projects consist of 6,182 drugs, and 325 therapeutic markets (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). 72% 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 II 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 the...			
... <i>Same Market, Different Technology</i>	254,069	0.54	0.50
... <i>Same Market, Same Technology</i>	254,069	0.02	0.14
... <i>Different Market, Same Technology</i>	254,069	0.13	0.34
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. Table 1 presents descriptive statistics at the project (drug-indication) level, and Table 2 displays information about the drug-indication-quarter panel data set. In Table 2, 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.

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

“Treatment” Window: within 2 quarters since competitor failure news	(1)	(2)	(3)	(4)	(5)	(6)
Competitor Failure Type:						
<i>Any Competitor</i>	0.014 (0.050)					
<i>Same Market Competitor</i>		-0.014 (0.050)				
<i>Same Technology Competitor</i>		0.274** (0.052)				
<i>Same Market, Different Technology</i>			-0.048 (0.050)	-0.029 (0.051)	-0.046 (0.050)	-0.040 (0.051)
<i>Same Market, Same Technology</i>			0.739** (0.100)	0.613** (0.126)	0.790** (0.101)	0.686** (0.102)
<i>Different Market, Same Technology</i>			0.158** (0.056)	0.159* (0.066)	0.259** (0.060)	0.220** (0.061)
3 Quarter Window Prior to Competitor News:						
<i>Same Market, Different Technology</i>				-0.054 (0.051)		
<i>Same Market, Same Technology</i>				0.042 (0.142)		
<i>Different Market, Same Technology</i>				-0.007 (0.068)		
<hr/>						
Controls:						
Number of Each Competitor Type					✓	✓
Firm Characteristics						✓
Nb. Drug-Indications	10,639	10,639	10,639	10,639	10,639	10,274
Nb. of Drugs	6,183	6,183	6,183	6,183	6,183	6,002
Nb. of Observations	213,302	213,302	213,302	213,302	213,302	202,080
Log Likelihood	-10,527	-10,514	-10,496	-8,013	-10,487	-9,902

Note: Estimates stem from Cox proportional hazard model specifications using panel data on drug projects by quarter. The outcome of interest is the focal project’s discontinuation. All models include a full set of year indicator variables and stratify the estimates by therapeutic indication. The competitor failure news variables are indicator 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. Column 4 tests the “no-anticipation” assumption by including indicator variables for the three quarters leading up to each type of competitor failure event. Column 5 includes control variables with the number of competitor drug projects of each type that were active in clinical trials. Column 6 further includes control variables for firm size and experience. Coefficients may be interpreted as an increase in the log hazard rate. Standard errors in parentheses.† $p < 0.10$, * $p < 0.05$, ** $p < 0.01$

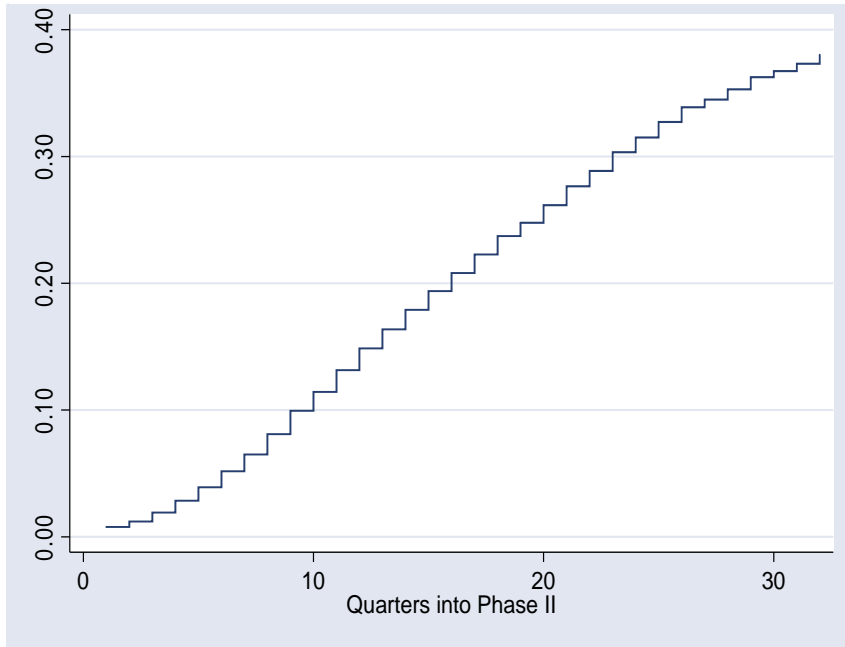
Table 4: Competitor Failure News Impact on Exit Rates, by Remaining Technological Learning Opportunities

	(1)	(2)
Tech. Learning Opportunities High (Above Median)	0.143 [†] (0.080)	0.212 ^{**} (0.081)
Competitor Failure Type (Within 2 Quarter Treatment Window):		
<i>Same Market, Diff. Technology</i> × Low Learning Opp.	0.002 (0.087)	-0.025 (0.088)
<i>Same Market, Diff. Technology</i> × High Learning Opp.	-0.119 [†] (0.068)	-0.127 [†] (0.068)
<i>Same Market, Same Technology</i> × Low Learning Opp.	0.803 ^{**} (0.227)	0.805 ^{**} (0.226)
<i>Same Market, Same Technology</i> × High Learning Opp.	0.687 ^{**} (0.110)	0.736 ^{**} (0.111)
<i>Diff. Market, Same Technology</i> × Low Learning Opp.	0.616 ^{**} (0.162)	0.629 ^{**} (0.162)
<i>Diff. Market, Same Technology</i> × High Learning Opp.	0.066 (0.063)	0.151 [*] (0.065)
Controls: Number of Each Competitor Type		✓
Nb. Drug-Indications	8,069	8,069
Nb. of Drugs	4,448	4,448
Nb. of Treating-Treated Quarter Obs.	158,817	158,817

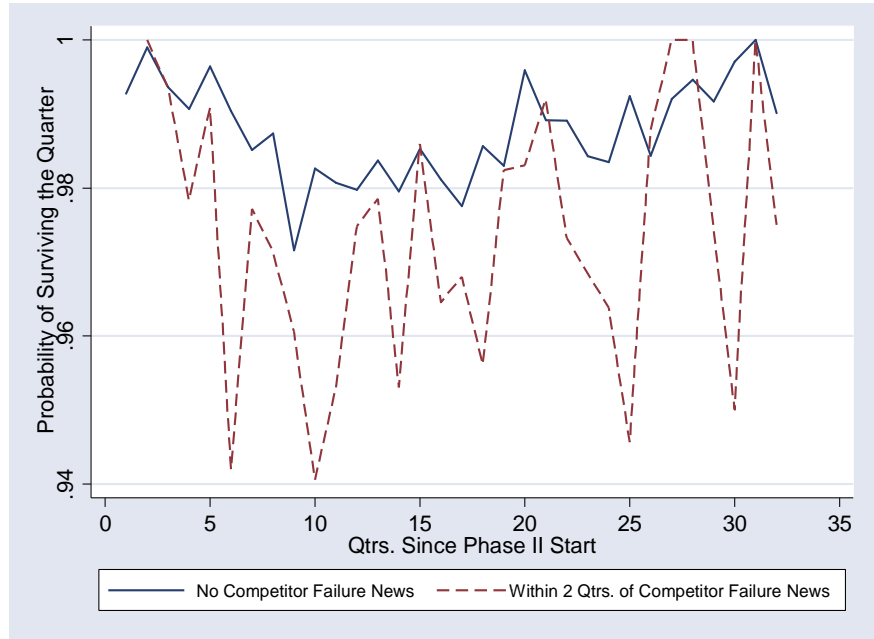
Note: Estimates stem from Cox proportional hazard model specifications using panel data of drug projects by quarter. The outcome of interest is the focal project's discontinuation. The sample excludes all projects without a primary mechanism of action (target-action) assigned in the Cortellis data. The regressions include a full set of year indicator variables and stratify the estimates by therapeutic indication. The high/low learning opportunity splits are based on the median number (5) of *same technology* competitor projects remaining in phase II or phase III trials. The competitor failure news variables are indicator 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: Project Death Rates in Phase II

A. Cumulative Hazard of Discontinuation

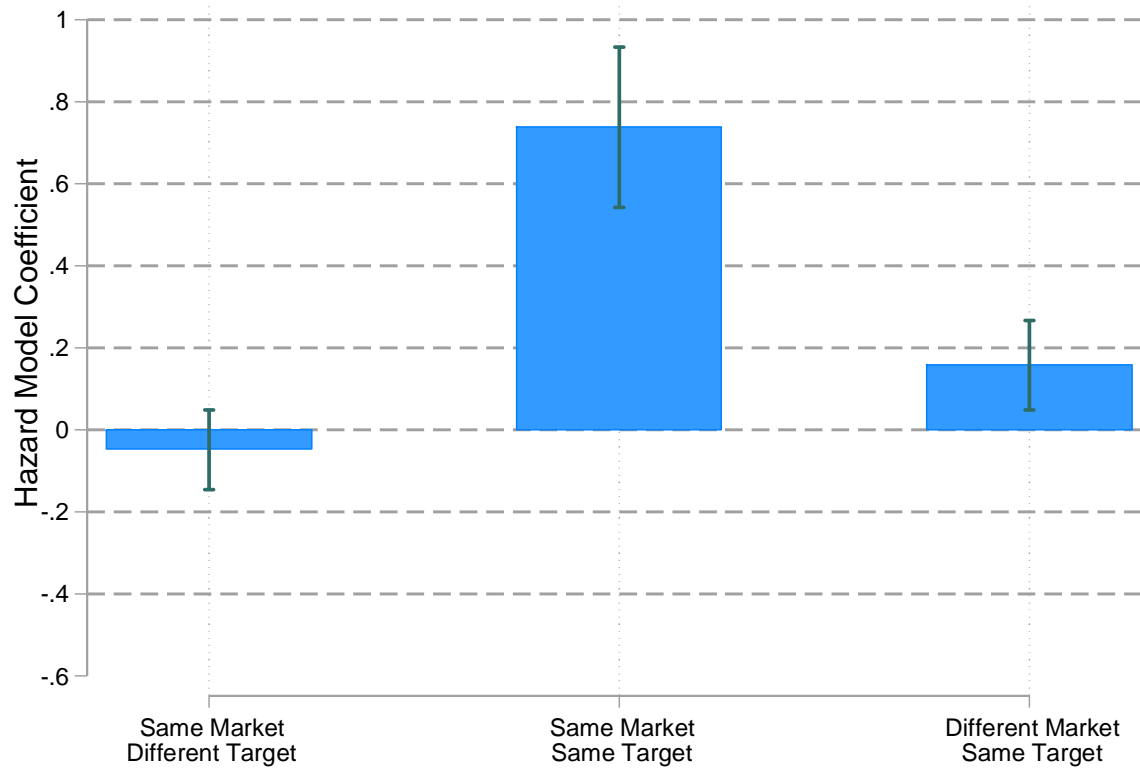


B. Project Survival Rates with and without Same Market and Technology Competitor Failure News



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 8th quarter of phase II clinical trials is not 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 window since the close competitor failure event.

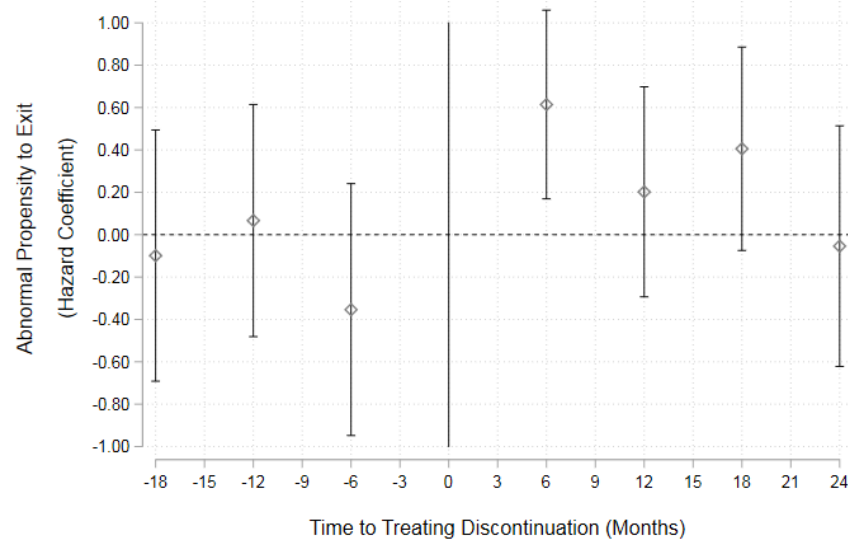
Figure 4: Competitor Failure News and Propensity to Exit



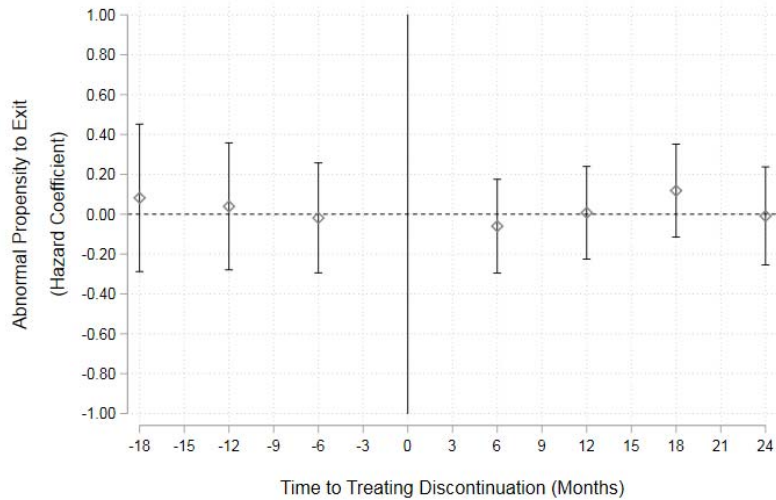
Note: The bars display the coefficients of interest from the main Cox proportional hazard model specification, which stratifies the sample by market and contains indicator variables for calendar time. The analysis sample includes 215,142 project-quarter observations (discontinued projects are censored out after exit). 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 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 capped cover the 95% confidence intervals for each regression coefficient

Figure 5: Dynamics of Response to Competitor Failure

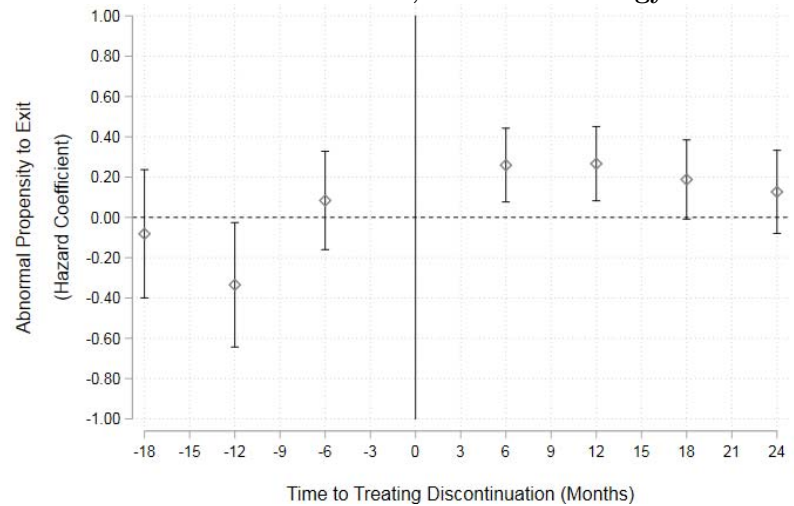
A. Same Market, Same Technology



B. Same Market, Different Technology



C. Different Market, Same Technology

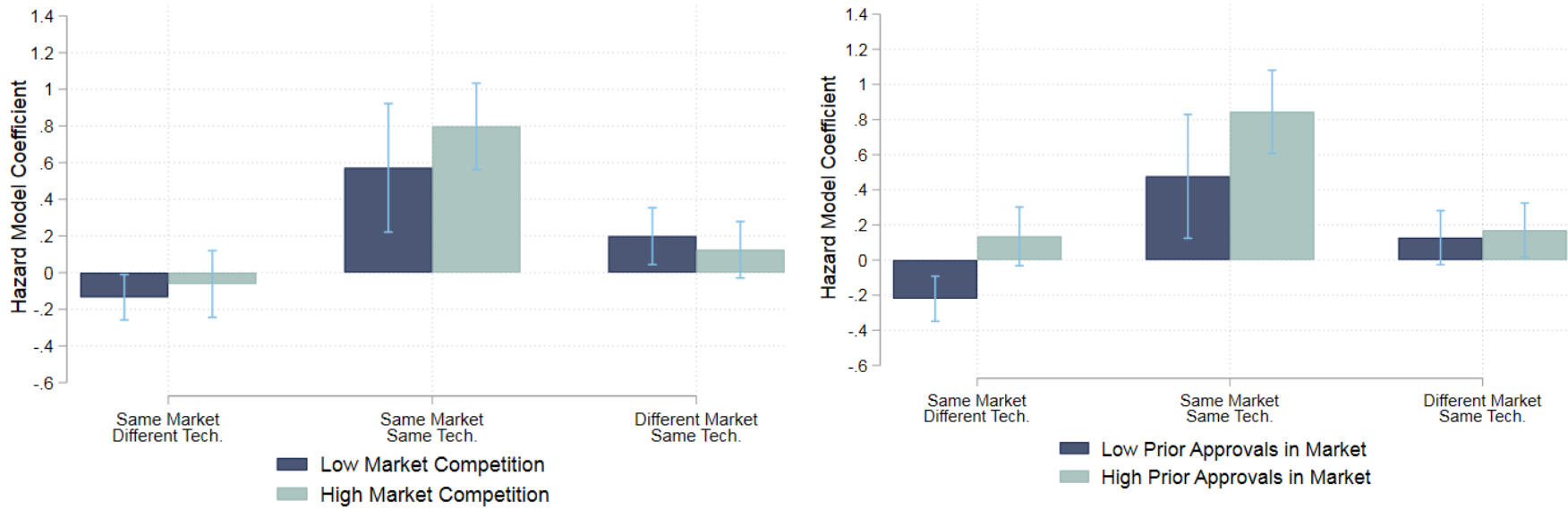


Note: The points in the above plots correspond to coefficient estimates stemming from the Cox proportional hazard model, where the variable for treatment status is interacted with the time (in six month increments) since the first competitor failure event (of each type). The six months prior to the first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

Figure 6: Level of Competition and Response to Competitor Failure

A. Level of Market Competition (in Development)

B. Level of Market Competition (Approved Drugs)



Note: The bars display the coefficients of interest from the main Cox proportional hazard model specification, split the median number of competitors, defined in two different ways. In Panel A, the level of competition is defined as the number of development projects working on the same therapeutic indication. In Panel B, the competition split is based off the number of previously approved drugs within the same therapeutic indication. The 95% confidence intervals are plotted with capped spikes.

Appendix A: Model Predictions and Proofs

This appendix repeats the theory propositions from Section 2.4 and provides formal proofs for each. All notations follow from the definitions in Section 2.

Proposition 1. *The two opposing effects, the technological learning and market competition effects, can each be the dominant effect for some initial beliefs p^0 and V^0 , updating parameters b and u , and payoff function $d(n)$.*

Corollary: *Though unobservable to the outside analyst, the continuation value underlies the decision to continue or terminate a project. Therefore, one can empirically measure the relative magnitudes of these two effects by comparing how each type of competitor failure news changes the likelihood of project discontinuation.*

The (pure) market effect—the change in continuation value induced by a SM-DT competitor failure—increases a project’s continuation value due to higher payoffs under reduced competition. The learning effect—the change in continuation value following a DM-ST competitor’s failure—decreases the probability of success and continuation value. While the direction of each effect is clear (by definition), the relative magnitude of these opposing effects is not fixed in the model (i.e., either could dominate). As a result, the relative size of the two effects is an empirical matter.

Proof.

The relevant decision occurs in the second level of the game tree, where the focal project updates the project valuation immediately following each type of competitors news. First, I generate the updated project values after receiving each type of news.

Project value after receiving *Same Market, Different Technology* news:

$$\begin{aligned} E[V|\text{SM-DT News}] &= \max[(p^0 V^H - c_2) - (1 - p^0)c_2, \bar{V}] \\ &= \max[(p^0(V^0 + d(n_0)) - c_2) - (1 - p^0)c_2, \bar{V}] \end{aligned}$$

Project value after receiving *Different Market, Same Technology* news:

$$\begin{aligned} E[V|\text{DM-ST News}] &= \max[(p^L V^0 - c_2) - (1 - p^L)c_2, \bar{V}] \\ &= \max[((p^0 - bu_0)V^0 - c_2) - (1 - (p^0 - bu_0))c_2, \bar{V}] \end{aligned}$$

Project value after receiving *Same Market, Same Technology* news:

$$\begin{aligned} E[V|\text{SM-ST News}] &= \max[(p^L V^H - c_2) - (1 - p^L)c_2, \bar{V}] \\ &= \max[((p^0 - b^1 u_0)(V^0 + d(n_0)) - c_2) - (1 - (p^0 - b^1 u_0))c_2, \bar{V}] \end{aligned}$$

Next, to evaluate the magnitude of the separate/independent market and technology effects, I compare the change in value of the “Go” continuation decision from baseline to after each type of news.

Baseline project valuation with no option to liquidate (“Stop”):

$$E_{GO}[V] = p^0 V^0 - c_1 - c_2$$

Project valuation conditional upon receiving *Same Market, Different Technology* competitor news and continuing (“Go”), and the difference (Δ) from the baseline “Go” valuation:

$$\begin{aligned} E_{GO}[V|\text{SM-DT News}] &= p^0 V^H - c_2 = p^0(V^0 + d(n_0)) - c_2 \\ \rightarrow \Delta E_{GO}[V|\text{SM-DT News}] &= E_{GO}[V|\text{SM-DT News}] - E_{GO}[V] = p^0 d(n_0) + c_1 \end{aligned}$$

Project valuation conditional upon receiving *Different Market, Same Technology* competitor news and continuing (“Go”), and the difference (Δ) from the baseline “Go” valuation:

$$\begin{aligned} E_{GO}[V|\text{DM-ST News}] &= p^L V^0 - c_2 = (p^0 - bu_0)V^0 - c_2 \\ \rightarrow \Delta E_{GO}[V|\text{DM-ST News}] &= E_{GO}[V|\text{DM-ST News, GO}] - E_{GO}[V] = -bu_0 V^0 + c_1 \end{aligned}$$

The relative magnitude of the technological learning and market competition effects can be represented by the following inequality, where either side of the equation might be larger depending on initial beliefs and level of updating.

Technological Learning Effect \lesseqgtr Market Competition Effect

$$\begin{aligned} \Delta E_{GO}[V|\text{DM-ST News}] &\lesseqgtr \Delta E_{GO}[V|\text{SM-DT News}] \\ | -bu_0 V^0 | &\lesseqgtr | p^0 d(n_0) | \end{aligned}$$

□

Proposition 2. *Simultaneous market and technology news (SM-ST) lead to the largest downwards updating on the likelihood of success ($b^1 u > bu$), and have an effect on the continuation value that is lower than the sum of the two opposing independent effects.*

The intuition for this prediction is that differences in product-market applications should moderate the relevance of competitor technology signals. For example, doctors might be willing to accept nasty side effects for some, but not other, diseases and patient populations (e.g., children vs. adults, slow vs. fast progressing diseases).

Proof.

To show that the SM-ST effect on continuation value is not equal (more negative) than the sum of its parts, I start by evaluating the project valuation conditional upon receiving *Same Market, Same Technology* competitor news and continuing (“Go”), and the difference (Δ) from baseline “Go” valuation:

$$E_{GO}[V|\text{SM-ST News}] = p^L V^H - c_2 = (p^0 - b^1 u_0) \times (V^0 + d(n_0)) - c_2$$

$$\rightarrow \Delta E_{GO}[V|\text{SM-ST News}] = E_{GO}[V|\text{SM-ST News}] - E_{GO}[V] = p^0 d(n_0) - b^1 u_0 V^0 - b^1 u_0 d(n_0) + c_1$$

The change in value from SM-ST News is less (i.e., more negative) than the sum of the two independent and oppositely signed effects:

$$\Delta E_{GO}[V|\text{SM-ST News}] < \Delta E_{GO}[V|\text{SM-DT News}] + \Delta E_{GO}[V|\text{DM-ST News}]$$

$$\rightarrow p^0 d(n_0) - b^1 u_0 V^0 - b^1 u_0 d(n_0) + c_1 < p^0 d(n_0) + c_1 - b u_0 V^0 + c_1$$

$$\rightarrow -b^1 u_0 V^0 - b^1 u_0 d(n_0) < c_1 - b u_0 V^0$$

The left hand side of the inequality must strictly be less than 0 because $b^1 u_0 V^0 > 0$ and $b^1 u_0 d(n_0) > 0$. The inequality must hold because $-b^1 u_0 V^0 < b u_0 V^0$ (by definition) and $c_1 \geq 0$. \square

Proposition 3. *Continuation values change more in response to (same market) competitor failures when the baseline number of same market competitors (n_0) is smaller.*

High levels of market competition can greatly diminish the payoff externalities of competitor failure. In markets with many existing products and/or intense R&D competition for the next generation products, losing a single pipeline competitor does little to the expected rewards of success. This prediction follows from the assumption that payoffs are a decreasing convex of competition.

Proof.

To assess how competition impacts the market competition effect, I take the derivative of the SM-DT news effect on continuation value with respect to the level of competition, n .

$$\Delta E_{GO}[V|\text{SM-DT News}] = E[V|\text{SM-DT News}, GO] - E_{GO}[V]$$

$$= p^0 d(n_0) + c_1 \frac{\partial \Delta E[V|\text{SM-DT News}]}{\partial n}$$

$$= \frac{\partial [p^0 d(n_0) + c_1]}{\partial n} = \frac{\partial p^0 d(n_0)}{\partial n}$$

$d(n)$ is defined as a decreasing, convex function of n , and p^0 is a constant between 0 and 1, so $\frac{\partial p^0 d(n)}{\partial n} < 0$. Therefore, the change in continuation value resulting from a SM technology competitor’s exit, $\Delta E[V|\text{SM-DT News}]$, is decreasing in n .

The same analysis can be applied to SM-ST news:

$$\Delta E_{GO}[V|\text{SM-ST News}] = p^0 d(n_0) - b^1 u_0 V^0 - b^1 u_0 d(n_0) + c_1$$

$$\frac{\partial \Delta E_{GO}[V|\text{SM-ST News}]}{\partial n} = \frac{\partial p^0 d(n_0)}{\partial n} - \frac{\partial b^1 u d(n_0)}{\partial n}$$

Again, the first part of the expression is negative ($\frac{\partial p^0 d(n)}{\partial n} < 0$). The second component, $\frac{\partial b^1 u d(n)}{\partial n}$ must also be a negative value because $b^1 u \geq 0$ (by definition) and again $d(n)$ is defined as a decreasing, convex function of n . However since $b^1 u$ is the downward updating response to SM-ST failure news, it must take on values between 0 and p^0 , so $p^0 > b^1 u$, and $\Delta E[V|\text{SM-ST News}]$ is also decreasing in n . \square

Proposition 4. *The impact of a same technology competitor dropping out on project value is increasing in the level of uncertainty (u).*

Competitor signals are most useful for belief updating when firms still have more uncertainty about their own project's quality.

Proof.

To see how the the level of uncertainty moderates the impact of competitor news, I start with how *Different Market, Same Technology* news changes the project continuation value:

$$\begin{aligned} \Delta E_{GO}[V|\text{DM-ST News}] &= E_{GO}[V|\text{DM-ST News}] - E_{GO}[V] \\ &= p^L V^0 - c_2 - (p^0 V^0 - c_1 - c_2) \\ &= (p^0 - b u_0) V^0 - c_2 - (p^0 V^0 - c_1 - c_2) = -b u_0 V^0 + c_1 \end{aligned}$$

Next, I take the derivative of that change with respect to the level of uncertainty, u :

$$\frac{\partial \Delta E[V|\text{DM-ST News}]}{\partial u} = \frac{\partial [-b u_0 V^0 + c_1]}{\partial u} = \frac{\partial [-b u_0 V^0]}{\partial u} < 0$$

V^0 is a positive constant and independent of u , while both b and u_0 are positive values between 0 and 1 (by definition). Therefore, the absolute impact ($|\Delta|$) of a ST competitor's exit on continuation value is increasing in u . Intuitively, $\Delta E[V|\text{DM-ST News}]$ is *decreasing* in u because as uncertainty rises, updating on p after DM-ST news increases—leading to a greater decrease in continuation value.

This relationship holds for SM-ST news, as well:

$$\begin{aligned} \Delta E[V|\text{SM-ST News}] &= E_{GO}[V|\text{SM-ST News}] - E_{GO}[V] \\ &= p^0 d(n_0) - b^1 u_0 V^0 - b^1 u_0 d(n_0) + c_1 \\ \frac{\partial \Delta E_{GO}[V|\text{SM-ST News}]}{\partial u} &= \frac{\partial [p^0 d(n_0) - b^1 u_0 V^0 - b^1 u_0 d(n_0) + c_1]}{\partial u} \\ &= \frac{\partial [-b^1 u_0 V^0 - b^1 u_0 d(n_0)]}{\partial u} < 0 \end{aligned}$$

Again, increases in uncertainty are associated with relatively greater decreases in continuation value (holding payoffs constant).

□

Proposition 5. *Continuation value is increasing in the number of technological learning opportunities (same technology competitors).*

Learning opportunities effectively speed up experimentation by resolving some uncertainty *earlier*. ST competitor failures provide new decision points where firms can cut losses and abandon projects. Due to the increased expectation of competitor news, the relative amount of belief updating on p (following competitor ST failure news) increases in n_{ST} for “no news” and decreases in n_{ST} for competitor failure news.

Proof.

To evaluate the relationship between the number of DM-ST competitors (n_{dm-st}), I begin by adapting the continuation value Equation (3) by fixing the number of market competitors (n_{sm}) and the payoffs conditional on success (V^0). This version of continuation value has two states: 1) receive DM-ST competitor failure news, and 2) receive no competitor failure news.

$$E[V] = g(p^0, n_{st}) \times \max[(p^L V^0 - c_1 - c_2) - (1 - p^L) - c_1 - c_2, \bar{V} - c_1] \\ + [1 - g(p^0, n_{dm-st})] \times \max[(p^H V^0 - c_1 - c_2) - (1 - p^H)(c_1 + c_2), \bar{V} - c_1]$$

The above and Equation (3) have two important difference. First, the probability of receiving competitor failure news is not only dependent on the firm’s baseline belief about the probability of success (p^0), but also on the number of DM-ST competitors. g is decreasing in p^0 and increasing in n_{dm-st} . The second change is that payoffs conditional on success (V^0) are unchanged under the news and no-news scenarios.

At first blush, more “bad” news sounds unlikely to increase project value, since more weight is shifted to the “worse” state ($p^L V^0 < p^H V^0$). But the shift in the *cost* from that “bad” state is what increases project value. More same technology competitors (n_{dm-st}) increase continuation value through the reduced cost of experimentation.

$$\frac{\partial E[c_1]}{\partial n_{dm-st}} < 0$$

$E[c_1]$ is decreasing in n_{st} , because (as described in Section 2.2) more potential competitor signals increases the chance of getting bad news *earlier*. When c_1 is small, the value of the option to stop early ($\bar{V} - c_1$) is larger—increasing the floor of the overall continuation value ($\bar{V} - c_1$). The option to stop limits the negative impact of a “bad” state outcome, and the reduction in expected cost essentially reduces the cost of entry.

□

Appendix B: The Drug Development Process and Disclosure Requirements

The Phases of Development. 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* (i.e., in a test tube) and *in vivo* (in a living organism) tests of their drug candidates—looking for signs that the compound interacts with the biological target of interest, as well as any potential toxicity success in fighting 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. This involves three phases.

Each phase of these pre-approval clinical trials includes 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 are larger (they include several hundred people who have the condition of interest), and typically require randomization into treatment and placebo (or the existing standard of care) groups. Phase III is essentially a larger scale version of the phase II trials, usually involving more participants (often thousands) who are tracked over a longer period of time. Trial costs range from thousands of dollars in phase I, to hundreds of millions in phase III (Manhattan Institute, 2012).

Before the Federal Drug Administration 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.ⁱ 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.

Often, the earliest steps of drug development are conducted in smaller firms or in collaboration with academic researchers, while only larger pharmaceutical or biotechnology firms can provide the scale and capital needed for later stage clinical trials and marketing activities. 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).ⁱⁱ

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 may reverberate throughout the industry, and

ⁱWhile 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).

ⁱⁱContract research organizations 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).

change 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).

Disclosing Discontinuation. Drug development firms disclose the discontinuation of a development project through various 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). For public companies, these disclosures often have a drastic and immediate impact on stock price. A number of studies have documented how negative clinical trial news consistently leads to large statistically significant stock drops for the developer firm (Sharma & Lacey, 2004; Girotra, 2007; Perez-Rodriguez & Valcarecel, 2012). These reactions corroborate that the disclosures qualify as a "shock" or surprise to market participants. To illustrate how these disclosures appear, I include two representative examples in the next section.

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. 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.

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 theoretically be 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. As mentioned at the end of Section 3.2, small firms do not have a greater proportion of "zombie" projects, which remain listed as active, despite having no development activity for a substantial period of time.

Disclosure Examples. It is common for firms to disclose that they are shuttering a drug development project via press release. For example, Evlutec Group announced that it would discontinue development of their drug Votucalis on January 3, 2007. Evlutec 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, the company put out a press release:

Evlutec 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 Evlutec, said: "Following this disappointment, no more investment will be made by Evlutec 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-Barré Syndrome where there are currently no curative therapies."

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 on 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.

On occasion, companies disclose when their project termination decisions are influenced by competitor outcomes. For example, in April 2012 Newlink Genetics used a press release to announce that due to a competitor failure, it was stopping a drug project (a combination therapy) for treating melanoma:

*...the Company has determined that it will not initiate the randomization portion of Indigo301, its study of indoximod in combination with pembrolizumab or nivolumab for patients with advanced melanoma. NewLink's clinical team will evaluate the design, trial size and feasibility of an alternative randomized evaluation of indoximod in melanoma **in the context of the failure of a competitor's trial of its enzymatic IDO inhibitor in a similar clinical setting.** The evaluation will include analysis of the full data set from the Company's single-arm Phase 2 melanoma study, the differentiated mechanism of action of indoximod, and the opinions of experts in the field. The Company will present final results from its Phase 2 trial in melanoma and its single-arm Phase 2 trial in pancreatic cancer at an upcoming medical conference in the first half of 2018. [emphasis added]*

Appendix C: Molecular Similarity and Competitor Failure News

Chemical Similarity Data. While shared target-actions serve as the primary measure of technological similarity in this paper and in related analyses from industry researchers (Cook et al., 2014; Shih et al., 2018), I also evaluate technological distance using chemical informatics techniques comparing the structural makeup of small molecule drugs. Rather than directly measuring functional similarity, this alternative approach quantifies the physical similarity of any two drug compounds.

Cortellis has chemical structure information for roughly 40% of Cortellis drug projects (drug-indications) and 60% of projects that reach phase II clinical trials. Those percentages rise to approximately 60% and 85%, respectively, when restricted to small molecule drugs (i.e., excluding biologic drugs and vaccines).

Pairwise chemical similarity measures are quantitative measures for comparing the structural elements of compounds. Chemists and drug developers often use drug similarity to predict chemical properties and to screen and compare drug candidates. For the analyses in this paper, I used the “tanimoto” chemical similarity data collected in Krieger, Li and Papanikolaou (2019). That paper takes the full set of SMILES codes associated with Cortellis drugs and uses the open source ChemmineR packageⁱⁱⁱ to calculate all pairwise chemical similarity scores (where the similarity score is greater than or equal to 0.1).

Chemical Similarity Results. Figure A.1 describes the pairwise similarity data in this paper’s analysis. These pairs include all the phase II focal projects and their relevant “frontier” competitors. The three panels in Figure A.1 separate drug dyads into the three types of competitor relationships: 1) SM-ST, 2) SM-DT, and 3) DM-ST.

The median same technology pair has a chemical similarity of less than 0.23 (where a score of 1 means 100% chemical structure overlap), and fewer than 4% have similarity scores over 0.9.^{iv} These distributions confirm that, despite sharing more structural features, that same target-action compounds still have plenty of chemical diversity.^v

While the SM-ST group has plenty of variation in pairwise similarity scores, the mean similarity scores are at least double in the same technology groups compared to those in the SM-DT group. This pattern is in line with Krieger, Li and Papanikolaou (2019) who find that sharing the same target-action is associated with doubling in chemical similarity (on average), while merely sharing the same indication is associated with an approximately 25% increase in compound similarity score. In other words, same target-action (“technology”) drugs are more likely to share structural features, even though many of these same target-action drugs are chemically quite different from one another.

Using the subset competitor pairs that are both small molecules, I analyze how compound similarity moderates the response to competitor failure news. For this survival analysis, I use the dyadic level data described in Appendix D, and Cox proportional hazard models similar to the main

ⁱⁱⁱFull documentation: <https://www.bioconductor.org/packages/release/bioc/vignettes/ChemmineR/inst/doc/ChemmineR.html>

^{iv}Krieger, Li, and Papanikolaou (2019) define “me-too” drugs as those with similarity to previously developed drugs of greater than or equal to 0.9.

^vAspects of the patent system also prevent too many copy-cat drugs. For a given new compound, firms can patent a “Markush” structure which covers very closely related chemical compounds.

results (Table 3), with three quarter treatment windows (“within two quarters since competitor failure news”).

The results show that chemically similar compounds are far more reactive to competitor discontinuation than chemically dissimilar focal projects. First, I pool the competitor dyads and separately estimate both the treatment coefficient and the treatment interacted with compound similarity of the the focal project to the “treating” competitor (Column 1). The isolated treatment coefficient insignificant, while the treatment interacted with similarity is highly significant. The latter’s coefficient implies that a one standard deviation increase in failing competitor’s chemical similarity (0.14) results in a 40% increase in the likelihood of project exit. Said differently, a jump from the 25th percentile to the 75th percentile in project similarity increases the competitor response (likelihood of exit) by 61%.

However, the relationship between similarity and competitor response is not uniform. When I further split the treatment variables by “type” of failure news and interact each type with focal and competitor project compound similarity, the results show more nuance (Column 2). On average, focal projects with low similarity to SM-DT competitors do not respond to low similarity competitor failure news. However, for the SM-DT news, a high level of structural similarity leads to roughly the same response as to competitors with SM-ST and low structural similarity. Even with low levels of compound similarity, SM-ST competitor failures induce significant competitor exit, and that effect increases with compound similarity. However, the additional impact of compound similarity does not show up for the DM-ST group. For this group, learning from more similar compounds’ trial outcomes appears to be secondary to the relevance of sharing the same technology (target-action). Column 3 further shows that same technology competitor signals are influential regardless of chemical similarity, while on average, the effect of same market signals is highly dependent on the level of chemical similarity.

Overall, the compound similarity data provides two helpful insights. First, these results confirm that chemical similarity is positively correlated with sharing a target-action, while the descriptive data still shows plenty of compound variation within target-action categories. Second, the regression results suggest that the degree of chemical distance is relevant for responses to competitor failure, but less relevant for same target-action competitor news. Together, these results suggest that chemical similarity provides an additional interesting layer of heterogenous spillovers, but is unlikely to be a better (more relevant) way of defining competitor sets than the straightforward same/different target-action distinction used in this paper and in Shih et al. (2018).

Appendix D: Alternative Econometric Specifications

In this section, 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 timeline, and allows one to control for different life cycles across therapeutic areas. Some of these same analysis qualities can be applied through alternative regression specifications. Below I describe three of these alternative specifications.

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).

Column 3 in Table A.5 reports the coefficients corresponding to β_1 , β_2 , and β_3 in the two-period (before and after competitor news), absorbing state treatment version equation above. At a high level, the results are qualitatively the same as the hazard model specifications: SM-ST news leads to the biggest change in propensity to exit, SM-DT news leads to a small and possibly negative impact on exit rates, and DM-ST leads to a modest increase in pulling the plug. f

Dyadic Data Construction

An alternative way to evaluate the impact of competitor exit on project continuation decisions is to analyze each event in project pairs. Under this approach, a unit of observation includes the relevant exiting drug-indication project i (“treating,” or signal “sender”), a focal 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, there may be only one “treating” event, and the “treating” project must exit prior to the “treated” project’s exit. The resulting data set has 11,017,691 observations with 151,840 treating-treated pairs.

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 A.5, Column 1. Again, we see the largest effect corresponds to the SM-ST news, with a smaller increase (about one half the magnitude) associated with DM-ST news. The major divergence from the single-level data set results is that the SM-DT coefficient is positive and significant, though smaller than the coefficients from the other two groups.

Figure A.10 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 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. A positive coefficient in 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., $t - 1$).

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” projects’ 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 A.5, 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 SM-DT 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 A.11, shows large spikes in the hazard rate of own project discontinuation in the first quarter after the competitor exit for both the SM-ST and DM-ST groups. The SM-DT coefficients are mainly flat, with a small increase immediately following the competitor news, but are not all significantly different from zero.

Appendix E: Additional Robustness Checks

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. To understand how the sequencing of failure events affects the response to competitor failure, I use two separate subsample analyses. In the first, I address how firms respond to the first competitor failure (of each type), 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 main regression 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 Appendix Figure A.7A. The magnitude of each treatment effect is quite similar and not statistically distinguishable between first and subsequent treatments. These results help rule out concerns about multiple signals leading to mis-measurement of dyadic peer influence (Bramouille, 2016).

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 motivating intuition is that multiple failure events might represent a stronger signal, and exit decisions might be influenced by watching other firms respond to an initial event (e.g., “if they think it’s bad news, then we should too”). The results (displayed in Appendix Figure A.7B) show some differences between the two scenarios. Most notably, the DM-ST 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 SM-ST coefficient appears larger than the clustered treatment version, but they are not statistically different since the rarity of the clustered SM-ST treatments results in a very noisy estimate.

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 surrogates 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 terminated trials early for safety concerns. While the former example may have involved safety concerns of its own, such concerns would have been indication-specific since 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 first looked at a sub-sample for which I could determine the reason for failure and examined the correlation between their reasons for failure and multiple-indication discontinuations. Clinicaltrials.gov requires that trial sponsors enter the reason for early stoppage when trials do not run until completion. Failure reasons are available for 300 of the “treating” projects in my sample because they involved early terminated trials. I found a statistically significant positive correlation between multiple-indication discontinuations and “safety” reasons for failure. However, I found no such correlation for “efficacy” or “strategic” reasons for project termination. These results make intuitive sense, because safety issues are more likely to affect all patients, while efficacy issues are likely disease-specific.

The results of this analysis are displayed in Appendix Figure A.8. In each case the magnitudes are greater for the multiple-indication failure group (within each competitor news type). The biggest difference is in the DM-ST failure news type, where the multiple-indication failure response is significantly larger than the single-indication failure response ($p < 0.05$), and the single-indication failure response is not statistically different from zero. The difference between the two subgroups shows that multiple-indication (likely safety) events are driving the main effects found for DM-ST news, despite being the minority of such events.^{vi} Safety concerns could be a sufficient signal for same technology learning, but efficacy problems only spark competitor response when the projects also share the same disease group.

I also investigated the proximity in time between discontinuation announcements and the end of the drug project’s last trial. If discontinuation announcements are completely decoupled from one’s own R&D results, they might reveal strategic concerns rather than information about the discontinued project’s quality.

To address these concerns, I compared the response to competitor discontinuations announced close (in time) to the end of the focal project’s last clinical trial to those more than one year following the last trial outcome. When I interacted the main treatment specifications with whether or not the failure news was within one year of the last trial date, I found no statistically significant differences between the sub-groups (results not shown). My primary interpretation of this result is that firms are indeed responding to competitor failure news 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.

^{vi}Thirty-seven percent of the DM-ST competitor events involve multiple-indication competitor failure events.

Table A.1: Competitor News Effects on Exit Rate, Alternative Treatment Definitions

	(1)	(2)	(3)	(4)	(5)	(6)
After Any Competitor Failure News	-0.005 (0.077)					
After Competitor Failure News (<i>Same Market</i>)		-0.083 (0.070)				
After Competitor Failure News (<i>Same Tech.</i>)		0.204** (0.044)				
After Competitor Failure News (<i>Same Market, Different Tech.</i>)			-0.106 (0.070)			
After Competitor Failure News (<i>Same Market, Same Tech.</i>)			0.421** (0.076)			
After Competitor Failure News (<i>Different Market, Same Tech.</i>)			0.113* (0.047)			
# Competitor Failure Events (<i>Any Type</i>)				0.009 [†] (0.005)		
# Competitor Failure Events (<i>Same Market</i>)					-0.003 (0.006)	
# Competitor Failure Events (<i>Same Tech.</i>)					0.025** (0.006)	
# Competitor Failure Events (<i>Same Market, Different Tech.</i>)						-0.006 (0.006)
# Competitor Failure Events (<i>Same Market, Same Tech.</i>)						0.154** (0.037)
# Competitor Failure Events (<i>Different Market, Same Tech.</i>)						0.012 (0.007)
Nb. of Observations	213,302	213,302	213,302	213,302	213,302	213,302
Log Likelihood	-10,527	-10,516	-10,504	-10,525	-10,520	-10,514

Note: Estimates stem from Cox proportional hazard model specifications using panel data on drug projects by quarter. The sample includes 6,183 drugs and 10,639 drug-indications. The first six variables are binary treatment variables that take on the value of one after the first competitor exit (of each type). Wald tests confirm that the coefficients in Column 3 are significantly different from one another. The bottom six variables are counts of each treatment type. All models include a full set of year indicator variables and stratify by therapeutic indication. Standard errors in parentheses. [†] $p < 0.10$, * $p < 0.05$, ** $p < 0.01$

Table A.2: Competitor Failure News Impact on Hazard Rate of Exit (Alternative Project “Death” Outcome)

“Treatment” Window: within 2 quarters since competitor failure news	(1) Project Death (Inclusive Definition)	(2) Project Death (Inclusive Definition)	(3) Project Death (Inclusive Definition)
Competitor Failure Type			
<i>Same Market, Different Technology</i>	0.058 (0.036)	0.058 (0.036)	0.057 (0.037)
<i>Same Market, Same Technology</i>	0.521** (0.080)	0.529** (0.082)	0.571** (0.081)
<i>Different Market, Same Technology</i>	0.114** (0.042)	0.124** (0.043)	0.211** (0.045)
3 Quarter Window <i>Prior</i> to Competitor News:			
<i>Same Market, Different Technology</i>		-0.016 (0.032)	
<i>Same Market, Same Technology</i>		-0.038 (0.092)	
<i>Different Market, Same Technology</i>		-0.033 (0.040)	
Controls: Number of Each Competitor Type			✓
Nb. Drug-Indications	10,639	10,639	10,639
Nb. of Drugs	6,183	6,183	6,183
Nb. of Observations	143,992	143,992	143,992
Log Likelihood	-22,110	-22,109	-22,095

Note: Estimates stem from Cox proportional hazard model specifications using panel data on drug projects by quarter. The outcome is project discontinuation; however, the alternative definition of discontinuation used here includes both officially discontinued projects and projects that completed their final phase II trial for a given drug-indication and do not have any subsequent development. Under this more liberal definition of project “death,” nearly 51% of the (non-right-censored) phase II projects in the sample are discontinued, as opposed to 18% in the more conservative definition used in the main specifications. All models include a full set of year indicator variables and stratify the estimates by therapeutic indication. The competitor failure news variables are indicator 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. Column 2 tests the “no-anticipation” assumption by including indicator variables for the three quarters leading up to each type of competitor failure event. Column 3 includes control variables with the number of competitor drug projects of each type that were active in clinical trials. Coefficients may be interpreted as an increase in the log hazard rate. Standard errors in parentheses.† $p < 0.10$, * $p < 0.05$, ** $p < 0.01$

Table A.3: Competitor Failure News Impact on Hazard Rate of Exit, Restricted Sample with No Previously Approved Target-Actions

	(1)	(2)	(3)
	Full Analysis Sample	Excluding Projects with One or More Previously Approved Target- Actions	Excluding Projects where Exact Combination of Target-Actions Previously Approved
“Treatment” Window: within 2 quarters since competitor failure news			
Same Market, Different Technology	-0.048 (0.050)	0.003 (0.062)	-0.006 (0.057)
Same Market, Same Technology	0.739** (0.100)	0.714** (0.144)	0.708** (0.116)
Different Market, Same Technology	0.158** (0.056)	0.333** (0.087)	0.322** (0.067)
Nb. Drug-Indications	10,639	6,664	7,919
Nb. of Drugs	6,183	4,065	4,661
Nb. of Observations	213,302	134,263	158,093
Log Likelihood	-10,496	-6,038	-7,461

Note: Estimates stem from Cox proportional hazard model specifications using panel data on drug projects by quarter. The outcome of interest is the focal project’s discontinuation. All models include a full set of year indicator variables and stratify the estimates by therapeutic indication (ICD9). The competitor failure news variables are indicator variables that take on the value of one when the focal project is within two quarters since the given type of competitor failure event. Column 1 reports the full sample version (same as Table 3, Column 3). Column 2 applies the same specification, but limits the analysis sample to drug projects that do not share any known mechanisms (target-actions) with any previously approved drugs. Similarly, Column 3 excludes drugs that share the exact same set of target-actions with at least one previously approved drug. The sample used to generate the Column 3 results is less restrictive than the sample in Column 2 because some drugs have multiple target-actions, where only one of those target-actions was associated with a previously approved drug. In all three models, Wald tests confirm that *same market*, *same technology* and the *same market, different technology* coefficients are statistically different from one another ($p < 0.05$). Coefficients may be interpreted as an increase in the log hazard rate. Standard errors in parentheses. † $p < 0.10$, * $p < 0.05$, ** $p < 0.01$

Table A.4: Competitor Failure News Impact on Exit Rates, by Molecular Similarity

“Treatment” Window: within 2 quarters since competitor failure news	(1) Project Exit (Dyadic Cox)	(2) Project Exit (Dyadic Cox)	(3) Project Exit (Dyadic Cox)
Competitor Discontinuation (<i>Any</i>)	0.051 (0.036)		
Competitor Discontinuation (<i>Any</i>) × Similarity	1.370** (0.167)		
Competitor Discontinuation (<i>Same Mkt, Diff. Tech.</i>)		-0.017 (0.043)	
Competitor Discontinuation (<i>Same Mkt, Diff. Tech.</i>) × Similarity		0.819** (0.290)	
Competitor Discontinuation (<i>Same Mkt, Same Tech.</i>)		0.903** (0.209)	
Competitor Discontinuation (<i>Same Mkt, Same Tech.</i>) × Similarity		0.831 [†] (0.429)	
Competitor Discontinuation (<i>Diff. Mkt, Same Tech.</i>)		0.829** (0.093)	0.828** (0.093)
Competitor Discontinuation (<i>Diff. Mkt, Same Tech.</i>) × Similarity		0.232 (0.284)	0.230 (0.284)
Competitor Discontinuation (<i>Same Mkt</i>)			-0.040 (0.042)
Competitor Discontinuation (<i>Same Mkt</i>) × Similarity			1.207** (0.248)
Nb. Drug-Indications	5,015	5,015	5,015
Nb. of Drugs	2,819	2,819	2,819
Nb. of Treating-Treated Quarter Obs.	1,476,105	1,476,105	1,476,105
Log Likelihood	-115,357	-115,275	-115,292

Note: Estimates stem from Cox proportional hazard model specifications, where the outcome is own project discontinuation. To allow for pairwise chemical compound comparisons, all models are at the dyadic (treating-treated) level, and is limited to pairs of small molecule drugs (i.e., no biologic drugs). All models include a full set of year indicator variables and stratify the hazard specification by therapeutic indication. The competitor failure news events (treatment variables) take on a value of one when the focal project is within two financial quarters since the given type of competitor failure event. Additional independent variables interact these treatment states with the pairwise Tanimoto chemical similarity between the treating and treated drugs. These similarity values range from zero (no chemical structure overlap) to one (100% structure overlap, not accounting for stereochemistry). Coefficients may be interpreted as an increase in the log hazard rate. Standard errors in parentheses.

[†] $p < 0.10$, * $p < 0.05$, ** $p < 0.01$

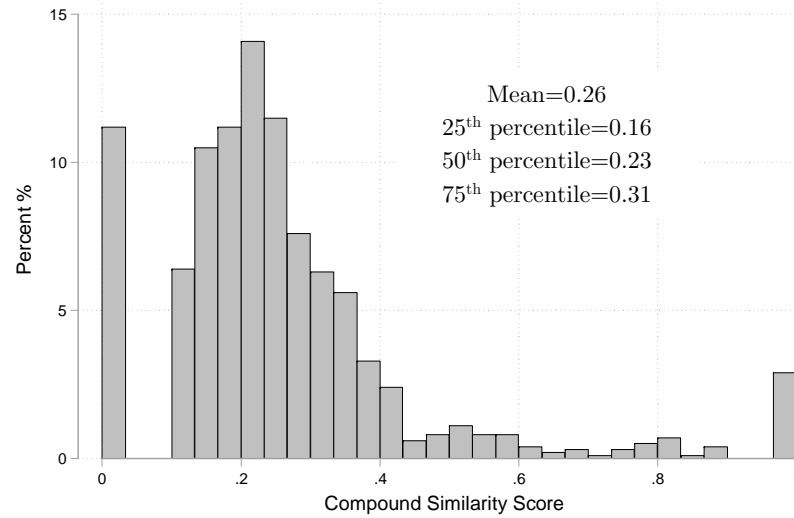
Table A.5: Comparing Regression Specifications for Competitor News Effects

	(1)	(2)	(3)	(4)
	Dyadic OLS	Dyadic Cox	Single-Level OLS	Single-Level Cox
After Competitor Failure News (Same Market, Different Tech.)	0.041** (0.002)	0.050 [†] (0.026)	-0.021** (0.008)	-0.106 (0.070)
After Competitor Failure News (Same Market, Same Tech.)	0.119** (0.019)	0.531** (0.086)	0.050** (0.015)	0.421** (0.076)
After Competitor Failure News (Different Market, Same Tech.)	0.062** (0.008)	0.228** (0.051)	0.015 [†] (0.009)	0.113* (0.047)
Nb. Observations	5,069,504	7,725,658	223,249	213,302
Nb. Drug-Indications	8,436	11,145	8,217	10,639
Log-Likelihood		-1,313,324		-10,504

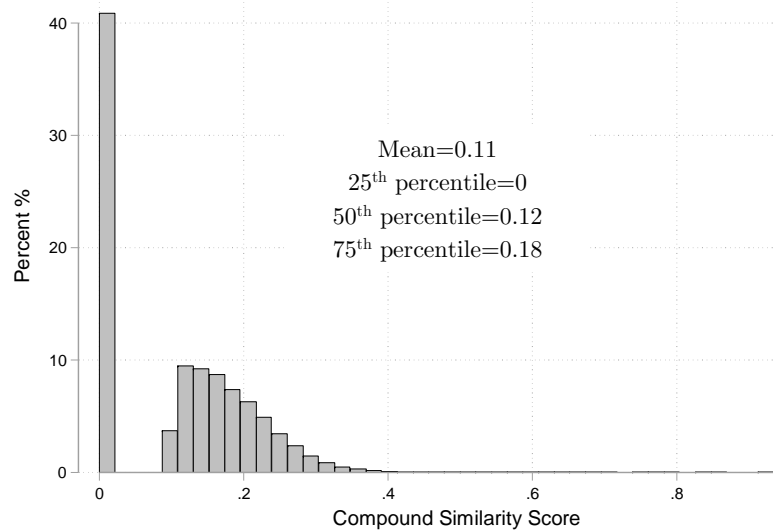
Note: Estimates in columns 1 and 3 stem from ordinary least squares regression specifications, while estimates in columns 2 and 4 are from cox proportional hazard models. The regression models in columns 1 and 2 analyze the dyadic panel data at the level of treating-treated project level. Column 2 contains more observations because the OLS analysis in Column1 is limited to projects that had either exited or graduated to Phase II 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 one after the first instance of the given type of competitor exit news experienced by the focal project. Standard errors in parentheses. [†] $p < 0.10$, * $p < 0.05$, ** $p < 0.01$

Figure A.1: Dyadic Molecular Similarity, Treating-Treated Drug Pairs

A. Same Market, Same Technology (N=1001)



B. Same Market, Different Technology (N=48,236)



C. Different Market, Same Technology (N=13,226)

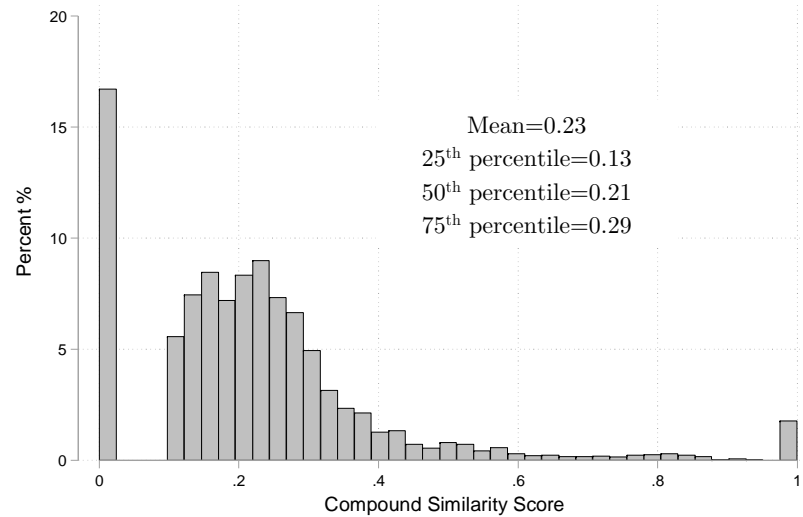
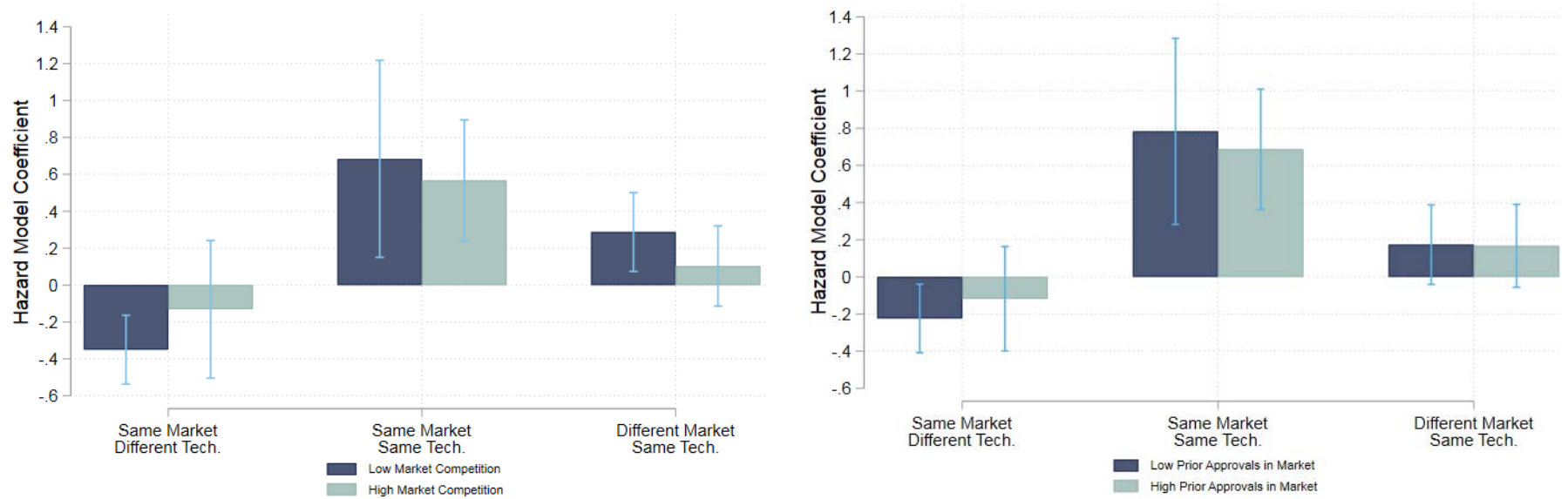


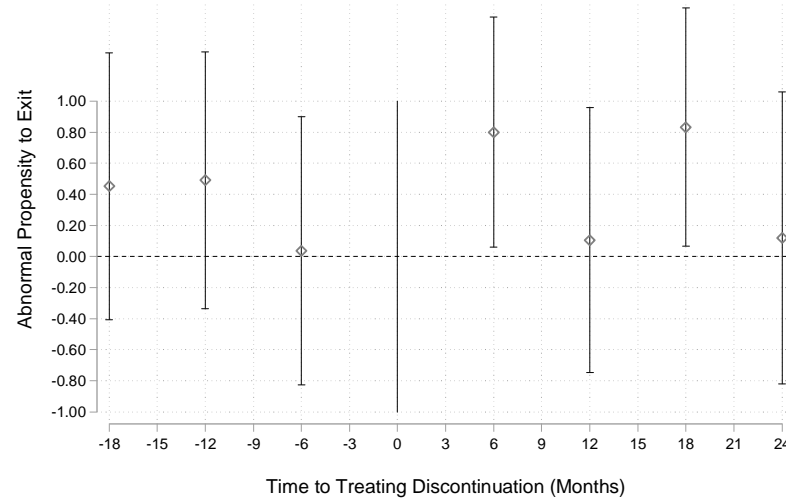
Figure A.2: Level of Competition and Failure News Response, Bottom vs. Top Quartile
 A. Level of Market Competition (in Development) B. Level of Market Competition (Approved Drugs)



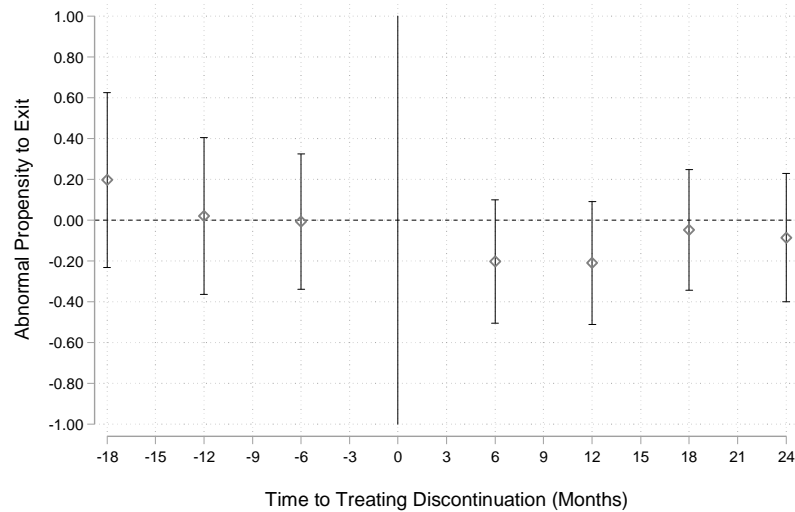
Note: The bars display the coefficients of interest from the main Cox proportional hazard model specification, split by bottom and top quartile of competition as defined in two different ways. In Panel A, the level of competition is defined as the number of development projects working on the same therapeutic indication. In Panel B, the competition split is based off the number of previously approved drugs within the same therapeutic indication. The capped spikes cover the 95% confidence intervals for each regression coefficient.

Figure A.3: Dynamics of Response to Competitor Failure, Low Competition Scenario

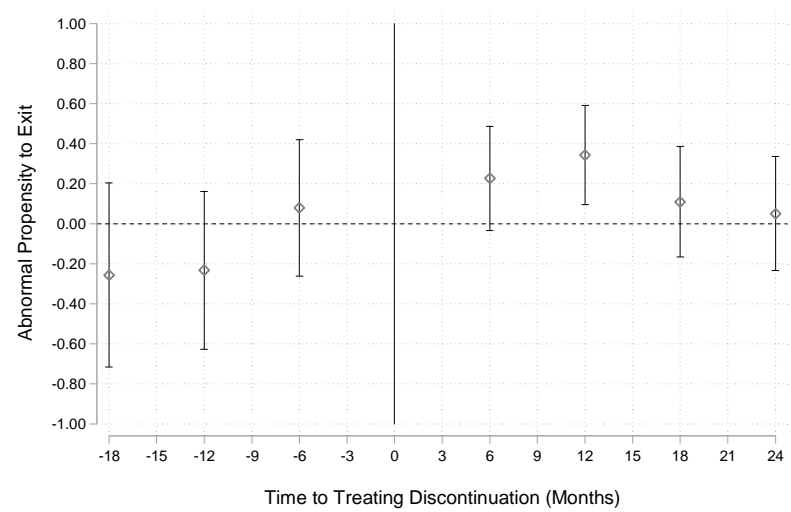
A. Same Market, Same Technology



B. Same Market, Different Technology



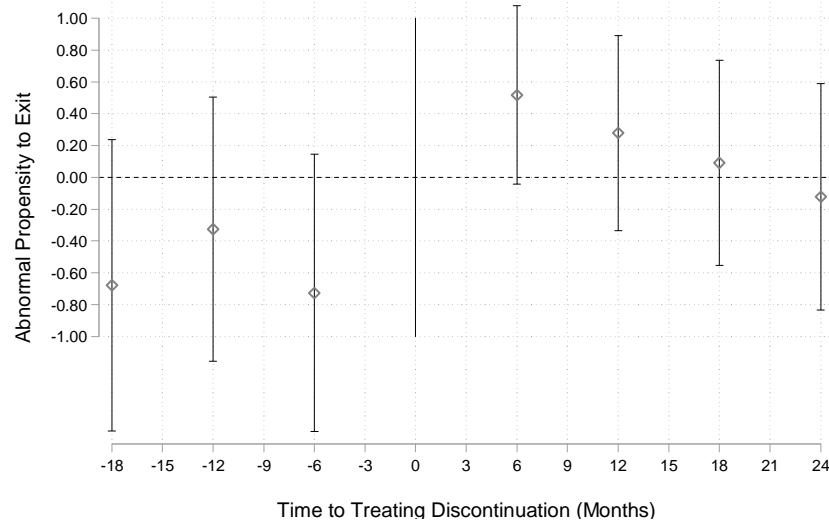
C. Different Market, Same Technology



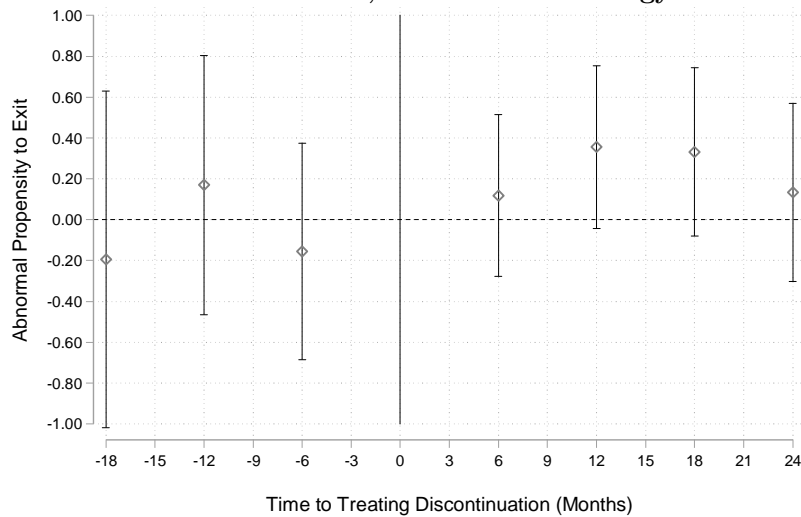
Note: The points in the above plots correspond to the event study coefficients stemming from the Cox proportional hazard model. The sample is limited to projects with low (below median) number of approved competitor drugs within the same therapeutic indication. The six months prior to the first competitor termination event is the omitted variable. The 95% confidence intervals (corresponding to robust standard errors) are plotted with capped spikes.

Figure A.4: Dynamics of Response to Competitor Failure, High Competition Scenario

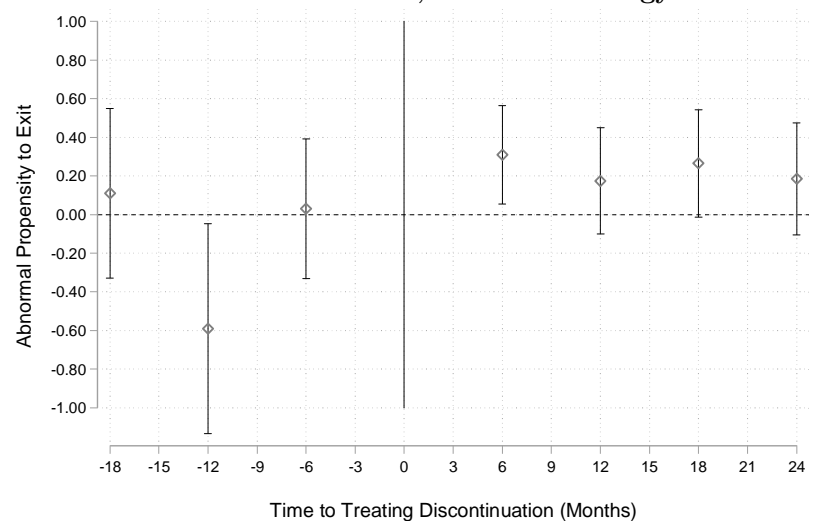
A. Same Market, Same Technology



B. Same Market, Different Technology



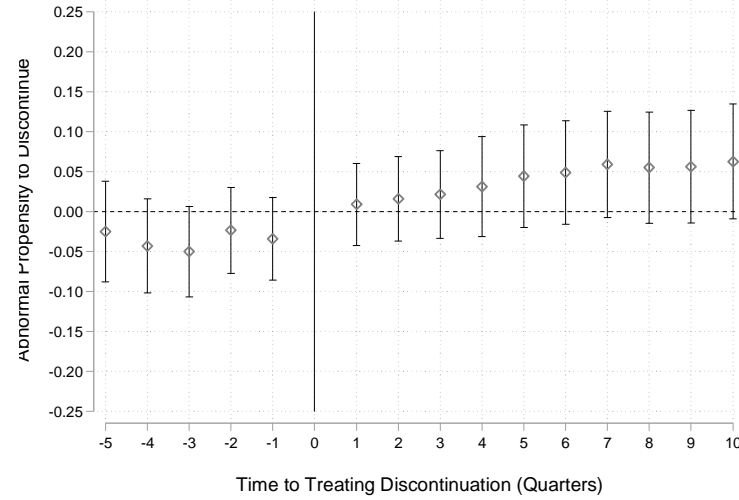
C. Different Market, Same Technology



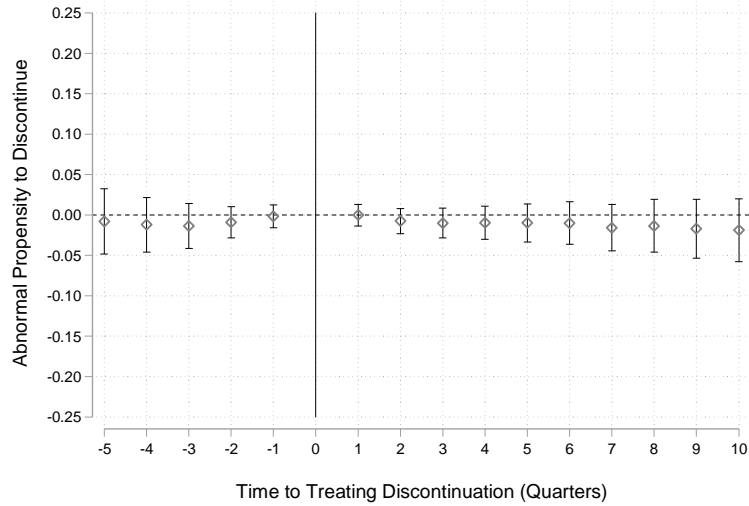
Note: The points in the above plots correspond to the event study coefficients stemming from the Cox proportional hazard model. The sample is limited to projects with high (above median) number of approved competitor drugs within the same therapeutic indication. The six months prior to the first competitor termination event is the omitted variable. The 95% confidence intervals (corresponding to robust standard errors) are plotted with capped spikes.

Figure A.5: Placebo Test, Phase III Projects and Phase II Failure News (Dyadic Data)

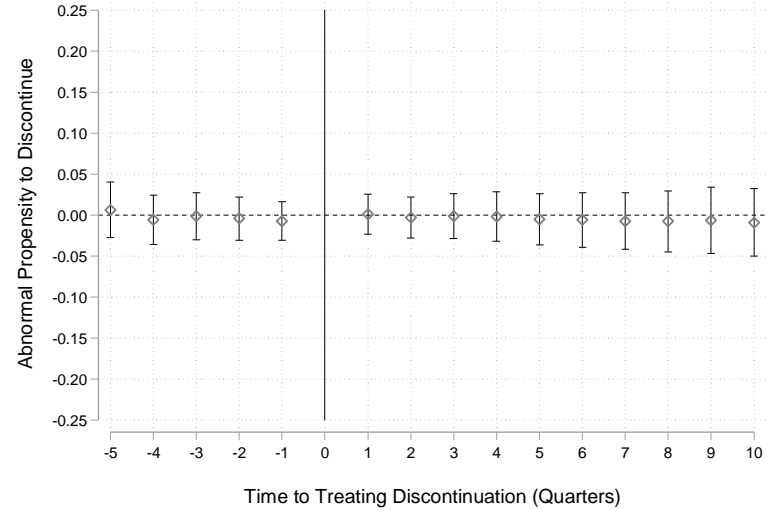
A. Same Market, Same Technology



B. Same Market, Different Technology

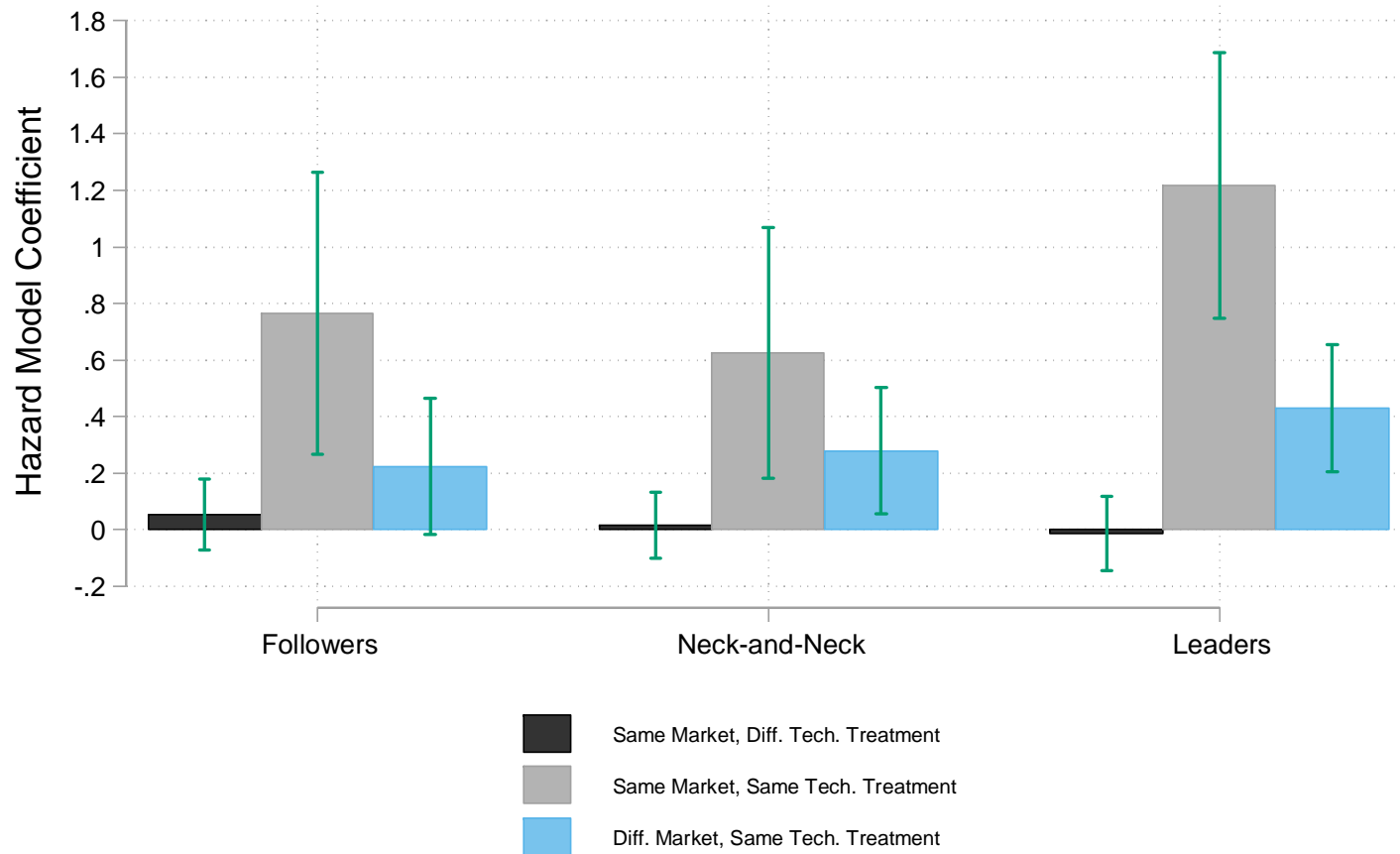


C. Different Market, Same Technology



Note: The points in the above plots correspond to the event study coefficients stemming from the Cox proportional hazard model using the dyadic data panel setup (see Appendix B). Unlike the main analysis sample, the focal projects in this analysis are Phase III projects and are “treated” by Phase II competitor failures of each type. The sample includes 3,195 focal projects--2,920 (92%) experience SM-DT news, 272 (9%) experience SM-ST news, and 1,368 (43%) experience DM-ST news. The 95% confidence intervals (corresponding to robust standard errors) are plotted with capped spikes.

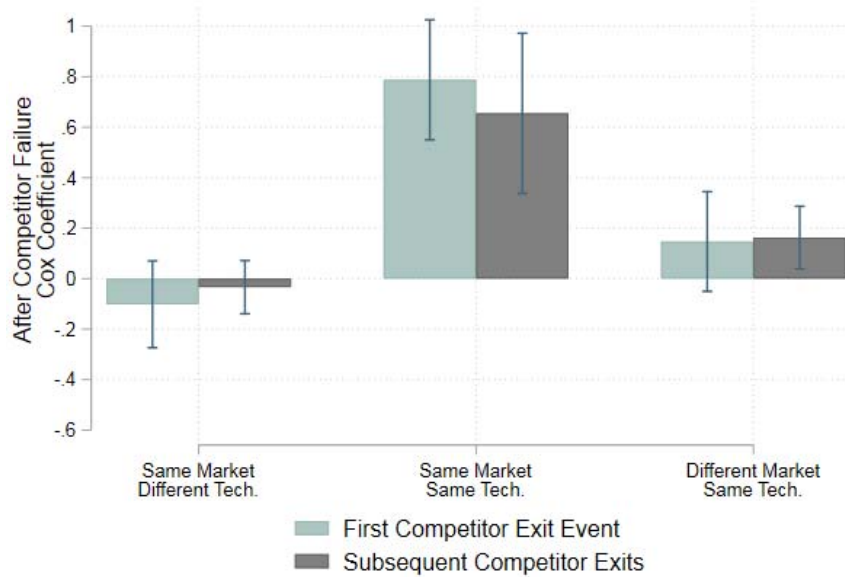
Figure A.6: Entry Order and Competitor Failure Response (Abnormal Propensity to Exit)



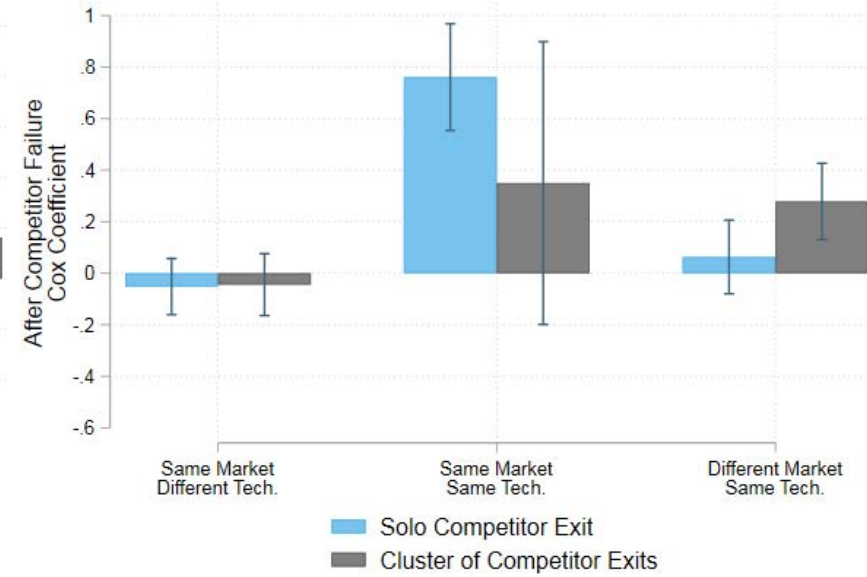
Note: The bars display the coefficients of interest from the Cox proportional hazard model specification, using analysis data which contains 212,759 project-quarter observations (discontinued projects are censored out after exit). Here, the coefficients of interest are the absorbing state of post-competitor failure news (as opposed 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 capped spikes cover the 95% confidence intervals for each regression coefficient.

Figure A.7: Treatment Order and Clustering

A. First vs. Subsequent Treatment Events

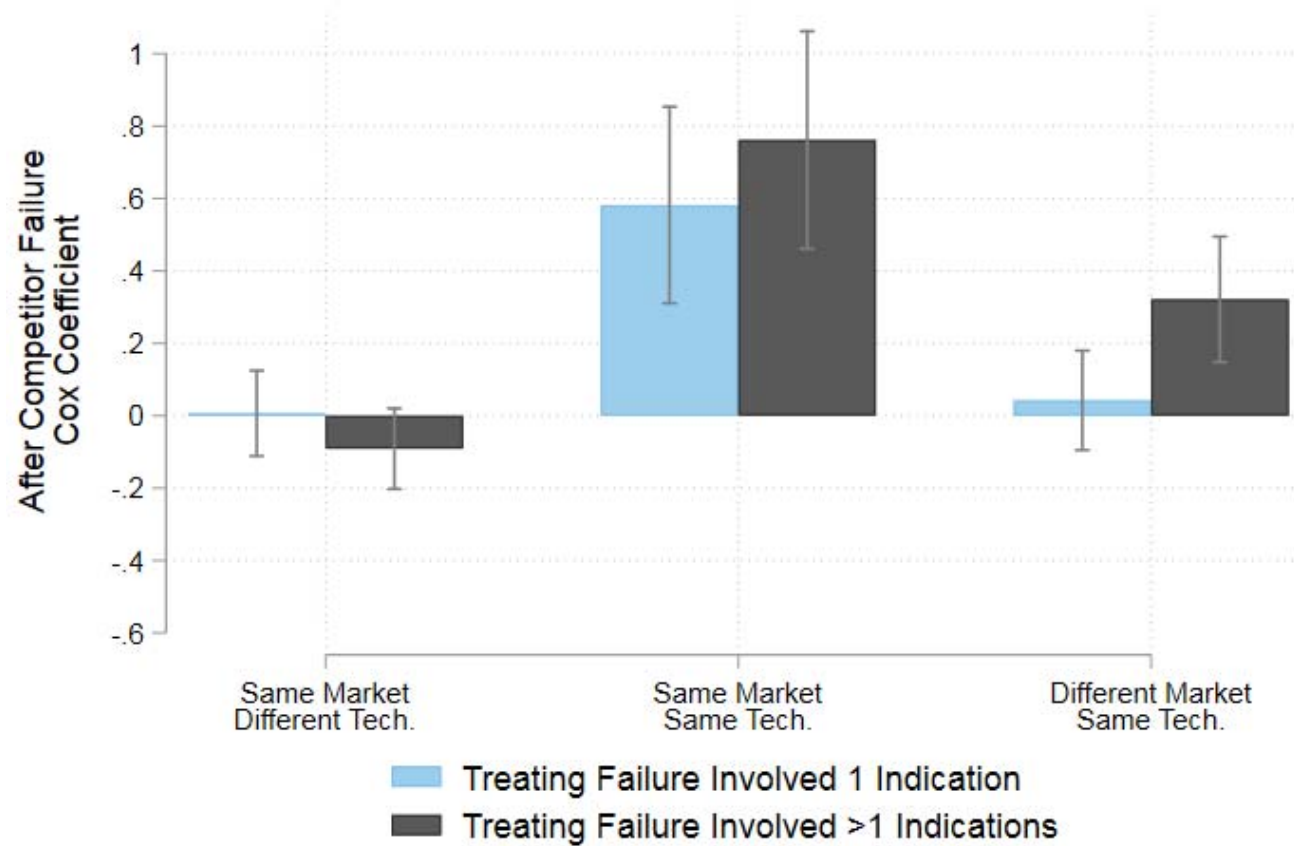


B. Solo vs. Clustered Treatment Events



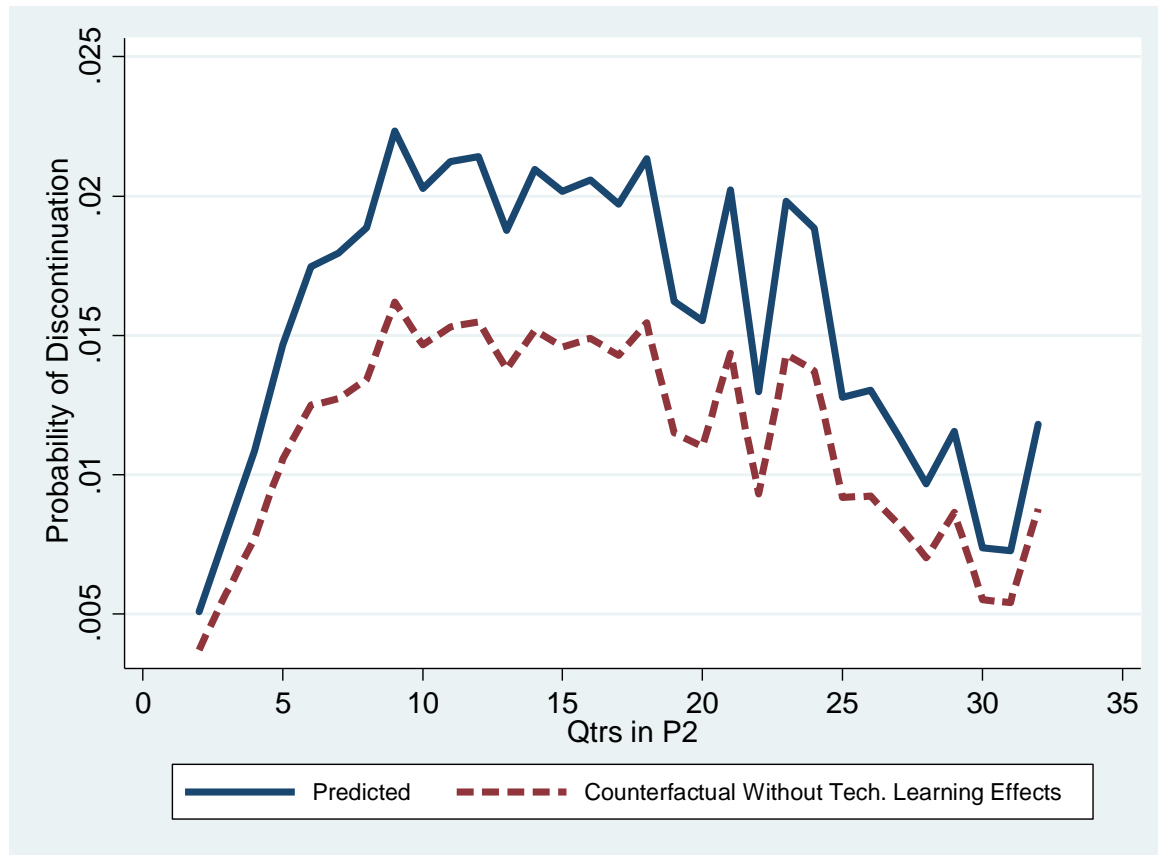
Note: The bars display the coefficients of interest from the main Cox proportional hazard model specification, where the type of competitor failure news event is interacted with whether the news event is the first of its kind or a subsequent event (Panel A), and whether the competitor failure news events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

Figure A.8: 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 or multiple indications. 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 capped spikes cover the 95% confidence intervals for each regression coefficient.

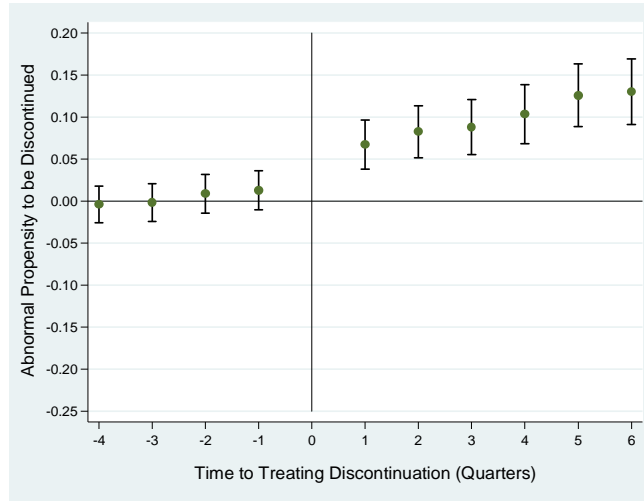
Figure A.9: Discontinuation Rate by Quarter for Projects that Experience Technological Competitor Failure News



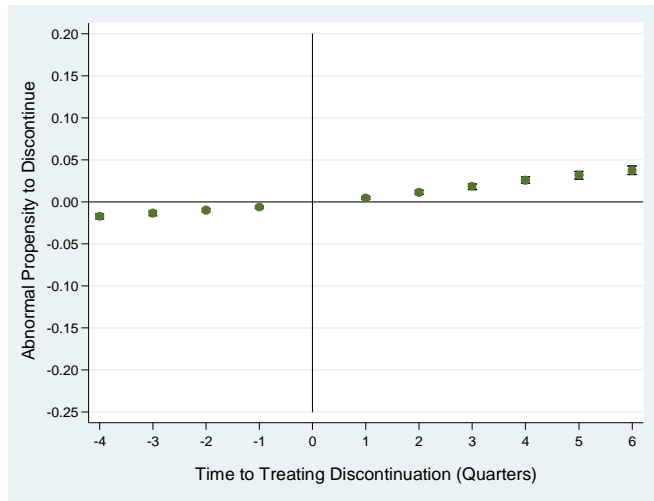
Note: The graph shows the average predicted probability that a phase II project is terminated, given that it survived until a given project age (quarters into phase II) and did not graduate to phase III. The solid line is the predicted values generated by the main econometric model (corresponding to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

Figure A.10: Dynamics of Response to Competitor Failure (Dyadic OLS Version)

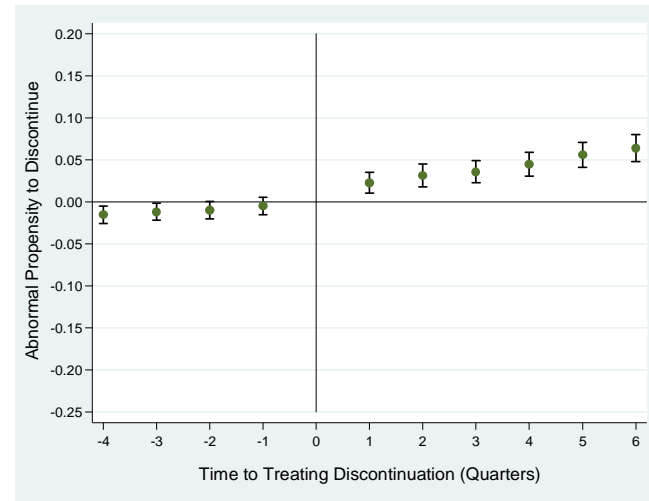
A. Same Market, Same Technology



B. Same Market, Different Technology



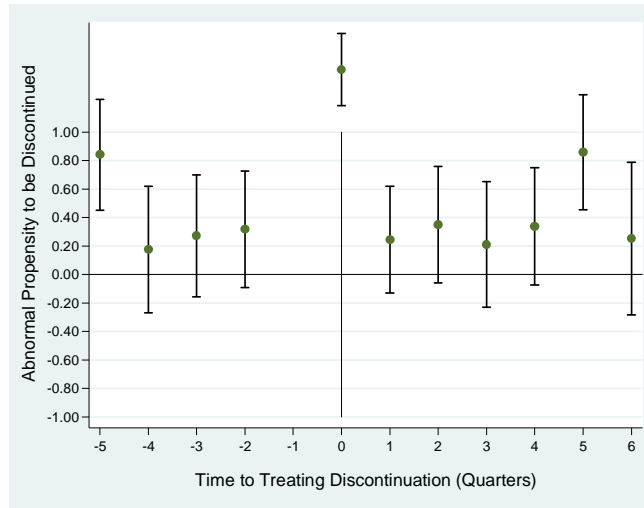
C. Different Market, Same Technology



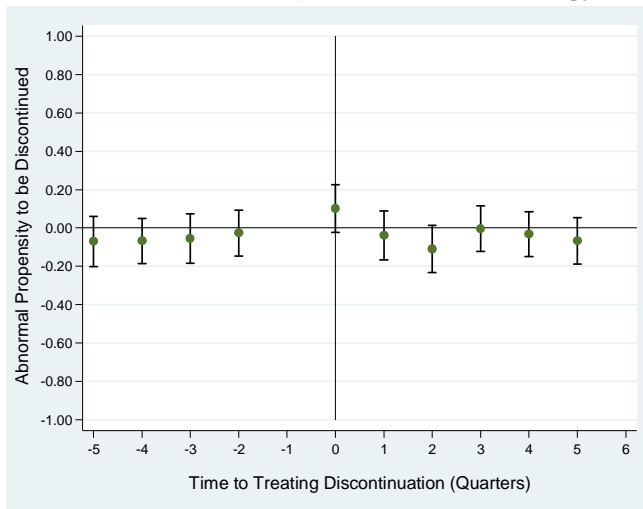
Note: The dots in the above plots correspond to coefficient estimates stemming from the ordinary least squares regression model, where the variables for treatment status are interacted with the time (in quarterly increments) until the first competitor failure event (of each type). The quarter of the 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 A.11: Dynamics of Response to Competitor Failure (Dyadic Hazard Model)

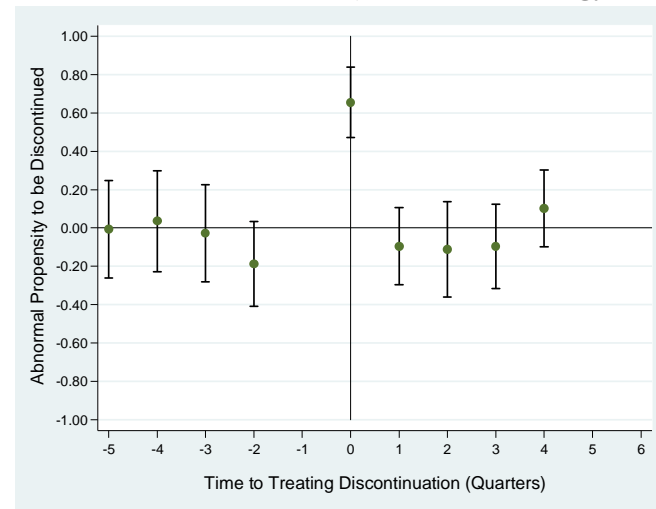
A. Same Market, Same Technology



B. Same Market, Different Technology



C. Different Market, Same Technology



Note: The dots in the above plots 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.