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

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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 tradeoffs 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 use 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.

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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 versus different *market*, same versus 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

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underlying quality—effectively lowering the cost of experimentation.

The choice of an empirical setting is crucial for R&D spillover analyses. Although innovation scholars have argued that disclosure and the ability to assimilate external information have positive effects on the rate of innovation (Cockburn and Henderson 1994, Henderson and Cockburn 1994, Bloom et al. 2013, Ederer 2013, Boudreau and 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. Furthermore, 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 because of 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 and 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 data set that comprises all clinical development projects over the period of 1997–2014, along with each project's development milestones. I focus on projects undergoing phase II clinical trials, which are typically the first major test of a drug's effectiveness and safety (versus 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 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. Although 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, whereas 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.

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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 use 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 5.5 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 and Pindyck 1994, McGrath 1997, Grenadier 1999, Miller and Folta 2002, McGrath and Nerkar 2003, Adner and Levinthal 2004, Manso 2011, Nanda and 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.

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 (Nelson 1961, Kerr et al. 2014, Manso 2016, Nanda and Rhodes-Kropf 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. Although existing real options models (Dixit and Pindyck 1994, Grenadier 1999, Kellogg and 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 prespecified opportunities to reevaluate an investment that occur at some regular interval (i.e., monthly valuation, annual planning meeting). 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.

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

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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:

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

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.

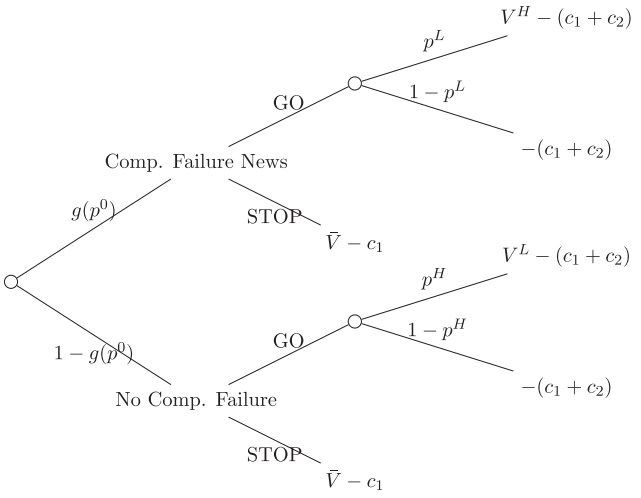
Next, I incorporate the possibility of vicarious learning into the model. The timing in this alternative setup is as follows. Rather than committing the entire investment amount c at the start, the focal firm invests c_1 to enter the stage, where $c_1 + c_2 = c$. The focal firm expects to get a failure 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 because of 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 $\overline{V}$ 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).

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):

Figure 1. Single R&D Stage with Competitor Learning



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

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 because of the abandonment option.[7]

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

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(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}—that is, the more ST competitors with risky technological hypotheses, the higher the likelihood that one fails. In Sections 2.3 and 2.4, 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, whereas 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:

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

The updating response to competitor news acts through the public components of the belief. After a DM-ST competitor failure, the *PublicSignal* value decreases by b and everything else stays the same. The decrease in the *PublicSignal* value is $b^1 > b$ if the competitor was also targeting the same market (SM-ST). Therefore, the change in probability of success after a single competitor's failure (or lack thereof) becomes

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

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 $d(n)$. Because the impact of less competition on profits is greater as the market approaches monopoly (Bresnahan and 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_{SMDT} and n_{SMST}) and priors about the probability of success for those projects (e.g., p_{SMST}, $p_{SMDT'}$, $p_{SMDT''}$). Regardless of whether the failed competitor shares the same technology as the focal project, the payoff updating

Figure 2. Updating

Competitor Failure News

Tech.	Product Market: *SameMkt*	*DiffMkt*
SameTech	p^{--}, V^+	p^-, V^0
DiffTech	p^0, V^+	p^0, V^0

No Failure News

Tech.	Product Market: *SameMkt*	*DiffMkt*
SameTech	p^{++}, V^-	p^+, V^0
DiffTech	p^0, V^-	p^0, V^0

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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.

Figure 2 summarizes the updating process following a single competitor failure. The 2×2's show the scenarios with and without a competitor failure of each type.

2.4. Model Predictions

Applying this framework to the empirical setting of drug development yields four main propositions. Proofs are presented in Online 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 1. *Although 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 because of 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. Although 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 downward 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 versus adults, slow versus 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. Because of 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 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

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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 multistage 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 laboratory (*in vitro*) and animal testing before drugs reach three sequential phases of human clinical trials. Online 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 U.S. Food and Drug Administration (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 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, whereas 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 unblinded 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

Because of 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 preregistering 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 shutdown 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 is 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 indoleamine-pyrrole 2,3-dioxygenase example). Online Appendix B presents examples of discontinuation disclosure statements that have different levels of transparency.

One empirical concern is that firms of different sizes or experience have different incentives to publicly report their trial failures (see Online Appendix B for a discussion of materiality and Regulation Fair Disclosure). However, I find that official discontinuation rates

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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 versus 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 the fall of 2019.

A recent high-profile failure in the burgeoning field of immono-oncology had a very public influence over rivals' investments. In the spring of 2018, pharmaceutical company Incyte announced the failure of its cancer drug, epacodastat, an indoleamine-pyrrole 2,3-dioxygenase (IDO) inhibitor. To map the epacodastat 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 epacodastat 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 data set 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) and uses professional curators. Cortellis links each milestone event to its applicable disclosure information (e.g., press release, company investor literature or pipeline documentation, financial filings). 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.

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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 nonmutually exclusive dimensions is aligned with how researchers at major drug developers categorize projects (Cook et al. 2014, Shih et al. 2018).

4.2.1. 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—although 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. Figure A.1 in Online Appendix A 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]

4.2.2. Target-Actions (Technology). A biological target is a molecule in the body on 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., andrenoreceptor 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). Roughly 65% of Cortellis drug candidate records (70% of projects in this paper's analysis sample) contain information about the drug's primary (and secondary, if applicable) biological mechanisms of action. Although 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. Fifty-nine 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 of five has more than one primary target action (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 et al. (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 Online 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 Online 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

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and that ST compounds still have plenty of chemical diversity. Therefore, although 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 capture 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 and 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 before the discontinuation of the competitor project.[24]

The analysis data are 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 projects* account for many of projects that persist in the panel for 32 quarters before I censor out their subsequent project-quarters. Section 5.6 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 ICD-9 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 and2 summarize the descriptive statistics for the analysis sample.

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 that 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, whereas 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 5.1. Section 5.2 explains the econometric strategy to identify the responses to competitor failure news. Section 5.3 then reports the results of the main regressions, which correspond to Propositions 1 and 2 from the model. Section 5.4 analyzes heterogeneous effects as they relate to Propositions 3–5.

Next, I test the robustness of the empirical results with a number of alternative specifications and sample splits (Section 5.5), as well as different project death definitions (Section 5.6). Finally, Section 5.7 describes a series of *back-the-envelope* calculations to quantify the magnitude of the overall competitor learning effects.

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Table 1. Descriptive Statistics, Phase II Projects That Experienced Competitor Failures

	Count	Mean	Standard deviation
Discontinued in first 32 quarters of phase II	10,637	0.24	0.43
Ever experience competitor failure in the *Same Market, Different Technology*	10,637	0.95	0.21
Ever experience competitor failure in the *Same Market, Same Technology*	10,637	0.10	0.31
Ever experience competitor failure in the *Different Market, Same Technology*	10.637	0.43	0.49
Active quarters in phase II	10,637	21.91	9.01

Notes. 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). Seventy-two percent 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 before the discontinuation of the focal project.

5.1. Overall Exit Rates

The econometric approach that follows isolates the impact of competitor failure news on firms' continuation decisions. However, as a first step, I establish the typical life cycle for projects in phase II. Figure 3(a) 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 3(b) 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.

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 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]

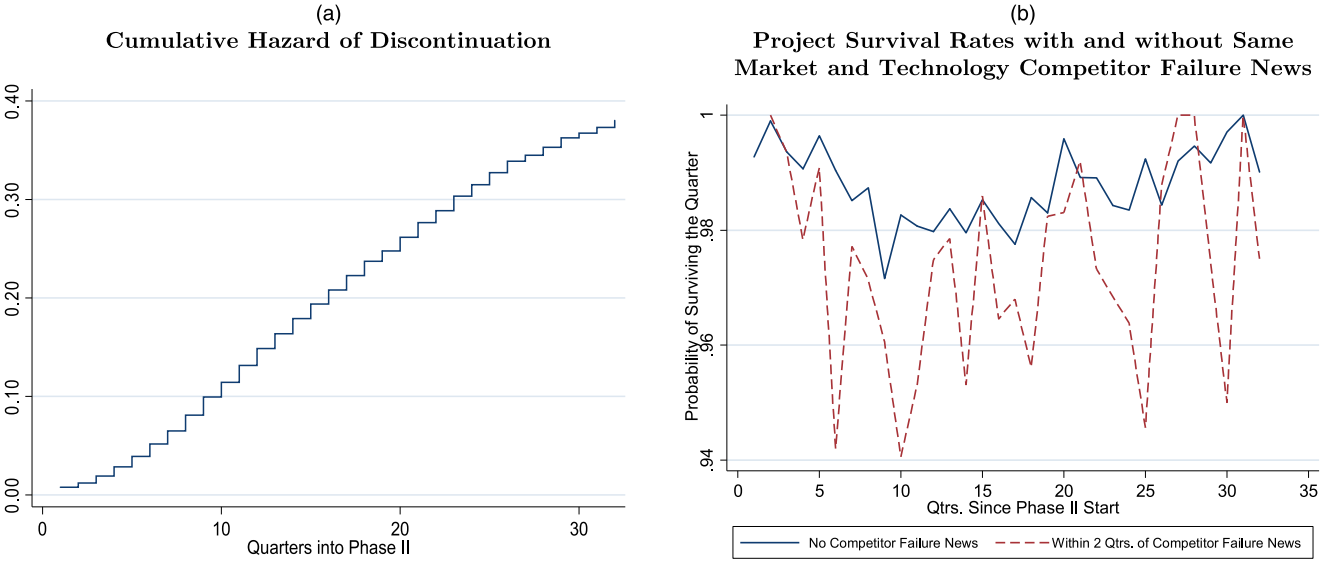
The baseline specification is a panel difference-in-differences proportional hazard model. The main regression coefficients are reported in Figure 4. The dependent variable is an indicator for whether the focal project was terminated as of a given period. Using hazard models on panel data helps account 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. 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 the following: How does recently learning of a competitor failure influence the propensity to exit compared with untreated projects of the same stage, age, and market?

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

	Count	Mean	Standard deviation
Within two quarters of competitor failure in the *Same Market, Different Technology*	254,069	0.54	0.50
Within two quarters of competitor failure in the *Same Market, Same Technology*	254,069	0.02	0.14
Within two quarters of competitor failure in the *Different Market, Same Technology*	254,069	0.13	0.34
Sponsor firm's number of development projects to date	251,077	164.32	304.26

Notes. 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.

Figure 3. (Color online) Project Death Rates in Phase II



Notes. Each panel represents a different way of tracking the overall rates of project exit throughout. (a) 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. (b) Probability of surviving a given quarter, conditional on entering that quarter (e.g., the likelihood that a project that enters its eighth 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.

This approach requires three identification assumptions. The first is the *no-anticipation* assumption (Abbring and Berg 2003), which is satisfied in the clinical trials setting because 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 toward 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 pretrends leading up to competitor discontinuation events (column 4 of Table 3; 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 because of wasting patent protection time. Nonetheless, I empirically test for differential responses for competing projects that entered later (follower projects; Figure A.6 in Online Appendix A).

Third, this approach assumes no unobserved common opportunity shocks. Other studies of R&D spillovers (Bloom et al. 2013, Schnitzer and Watzinger 2017, 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 laboratory). To reach phase II clinical trials, the compounds have already gone through rigorous preclinical laboratory (in vitro) and animal studies and 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 out. Any general macroeconomic shocks should impact different drug development areas equally and are captured in the calendar time fixed effects in the regressions.

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

Treatment window: Within two quarters since competitor failure news	(1)	(2)	(3)	(4)	(5)	(6)
Competitor failure type						
Any Competitor	0.014					
	(0.050)					
Same Market Competitor		–0.014				
		(0.050)				
Same Technology Competitor		0.274**				
		(0.052)				
Same Market, Different Technology			–0.048	–0.029	–0.046	–0.040
			(0.050)	(0.051)	(0.050)	(0.051)
Same Market, Same Technology			0.739**	0.613**	0.790**	0.686**
			(0.100)	(0.126)	(0.101)	(0.102)
Different Market, Same Technology			0.158**	0.159*	0.259**	0.220**
			(0.056)	(0.066)	(0.060)	(0.061)
Three-quarter window before competitor news						
Same Market, Different Technology				–0.054		
				(0.051)		
Same Market, Same Technology				0.042		
				(0.142)		
Different Market, Same Technology				–0.007		
				(0.068)		
Controls						
Number of each competitor type					✓	✓
Firm characteristics						✓
No. of drug indications	10,639	10,639	10,639	10,639	10,639	10,274
No. of drugs	6,183	6,183	6,183	6,183	6,183	6,002
No. 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

Notes. Estimates stem from Cox proportional hazard model specifications using panel data on drug projects by quarter. The outcome event 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. The check marks in Columns 5 and 6 indicate additional sets of control variables (number of each competitor type and firm characteristics) used in those regression specifications. Coefficients may be interpreted as an increase in the log hazard rate. Standard errors in parentheses.

$^{\dagger}p < 0.10$; $^{*}p < 0.05$; $^{**}p < 0.01$.

Unlike other product development areas with trends in consumer preferences (e.g., software, self-driving cars, food and beverage), 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). 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 and Dutta (2012), and Aral and Walker (2012), where the timing of both treatment and response is of central importance in interpreting the results. In practice, I use a Cox proportional hazard model specification, using drug-market-quarter level data:

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

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;

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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). Table A.1 in Online Appendix A 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 (Figure 5). Online 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

I describe the paper's main empirical results on responses to competitor failure of each type. Using the survival model approach described previously, these results speak directly to Propositions 1 and 2. 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 (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 3–6 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.

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.

SM-ST competitor discontinuations lead to large and highly significant ($p < 0.01$) increases in the hazard rate of project exit, whereas 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 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. Although the pretreatment 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, whereas the DM-ST effect lingers a bit longer, despite being smaller.

Although 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 posttreatment SM-ST coefficient. Because 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

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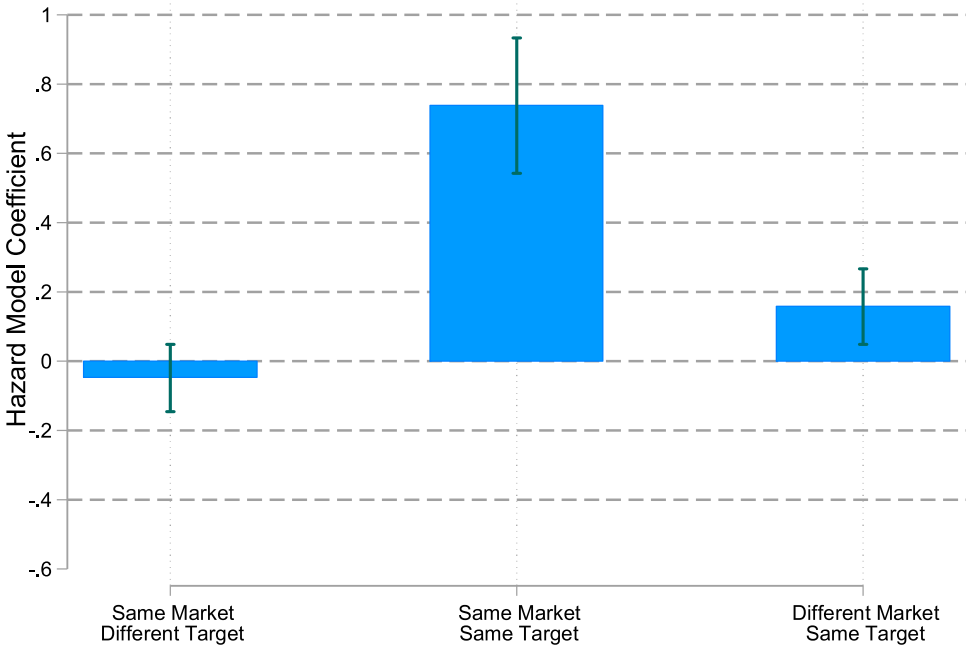
Figure 4. (Color online) Competitor Failure News and Propensity to Exit



Notes. 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 spikes cover the 95% confidence intervals for each regression coefficient.

over time and the base of active projects is smaller in later periods.[31]

At first look, the different magnitudes of 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 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*.

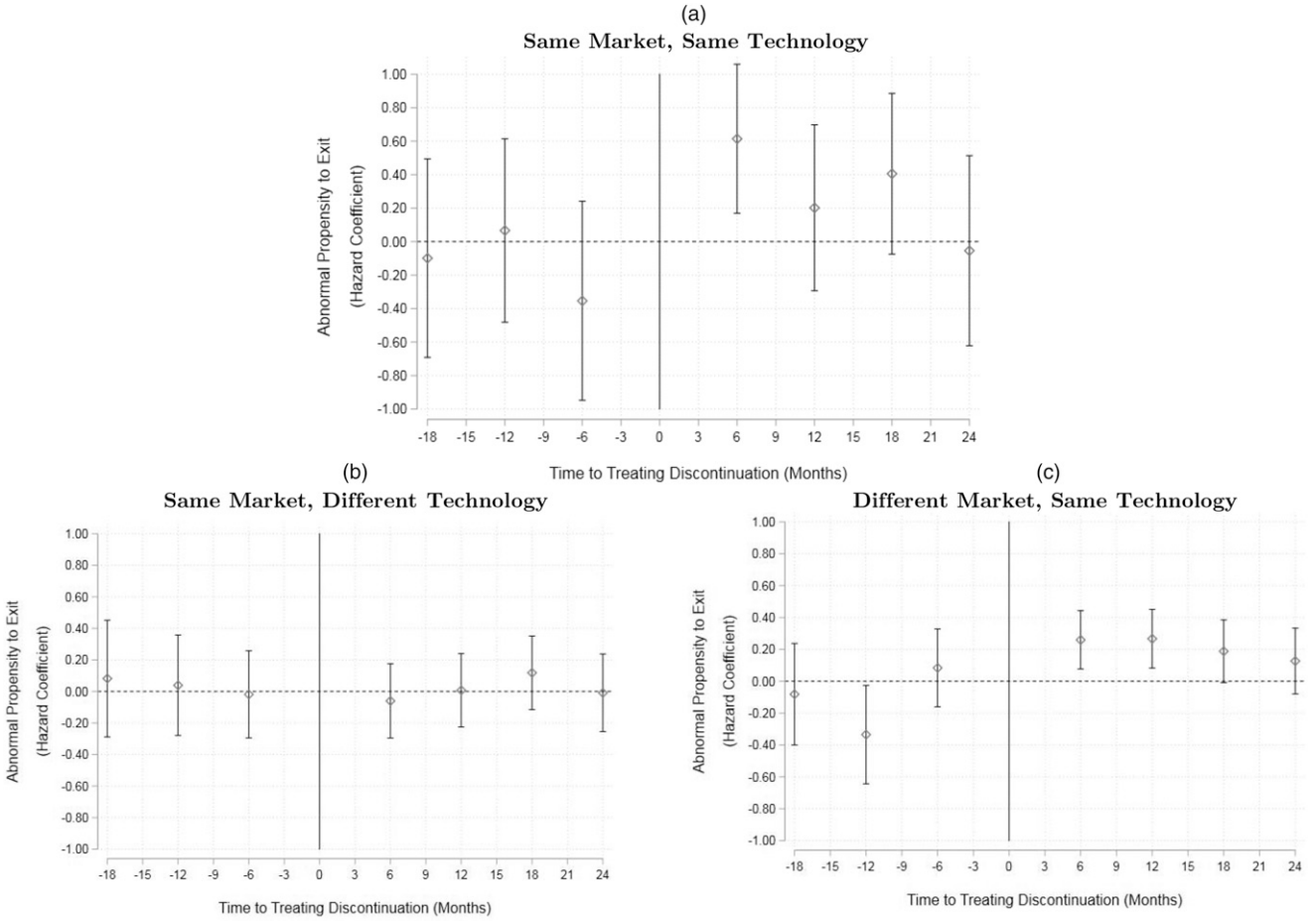
A related explanation is that SM-ST news is more salient, even if not more valuable, than DM-ST news. The additional time it takes for DM-ST news to affect decisions (Figure 5) suggests that salience might play a role in the differential responses. Both stories highlight the importance of identifying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

Figure 5. Dynamics of Response to Competitor Failure



Notes. The points in the 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 before the first competitor termination event is the omitted variable. The 95% confidence intervals (corresponding to robust standard errors) are plotted with capped spikes.

number of observations), with a much smaller and noisier coefficient.

Next, I evaluate the subset of phase II projects in therapeutic markets with low versus 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. Figures A.3 and A.4 in Online Appendix A show the event study versions of these regressions for the low and high competition subgroups, respectively.

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 and 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

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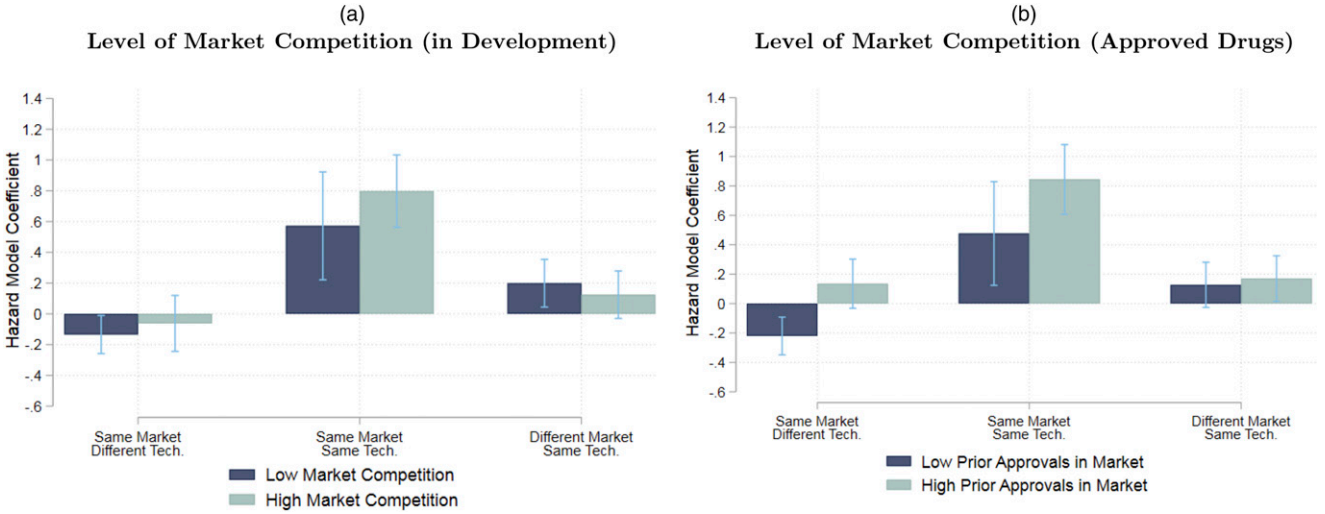
Figure 6. (Color online) Level of Competition and Response to Competitor Failure



Notes. 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. (a) Level of competition is defined as the number of development projects working on the same therapeutic indication. (b) 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.

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 Figure A.5 in Online Appendix A, 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 in Online Appendix A implies that developers only update their expectations about R&D success when their own project uncertainty is high. These 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 versus 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

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

	(1)	(2)
Technological learning opportunities high (above median)	0.143†	0.212**
	(0.080)	(0.081)
Competitor failure type (within two-quarter treatment window)		
Same Market, Different Technology × Low Learning Opportunity	0.002	–0.025
	(0.087)	(0.088)
Same Market, Different Technology × High Learning Opportunity	–0.119†	–0.127†
	(0.068)	(0.068)
Same Market, Same Technology × Low Learning Opportunity	0.803**	0.805**
	(0.227)	(0.226)
Same Market, Same Technology × High Learning Opportunity	0.687**	0.736**
	(0.110)	(0.111)
Different Market, Same Technology × Low Learning Opportunity	0.616**	0.629**
	(0.162)	(0.162)
Different Market, Same Technology × High Learning Opportunity	0.066	0.151*
	(0.063)	(0.065)
Controls: Number of each competitor type		✓
No. of drug indications	8,069	8,069
No. of drugs	4,448	4,448
No. of treating-treated quarter observations	158,817	158,817

Notes. 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.

†$p < 0.10$; *$p < 0.05$; **$p < 0.01$.

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.

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. Therefore, 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 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

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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

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

5.5.1. 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. Figure A.6 in Online Appendix A 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) 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. Table A.3 in Online Appendix A 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 postapproval 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.

5.5.2. Competitor Signal Strength. I use 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 versus subsequent failure news (Figure A.7A in Online Appendix A). Similarly, I compare solo treatment events (a single competitor exit) to clusters of treatment for each type of failure news (Figure A.7B in Online Appendix A) and events wherein the competitor drug's failure news involved only one discontinued indication versus multiple discontinued indications (Figure A.8 in Online Appendix A). 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 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

5.6.1. 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 although the firm does not commit any further resources to the project

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(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 mischaracterization 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). Table A.2 in Online Appendix A presents these regression results. These hazard models yield results very similar to the main results in Table 3.

5.6.2. Chemical Similarity as Technological Distance.

Online 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 et al. (2019) to quantify chemical distance between project pairs. I interact compound similarity with different types of competitor discontinuation news.

Table A.4 in Online Appendix A 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.

5.7. Overall Impact of Competitor Learning

A series of *back-of-the-envelope* calculations helps 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). Because 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.

Figure A.9 in Online Appendix A displays the learning channel's magnitude. The figure graphs the predicted probability of project discontinuation by project age (quarters in phase II), compared with the hypothetical discontinuation rate—if one was 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 1,000 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. Although 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 and Levinthal 1990, Cockburn et al. 2000). Developing new technologies is an inherently

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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 subfield. This type of herding may be privately optimal but result in an overall lack of diversity in R&D (Dixit 1989, 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. 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.

Although 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 and 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) 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)? 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, because 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. Although 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.

Although 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.

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Endnotes

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

[2] Economists have studied how events like bankruptcies and product recalls influence stock market valuations of competitor firms (Lang and Stultz 1992, 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 versus successful drug candidates by comparing citations to patents associated with those drug candidates.

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

[4] Bennett and 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.

[5] This approach also relates to models of strategic experimentation (Malueg and Tsutsui1997, Keller et al. 2004, Akcigit and Liu 2016, Bonatti and Hörner 2017, Bryan and Lemus 2017, Awaya and Krishna 2020) and the analysis of static auctions with correlated signals (Dasgupta and Maskin 1987, Kagel et al. 1987, Hendricks and 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.

[6] If a product is the first of its kind, then failure signals may include information about demand, as well as information about the technology and competition. For example, when Google discontinued sales of its controversial wearable device Google Glass, the failure might have conveyed as much about consumer preferences and marketing as the technology itself.

[7] All 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.

[8] For 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.

[9] To approximate u, one might estimate one minus the percentage of a project's experiments are complete. Project uncertainty is highest before the first experiment and decreases as the firm gathers more proprietary data.

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

[11] Similar 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.

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

[13] The length of a trial depends on the disease and endpoint (e.g., mortality, blood pressure, tumor growth) 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 2.5 years.

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

[15] See 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.

[16] Patent data are most commonly used to study innovation spillovers and measure the relatedness of R&D projects (Griliches 1991, Lerner and 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.

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

[18] The drug similarity measure is detailed in Online Appendix C.

[19] Assigning ICD-9 codes to the Cortellis indication names is a challenge that requires knowledge about both the medical conditions and how healthcare 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 subcategories 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 am grateful to Manuel Hermosilla for providing the mapping from Cortellis indication names to ICD-9 codes.

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

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

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[22] The 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 Table A.3 in Online Appendix A.

[23] Although 10 years may seem like a long window, the median time in phase II is 2.5 years, and the 90th percentile is greater than 6 years. The median length of a phase III trial is 4 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.

[24] Because 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.

[25] For example, Ingram and Baum (1998), Haunschild and Sullivan (2002), Baum and Dahlin (2007), Kim and Miner (2007), Madsen and Desai (2010), and Rao (2018).

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

[27] The 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.

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

[29] Prescription drug spending in the United States (as a percentage of gross domestic product) 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).

[30] Testing the proportional-hazards assumption yields nonsignificant results (i.e., the proportionality assumption holds.)

[31] Using a two-period difference-in-differences model, where treatment is binary for postcompetitor news (absorbing state version), I still find that the SM-ST coefficient is significantly larger than the DM-ST effect (Table A.1 in Online Appendix A). 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.

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

[33] The primary analyses use both phase II and phase III failure news as relevant signals for phase II projects. I also tested whether competitor failure news originating from 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.

[34] By comparison, Budish et al. (2015) find that a 10-percentage-point decrease in trial length (five-year survival rate) is associated with an 8.7% 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.

[35] For 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 and 0.8.

[36] In 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.

[37] The U.S. 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) because of competitor learning.

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