Corporate R&D Investments Following Competitors' Disclosures: Evidence from the Drug Development Process

by

Yue Zhang

Bachelor of Arts, Peking University, 2011

Master of Arts, Pennsylvania State University, 2013

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JOSEPH M. KATZ GRADUATE SCHOOL OF BUSINESS

This dissertation was presented

by

Yue Zhang

It was defended on

May 11, 2020

and approved by

Dissertation Co-Chair: John Harry Evans III
Alumni Professor of Accounting and Area Director for Accounting, University of Pittsburgh

Dissertation Co-Chair: Mei Feng
Associate Professor of Accounting, University of Pittsburgh

Guojin Gong
Associate Professor of Accounting, Pennsylvania State University

Pierre Jinghong Liang
Professor of Accounting, Carnegie Mellon University

Mark (Shuai) Ma
Assistant Professor of Accounting, University of Pittsburgh

Dhinu Srinivasan
Associate Professor of Accounting, University of Pittsburgh

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Yue Zhang, PhD

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Abstract

This dissertation studies the role of peer disclosures in shaping corporate R&D investments. Using the online registration of clinical trials in the drug development process, I find that a firm's R&D investments are *deterred* by disclosures of clinical trial initiation from strong rivals but *encouraged* by disclosures from weak rivals. The cross-sectional analyses suggest that the deterrence effect of peer disclosure is stronger when the therapeutic area has a high clinical-trial success rate, the encouragement effect is stronger when the market has fewer competing firms, and both effects are strengthened when the focal firm has a diversified R&D portfolio. Overall, my findings suggest that the way a firm reacts to peer disclosure varies with the disclosing firms' relative competitiveness in the R&D race.

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Preface

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1.0 Introduction

Most empirical accounting studies argue that a firm's disclosure of proprietary information will hurt its competitive position, e.g., by creating knowledge spillovers to competitors. However, theory suggests that disclosure could also deter competition by signaling competitive advantages, such as cost efficiency or leadership in the innovation race (e.g., Hughes and Pae 2015). Few empirical studies have documented either of these two potential product market consequences of corporate disclosure (Leuz and Wysocki 2016).[1] In this paper, I study the role of corporate disclosures in shaping peer firms' research and development (R&D) investments. Firms' R&D investments lie at the heart of technological changes that drive economic growth (e.g., Romer 1990). Using the online registration of clinical trials in the drug development process, I find that a firm can either increase or decrease its R&D investments following competitors' disclosures of interim R&D success. Specifically, a firm's R&D investments are *deterred* by disclosures of clinical trial initiation from strong competitors but *encouraged* by disclosures from weak competitors.

My theoretical framework draws on game-theoretical models of the R&D race in industrial organization (IO). This literature models the R&D competition as a two-stage race; successful completion of the preliminary stage has no intrinsic value but is a prerequisite for beginning work on the final stage. The first firm to complete the final stage wins the race and receives the entire

[1] Most prior studies examine how disclosure is shaped by product market competition (e.g., Li 2010; Ellis et al. 2012; Ali et al. 2014; Huang et al. 2016; Bernard 2016; Li et al. 2018; Cao et al. 2018).

prize.[2] Given this structure of the R&D race, a rival's announcement of preliminary-stage completion can have two opposite effects on the investment decision of a focal firm that remains in the preliminary stage. On the one hand, peer disclosure of interim success reduces the focal firm's chance of winning, thus discouraging the focal firm from staying in the race (Fudenberg et al. 1983; Harris and Vickers 1987; Lippman and McCardle 1987). I call this the *deterrence effect* of peer disclosure. On the other hand, peer disclosure may also encourage the focal firm to increase R&D investments to catch up with the rival, because the information revealed in peer disclosure can create knowledge spillovers and/or imply the R&D project is more feasible than previously expected (Choi 1991; Doraszelski 2003). I call this the *encouragement effect* of peer disclosure.

I hypothesize that whether the encouragement effect or the deterrence effect of peer disclosure dominates depends on the disclosing rival firm's R&D strength, for two reasons. First, the encouragement effect of peer disclosure will be strengthened when the rival appears weak. Firms working on the same R&D project share a common uncertainty over project feasibility. Observing a rival's disclosure of interim success, the focal firm revises upward its own belief about the feasibility of the preliminary stage. The weaker the disclosing rival appears, the more optimistic is the focal firm's updated prospect of also completing the preliminary stage, and hence the more likely the focal firm will increase its R&D investments in an effort to catch up. Second, the deterrence effect of peer disclosure will be strengthened when the rival appears strong. The more likely that the rival can successfully complete the final stage, the lower expected payoff the focal firm obtains from remaining in the race. Taken together, I hypothesize that the encouragement effect dominates when the disclosure of interim R&D success comes from a weak

[2] This "winner-takes-all" assumption is consistent with evidence that firms in R&D-intensive industries often compete fiercely for the ultimate prize such as a patent. An innovation is only patentable if it is novel when judged relative to "prior art", i.e., all information that has been made available to the public before the patent filing date.

rival, which induces the focal firm to subsequently increase its R&D investment in that R&D race. In contrast, the deterrence effect likely dominates when the disclosure comes from a strong rival, which leads the focal firm to subsequently decrease its R&D investment or even drop out of that R&D race.

The general lack of evidence on the product market consequences of disclosures is partly due to data availability issues – firms' real decisions are usually not directly observable (Leuz and Wysocki 2016). To address this empirical challenge, I exploit the empirical setting of pharmaceutical R&D. This setting has at least three advantages. First, successful drug development is a key driver of commercial success and pharmaceutical companies invest heavily in R&D. In 2018, worldwide pharmaceutical R&D spending totaled $179 billion or 22% of sales revenue, the highest percentage of any industry except semiconductors (EvaluatePharma 2019). In the time of a pandemic, drug development becomes critically important for the global economy and public health. For example, economists estimate that an effective drug against COVID-19 could restore $1 trillion in economic activity (Gottlieb 2020).[3] Second, characteristics of pharmaceutical R&D map well into the two-stage R&D race widely studied in the IO theories. The drug development process consists of two stages – pre-clinical studies, which are done in laboratories and on animals, and clinical trials, which further test drug safety and efficacy on human beings. Also, first-to-market drugs typically enjoy significantly greater market shares than drugs launched later to the market, similar to the "winner-takes-all" assumption made in theories on the R&D race (Regnier and Ridley 2015). This skewed payoff distribution magnifies the role of information regarding firms' relative positions in the race. Finally, pharmaceutical firms publicly disclose rich data about

[3] As of May 2020, more than 120 research teams around the world are working on drugs and vaccines for COVID-19, with more than 900 interventional studies (clinical trials) related to COVID-19 registered on ClinicalTrials.gov.

clinical trials. Since 2007, the Food and Drug Administration (FDA) has required firms to register all drug candidates' later-stage clinical trials on ClinicalTrials.gov, a publicly accessible online database.[4] These trial registrations provide detailed and timely information about firms' R&D progress and are closely watched by industry peers.

I hand collected all clinical trials registered by the 50 firms with the largest number of clinical trial registrations on ClinicalTrials.gov between 2007 and 2017. To facilitate comparison of R&D projects across firms, I classify all clinical trials into 162 "markets", as new drug candidates treating diseases in the same therapeutic area are competing in the same product market. This classification allows me to capture R&D investments and R&D race at a more granular level than prior studies that rely on firm-year level data. Specifically, I measure a firm's R&D investments at the firm-market-year level using the number of later-stage clinical trials the firm conducted and registered online to comply with FDA regulations. Leveraging the fact that gaining FDA approval to initiate clinical trials marks the successful completion of pre-clinical studies, I capture peer disclosure of interim R&D success using the number of rival firms' early-stage clinical trial registrations in the same market in the two preceding years. I further distinguish between a strong and a weak rival using the relative ranking of firms' accumulated "knowledge stock" in that market, measured using the number of clinical trials conducted and registered to comply with FDA regulations.

[4] Clinical trials account for about 70% of total costs per approved new drug (DiMasi et al. 2016). A new drug candidate is typically tested in three phases of clinical trials before it can apply for FDA approval for marketing in the U.S. Phase 1 trials determine safety and dosing using healthy volunteers; Phase 2 trials evaluate efficacy and further explore safety in small numbers of patients with the targeted disease; Phase 3 trials further confirm safety and efficacy in larger numbers of patients. Since 2007, firms are required by the FDA to register their clinical trials, starting in Phase 2, on ClinicalTrials.gov. See Section 4.1 for more discussion.

My main findings suggest that a firm's R&D investments are *deterred* by disclosures of interim R&D success from strong rivals but are *encouraged* by disclosures from weak rivals. Specifically, I find that the focal firm's initiation of later-stage trials is *negatively* associated with the number of strong rivals' registration of early-stage trials in the same market in the last two years. This result is consistent with peer disclosure of interim success deterring subsequent R&D investments by the focal firm. In contrast, the focal firm's R&D investments are *positively* associated with disclosures by weak rivals, consistent with peer disclosures by weak rivals encouraging catch-up behavior by the focal firm. The economic magnitude of both effects is significant. When a firm's strong (weak) rivals increase their last two years' disclosure of early-stage trials by one standard deviation, the expected log-odds of the focal firm conducting later-stage trials in the same therapeutic area drops by 18.9% (increases by 15.4%).

I further conduct three cross-sectional analyses to identify situations that strengthen the encouragement and/or deterrence effects of peer disclosure. First, I hypothesize and find that in therapeutic areas with a higher clinical-trial success rate, the association between a focal firm's R&D investments and its strong rivals' disclosures of early-stage trial initiation is more negative. This result is consistent with the deterrence effect of strong rivals' disclosure being strengthened when tasks in later stages of the R&D race are expected to be more feasible. Second, the encouragement effect of weak rivals' disclosures is more pronounced in markets with fewer competing firms, presumably because the existence of fewer rivals increases the focal firm's prospects of defeating its rivals in later stages of the R&D race. Third, both the deterrence and encouragement effect of peer disclosure are strengthened when the focal firm has a diversified R&D portfolio, consistent with greater flexibility in resource allocation making the focal firm more responsive to new information.

In supplementary analyses, I first show that my main results are unlikely to be driven by firms' self-selection into voluntary disclosure. I examine peer firms' online registration of later-stage clinical trial initiation, which is public disclosure mandated by the FDA. Consistent with my main hypothesis, I find that a firm's R&D investments are deterred by strong rivals' and encouraged by weak rivals' mandatory disclosures of later-stage clinical trial initiation. Another endogeneity concern is omitted variable bias, i.e., uncontrolled market-level characteristics could drive both peer disclosure and the focal firm's R&D investments. To address this concern, I conduct a lead-lag analysis to examine the dynamic effects of peer disclosure. I find that the effects of both strong and weak rivals' disclosures become increasingly insignificant in subsequent years after disclosure, consistent with product market consequences of peer disclosures fading over time as those disclosures become stale news and thus less decision-relevant. Next, I examine the moderating effect of disclosure quality. I find that peer disclosures with more specific information are more effective at deterring competition. Finally, I evaluate the generalizability of my findings using a comprehensive sample of all clinical trials registered between 2007-2018. Classifying firms into pharmaceutical or biotechnology firms using machine learning, I find that my key results are stronger for pharmaceutical and larger firms than for biotechnology and smaller firms, presumably because the former have more diversified R&D portfolios and thus greater leeway in allocating resources across R&D projects.

My study contributes to the emerging literature on the peer effects of corporate disclosure. Leuz and Wysocki (2016) and Roychowdhury et al. (2019) highlight a lack of evidence on the effects of disclosure on peer firms' real decisions, yet such evidence is central to the economic justification of disclosure regulation. Some recent studies examine the effects of financial reporting and patent disclosure on peer firms' investment efficiency, market entry, and innovation (e.g.,

Badertscher et al. 2013; Beatty et al. 2013; Breuer et al. 2019; Zou 2019; Kim and Valentine 2019; Hegde et al. 2019). My study adds to this literature in two ways. First, I exploit the empirical setting of the drug development process and measure firms' R&D investments using the number of clinical trials at the firm-market-year level. This level of aggregation corresponds to the level of analysis at which firms generally make budgeting decisions (Cockburn and Henderson 1995). Compared with R&D expense and patents, clinical trials present a more welfare-relevant measure of pharmaceutical innovation that is directly tied to new product launch (Azoulay et al. 2019). The granular data of clinical trials also enable me to identify R&D races within the pharmaceutical industry and measure firms' relative positions within each race. Second, drawing on game-theoretical models of the R&D race, I hypothesize and find that a firm's R&D investment can be either deterred or encouraged by peer disclosure, depending on the disclosing firms' relative competitiveness in the R&D race. While most prior studies implicitly assume that disclosure always entails proprietary costs, my study provides a more nuanced view of the product market consequences of R&D disclosure.

2.0 Related Literature

While the accounting literature has provided substantial evidence on the capital-market benefits of corporate disclosure, limited evidence exists on the economic consequences of disclosure in the real economy. My study contributes to the emerging literature on the real effects of peer-firm disclosure (henceforth "peer effects of disclosure"). Besides the direct real effects of disclosure on the disclosing firm, the indirect effect of disclosure on peer firms is also of interest to regulators, as evidence on disclosure externalities is central to the economic justification of disclosure regulation (Leuz and Wysocki 2016).[5] Dye (1990) argues that a firm's disclosure can have two types of externalities: it can alter investors' perceptions about the distributions of other firms' cash flows (i.e., "financial externalities"), and possibly the actual distributions of other firms' cash flows (i.e., "real externalities"). Numerous studies provide evidence on the financial externalities of disclosure, in the form of intra-industry information transfers around earnings announcements (e.g., Baginski 1987; Han et al. 1989; Han and Wild 1990). Yet, evidence on the real externalities of disclosures remains limited.

Leuz and Wysocki (2016) and Roychowdhury et al. (2019) call for more research on whether and how a firm "learns" from peer firms' public disclosures and changes its real decisions. To address the empirical challenge that corporate behavior is usually not directly observable, these researchers encourage future work to generate new insights by studying disclosure regulations

[5] I use the terms "peer effects", "externalities", and "spillover effects" interchangeably to indicate the effects of firms' disclosures on peer firms in the same industry.

outside the traditional capital-market settings. My study answers their call by identifying an empirical setting, R&D race in drug development, in which firms' R&D decisions are observable.

My study also relates to archival studies on the effects of competition on voluntary disclosure. A large literature argues that a firm's disclosure decisions are affected by proprietary cost concerns, but empirical evidence from existing studies is mixed (e.g., Beyer et al. 2010).[6] For example, prior studies have documented that the extent of R&D disclosure (in IPO prospectuses, 10-K, new product press release, patent disclosure) is either not associated, negatively associated, or positively associated with various measures of competitive pressure (e.g., Guo et al. 2004; Merkley 2014; Cao et al. 2018; Glaeser and Landsman 2019; Enache et al. 2020). My study contributes to this literature by providing evidence that competitors indeed incorporate peer firms' proprietary disclosures into their real decisions. Moreover, one implication of my findings is that a strong (weak) firm has incentive to increase (decrease) its disclosures in anticipation of peer firms' reaction. Future research can explore this hypothesis to partially reconcile the mixed findings.

The remainder of this section reviews the emerging literature on the peer effects of financial reporting and disclosure, with a focus on R&D disclosures.

[6] The mixed empirical evidence is partly due to ambiguous theoretical predictions for the relation between proprietary costs of disclosure and market structure (Cheynel and Ziv 2020). Although most empirical studies argue that greater competition leads to greater proprietary costs, in the original proprietary cost hypothesis the exogenous disclosure costs are a reduced-form interpretation of lost competitive advantage in product markets (Verrecchia 1983; Verrecchia 1990).

2.1 Peer Effects of Mandatory Financial Reporting

Badertscher et al. (2013) provide early evidence on the effects of firms' mandatory financial reporting on peer firms' investment efficiency. They find that private firms operating in industries with greater public-firm presence are more responsive to industry investment opportunities. They interpret these results as evidence that mandatory disclosure requirements for public firms reduce overall industry uncertainty, leading to more efficient investment by private firms in the same industry.

Using detailed data from the U.S. airline industry, Zou (2019) studies the product market consequences of hedge accounting disclosure. She finds that potential entrants are more likely to enter routes in which incumbents' hedge accounting disclosure implies higher future production costs. Her results suggest that hedge accounting disclosure can shape product market competition by revealing firm-specific cost information to potential entrants.

Relatedly, if managers rely on peer disclosure to evaluate investment opportunities, they can make distorted investment decisions when peer firms misstate their financial statements. Beatty et al. (2013) examine how high-profile accounting frauds affect peer firms' investment. They find that peer firms increase investments during periods when the industry-leader reports fraudulently overstated earnings. They argue that these overstated earnings make managers of peer firms over-optimistic about industry outlooks, which leads them to overinvest. Li (2016) extends Beatty et al. (2013) by providing evidence that financial misreporting distorts not only peer firms' capital expenditure decisions but also their R&D and advertising decisions.

Several recent studies examine the effects of mandatory financial reporting on firm innovation. Two cross-country studies, Zhong (2018) and Brown and Martinsson (2019), find that firm transparency is positively associated with R&D intensity and patenting; they further argue

that transparency plays a role through reduced agency frictions and cost of capital. Breuer et al. (2019) provide causal evidence on the real effects of financial reporting regulation on corporate innovation activity. They exploit reporting thresholds in Europe's regulation and an enforcement reform in Germany, and find that forcing a greater share of firms to publicly disclose their financial statements 1) reduces innovative activities at the industry level, and 2) increases firms' reliance on patenting to protect innovation. Their evidence suggests that financial reporting mandates diminish firms' incentives to innovate, and that these proprietary costs of disclosure are not fully compensated by positive information spillovers across industry peers.

2.2 Peer Effects of R&D Disclosure

Prior research generally does not distinguish between peer effects that arise from the disclosure of proprietary versus non-proprietary information (Roychowdhury et al. 2019, p.16). Conceptually, while some disclosures such as management earnings forecasts likely benefit peer firms without hurting the disclosing firm (Lang and Sul 2014), more disaggregated disclosures about ongoing investment projects could benefit peer firms but erode the disclosing firm's competitive advantage, e.g., through knowledge spillovers.

R&D disclosure presents a setting that manifests managerial concerns regarding proprietary costs, as evidenced by the industry's opposition to disclosure mandates (e.g., IFPMA 2009). Two recent studies provide archival evidence using mandatory patent disclosures. Hegde et al. (2019) study how the publication of patents affects innovation. They exploit the passage of the American Inventor's Protection Act (AIPA), which accelerated the public disclosure of most patents in the U.S. by two years. They find that, after the passage of AIPA, 1) patents receive more

and faster follow-on citations, consistent with technology diffusion, and 2) technological overlap decreases between highly similar patents, consistent with a reduction in duplicative R&D. Using the same empirical setting, Kim and Valentine (2019) provide evidence that the forward citations of a firm's patents increase (decrease) after AIPA in situations where the firm-specific net benefit of accelerated patent disclosure is likely positive (negative).

A contemporaneous working paper by Krieger (2019) also examines how pharmaceutical companies adjust their R&D investments following peer disclosure of clinical trial information. My study differs from Krieger (2019) along three dimensions. First, the nature of peer disclosure is different. I study peer firms' disclosure of clinical trial initiation, which is mandated by the FDA and signals interim R&D success. Krieger (2019) studies peer firms' announcement of trial termination, which conveys bad news and is disclosed voluntarily. Second, we use different theoretical frameworks -- I draw on game-theoretical models of the R&D race, whereas Krieger (2019) develops a real options model. Finally, our key findings are different and complementary. I hypothesize and find that firms react in *opposite* directions to disclosures from strong and weak rivals within the same market. Krieger (2019) finds that firms decrease R&D investments after competitors' trial termination news, especially when the terminated trial is in the same market and uses the same technology.

3.0 Hypotheses Development

Analytical studies on disclosure decisions in a product market setting focus primarily on a duopoly in which firms compete on quantity (Cournot competition) or price (Bertrand competition). In this environment, there is common uncertainty over aggregate demand and/or private uncertainty over firm-specific production costs. Corporate disclosure can reduce uncertainty and change the rival's production or pricing decisions. For example, in a Cournot duopoly, a firm's disclosure of a high aggregate demand entails "proprietary costs" because such disclosure encourages the firm's rival to increase its production, which reduces the equilibrium price and in turn, the disclosing firm's profit (e.g., Darrough 1993).[7]

While the Bertrand-Cournot dichotomy can capture the essence of competition in manufacturing or service industries, R&D competition better reflects the type of environment that generates proprietary information in a modern economy (Dye 2001). To establish the theoretical foundation for the role of proprietary information in R&D competition, I draw on game-theoretical models of R&D races in industrial organization (IO). The IO literature typically models the R&D competition as a two-stage race, in which the preliminary stage is research and the final stage is development. Successful completion of the preliminary stage has no intrinsic value but is a prerequisite for beginning work on the final stage. Two firms compete for an indivisible prize; the first firm to complete the final stage wins the race and receives the entire prize. A two-firm, two-

[7] For summaries of this literature, see Verrecchia (2001), Dye (2001), Beyer et al. (2010).

stage R&D race involves four success rates that combine to determine firms' probabilities of winning: preliminary-stage success rate of each firm, and final-stage success rate of each firm.[8]

Consider the scenario in which a rival advances to the final stage when the focal firm remains in the preliminary stage. With a widened gap between the two firms, the focal firm will only continue to invest in the project if its chance of winning the race is sufficiently high.[9] The rival's interim success resolves the uncertainty over its preliminary-stage success rate, and the remaining three success rates combine to determine the focal firm's chance of winning the race. Intuitively, staying in the race is more likely to be worthwhile for the focal firm if it is confident about succeeding in the preliminary and final stage and skeptical about the rival's prospect of completing the final stage.

A rival's announcement of preliminary-stage completion can have two opposite effects on the focal firm's investment decision.[10] On the one hand, peer disclosure of interim success reduces the focal firm's chance of winning, because the uncertainty over the rival's preliminary-stage success rate has resolved and the technological gap between the two firms has increased. This effect is negative, and I call it the *deterrence effect* of peer disclosure. On the other hand, firms working on the same R&D project share the common uncertainty over project feasibility, and peer disclosure of interim success can signal that the preliminary stage is less difficult than expected.

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[8] By "success rate" I mean "hazard rate" in the stochastic R&D process, which equals the conditional probability density of success given no success to date. Formally, denote the random discovery date of any stage of the R&D process by τ, and assume the probability of success by a given time t follows an exponential function: $\Pr(\tau < t) = 1 - e^{-\lambda t}$, then λ is the "hazard rate". In models such as Choi (1991), λ is a random variable with both common and idiosyncratic components.

[9] More rigorously, the expected payoff from staying in the race is roughly determined by two factors, the probability of winning and the expected time still needed for the discovery (Choi 1991). I focus on the former factor because there is a lack of data on the starting time of each preliminary-stage R&D project.

[10] Theoretical models of the R&D race typically assume the perfect observability of all firms' R&D progress. One exception is Bag and Dasgupta (1995), who study firm's strategic announcement of R&D success in the initial stage. They establish conditions under which interim success will be announced if and only if it occurs early enough in the R&D race, and the rival drops out immediately upon observing this early announcement.

Dasgupta and Maskin (1987) describe this effect of peer disclosure as, "To know that someone has solved a problem is to know a great deal: specifically, that the problem is solvable." This knowledge increases the focal firm's expectation of preliminary-stage project feasibility, boosts the focal firm's confidence in its own preliminary-stage success rate, and increases the focal firm's expected payoff from staying in the race. This effect is positive, and I call it the *encouragement effect* of peer disclosure.[11]

I hypothesize that whether the encouragement effect or the deterrence effect of peer disclosure dominates depends on the disclosing rival firm's R&D efficiency, for two reasons. First, the deterrence effect of the rival's disclosure of interim success stems from the rival's final-stage success rate, which in turn depends on the rival's strength. A rival that is perceived as weak may experience difficulty completing the final stage, which gives the focal firm opportunities to catch up. In contrast, a rival that appears strong is expected to succeed in the final stage within a shorter period, which reduces the focal firm's chance of winning to a greater extent. Therefore, compared with a weak rival's disclosure of interim success, a strong rival's disclosure will have even greater deterrence effect on the focal firm - "Why compete if you can't catch up?" (Fudenberg et al. 1983).

Second, the encouragement effect of peer disclosure of interim success is due to the reduction in common uncertainty over project feasibility. I hypothesize that the focal firm's updated belief about preliminary-stage project feasibility is negatively associated with the rival's perceived strength, and I provide reasoning for this claim using a Bayesian updating model and a numerical example in Appendix B. The rival's actual success is a function of two factors - project feasibility and the rival's strength. The extent to which the focal firm attributes the rival's success

[11] In addition, technical details revealed in peer disclosure can create knowledge spillovers that directly improve the focal firm's R&D productivity. This scenario can also encourage the focal firm's catch-up behavior (Bhattacharya and Ritter 1983; Scotchmer and Green 1990; Gill 2008).

to project feasibility depends on prior beliefs about the rival's type. When the focal firm believes its rival to be the strong type, the interim success by the rival will be primarily attributed to such prior beliefs, and so the focal firm only update its beliefs about project feasibility moderately when it learns of the rival's interim success. In contrast, when the rival is perceived as weak, the observed success is attributed to a greater extent to the alternative explanation that the preliminary stage of this project is relatively easy. As a result, the focal firm grows more optimistic of its own prospect of completing the preliminary stage soon - "If you can do that, why not me?" (Choi 1991).

Taken together, a rival's disclosure of interim success always has both the encouragement effect and the deterrence effect on the focal firm's investment decision. A weak rival's disclosure entails a strengthened encouragement effect whereas a strong rival's disclosure entails a strengthened deterrence effect. I further hypothesize that the encouragement effect dominates when the disclosure of interim R&D success comes from a weak rival, which induces the focal firm to subsequently increase its R&D investment in an effort to catch up. In contrast, the deterrence effect likely dominates when the disclosure comes from a strong rival, which leads the focal firm to subsequently decrease its R&D investment. Formally, I propose the following hypothesis concerning a firm's reaction to peer disclosure of interim R&D success:

H1: A firm's R&D investments are positively (negatively) associated with its weak (strong) rivals' disclosures of interim R&D success.

In addition to the rival firm's R&D strength, the inherent difficulty of the R&D project may also moderate a firm's reaction to peer disclosure of interim success. In particular, I hypothesize that the ex ante success rate of the R&D project's final stage influences the magnitude of the deterrence effect of peer disclosure. As discussed earlier, the focal firm's chance of winning is negatively associated with the rival's final-stage success rate - the more likely the rival can

successfully reach the finish line, the less is the value to the focal firm of staying in the race. When the project's final stage appears difficult, there is more likely to be sufficient time before the rival reaches the finish line, if he ever does. In the meantime, the focal firm should stay in the race with the hope of catching up with the rival. In contrast, when the final stage appears less demanding, the rival is expected to win within a short period, and the focal firm's prospect of catching up with the rival is bleak. Comparing these two scenarios suggests that a high (low) final-stage success rate strengthens (alleviates) the deterrence effect of peer disclosure of interim success. Combining H1 and the above discussion, I propose the following hypothesis concerning the moderating effect of a project's final-stage success rate:

H2: The association between a firm's R&D investments and its strong rivals' disclosures of interim R&D success is more negative when the R&D project has a high success rate in the final stage.

To simplify calculations, game-theoretical models in IO typically assume only two firms compete in the R&D race. Extending the theoretical predictions to a multi-firm setting, I hypothesize that the encouragement effect of peer disclosure of interim success is negatively associated with the number of firms competing in the R&D race. As discussed in H1, the encouragement effect of peer disclosure is driven by an updated belief about the preliminary-stage project feasibility and, in turn, the focal firm's preliminary-stage success rate. To win the race, the focal firm needs to not only complete the preliminary stage to catch up with rivals, but also to finish the final stage before any other rival does. The difficulty of the latter task increases with the number of competitors, because the existence of more rivals makes it harder for the focal firm to surpass all rivals in the final stage. Intuitively, staying in the race is more beneficial when the focal firm becomes more optimistic about preliminary-stage project feasibility, and even more so when

the focal firm has fewer rivals to compete with in the final stage. Combining H1 and the above discussion, I propose the following hypothesis concerning the moderating effect of market concentration:

H3: The association between a firm's R&D investments and its weak rivals' disclosures of interim R&D success is more positive in markets with fewer competing firms.

The analysis so far assumes that 1) when a firm's chance of winning drops, e.g., when it is deterred by strong rivals, it reduces investments or even drops out of the race, and 2) when a firm's chance of winning increases, e.g., when it is encouraged by weak rivals, it stays in the race and invests more to catch up. Both assumptions are more likely to hold when the firm has a diversified R&D portfolio. Projects in similar fields share common uncertainties over project feasibility and thus have correlated net present values. A diversified R&D portfolio allows a firm to reallocate its resources from projects with a lower chance of winning to alternative projects with better prospects. In contrast, a firm with a focused R&D agenda may lack the flexibility to either quit a losing race or increase investments to catch up. Combining H1 and the above discussion, I hypothesize that a firm with a more diversified R&D portfolio is more responsive to new information, which strengthens both the encouragement effect and deterrence effect of peer disclosure:

H4: The association between a firm's R&D investments and its weak (strong) rivals' disclosures of interim R&D success is more positive (negative) when the firm has a more diversified R&D portfolio.

4.0 Institutional Background

The end product of pharmaceutical innovation is a new drug, which receives much more regulatory scrutiny than most goods. The FDA supervises the drug development process in the United States. Below I describe key FDA regulations regarding 1) transition through major milestones in drug development, and 2) disclosure of clinical trial information.

4.1 Milestones in the Drug Development Process

On average it takes 12 years to develop a FDA-approved new drug, with an estimated total capitalized R&D cost of $2.6 billion (DiMasi et al. 2016). Figure 1 illustrates the milestones in the drug development process, which can be divided into pre-clinical studies and clinical trials. Pre-clinical studies collect data on a drug's toxicity and mechanisms of action from 5-6 years of laboratory and animal studies. Firms usually remain secretive about their progress in pre-clinical studies, but disclose more information as the new drug candidate enters the clinical trial stage to be tested on human beings. Clinical trials are usually conducted in three phases and can take a total of 6-7 years to complete. The initiation of Phase 1 trial and the advancement from one phase to the next involve both the firm's own cost-benefit analysis and the FDA's formal approval. Phase 1 trials evaluate the safety of the drug and gather early evidence of efficacy in 20-100 healthy volunteers. About 60-70% of drugs tested in Phase 1 trials advance to Phase 2 trials, which evaluate a drug's efficacy and side-effects in 100 to 250 patients. Next, about 33% of drugs tested in Phase 2 trials advance to Phase 3 trials, which further test the drug's safety and efficacy in thousands of

patients. At the end of the Phase 3 trial, the firm submits the New Drug Application (NDA) to the FDA for permission to market the drug in the United States.

[Inset Figure 1 here]

The FDA's supervision over these major milestones allows me to use a clinical trial's phase as a uniform benchmark to classify a new drug candidate's intermediate R&D progress across firms and therapeutic areas. In particular, a firm's initiation of Phase 1 trial marks its completion of pre-clinical studies, sending a credible signal of interim R&D success. Pre-clinical studies have a 98% likelihood of termination for scientific or economic reasons. In fact, firms with a higher termination rate in pre-clinical studies tend to have higher R&D productivity, presumably because their managers resist the temptation to advance projects with low probability of ultimate success into costly clinical trials (Ringel et al. 2013).

4.2 Public Disclosure of Clinical Trial Information

Until a decade ago, firms could keep all information about a clinical trial, including its very existence, private. In 2007 Congress passed the Food and Drug Administration Amendments Act (FDAAA) to address the effects of concealed negative results on medical practice and to protect human participants in clinical trials (Zarin et al. 2015). Section 801 of FDAAA requires sponsors of all "applicable trials" to register their studies, at inception, in a publicly accessible online database ClinicalTrials.gov.[12] These "applicable trials" include controlled clinical investigations,

[12] ClinicalTrials.gov is the U.S. clinical trial registry website. It was created as a result of the Food and Drug Administration Modernization Act of 1997 and was made available to the public in 2000. The ClinicalTrials.gov registration requirements were expanded after Congress passed the FDAAA. Section 801 of FDAAA requires more types of trials to be registered and additional trial registration information to be submitted. The law also requires the

other than Phase 1 trials, of drugs, biological products, and devices that have at least one trial site in the U.S. FDAAA also included penalties for noncompliance, such as the withholding of NIH grant funding and civil monetary penalties. The number of registered trials on ClinicalTrials.gov grew from 40,000 in 2007 to 227,000 in 2016, and the website now has about 170 million page views per month (Zarin et al. 2017).

Proponents of trial registration argue that it can both "foster innovation and research" and "reduce unnecessary duplication of trials" (World Health Organization 2018). Importantly, the first and second half of this statement map respectively into the encouragement effect and deterrence effect of peer disclosure discussed in Section 3.0.

Potential costs of trial registration are primarily voiced by the pharmaceutical industry. For example, the trade association of pharmaceutical firms has expressed concerns that registering early-stage trials could harm the competitive advantage of the disclosing firm, which in turn hurts innovative efforts (IFPMA 2009).

submission of results for certain trials. This led to the development of the ClinicalTrials.gov results database in 2008, which contains summary information on study participants and study outcomes.

5.0 Empirical Design

5.1 Sample Selection

My main data source is ClinicalTrials.gov, an online database where firms register their clinical trials to comply with FDAAA as described in Section 4.2.[13] I collected all clinical trials of investigational drugs registered by the 50 firms with the largest number of clinical trial registrations on ClinicalTrials.gov between September 2007, the first month FDAAA became effective, and December 2017.[14] These 50 firms represent the most research-active firms in the industry, and thus are more likely to have the resources to behave strategically.[15]

The firm sponsoring a clinical trial (the "sponsor") submits information about the trial to ClinicalTrials.gov when the trial begins. This data submission process is called "trial registration". The sponsor is then required to update the registration information on the website throughout the trial, and in some cases, submit the results after the trial ends. All the self-reported information by the sponsor is reviewed by staff at the National Library of Medicine (NLM). The following items are required to be disclosed for all trial registrations: sponsor, phase, medical condition being treated, number/age/gender of human participants, trial start/end time, intervention, and trial status

[13] Firms may collect information about rivals' clinical trials via other channels. However, ClinicalTrials.gov is considered the top information source for pharmaceutical industry's competitive intelligence (e.g., Russell 2018). Also, given that firms comply with the FDAAA to register their Phase 2 and Phase 3 trials on ClinicalTrials.gov in a timely fashion, I expect ClinicalTrials.gov to be the most relevant and reliable channel for the disclosure of Phase 1 trials as well.

[14] An investigational drug is a substance that has been approved by the FDA for testing in human participants in clinical trials but has not been approved for marketing.

[15] Out of the 1,223 firms with more than 10 clinical trials registered on clinicaltrials.gov, the top 50 firms contribute 58% of all the clinical trials registered. My additional tests in section 7.3 suggest that large firms are more responsive to peer disclosures than smaller firms.

(completed, suspended, withdrawn). Figure 2 provides an example of a trial registration of Remdesivir, a drug candidate that treats COVID-19, on ClinicalTrials.gov.

[insert Figure 2 here]

Each trial registration must disclose the medical conditions treated in the trial. To facilitate comparison of R&D projects across firms, I classify my sample of 35,120 trials into 162 "markets", according to the therapeutic areas of the medical conditions treated in each trial.[16] Conceptually, drug candidates treating diseases in the same therapeutic area are competing in the same R&D race, so this classification of R&D races matches the theoretical framework of the IO models. Empirically, this classification allows me to measure a firm's R&D investments and competitive position at the firm-market-year level, which captures R&D competition at a more granular level than prior studies that rely on firm-year level data.

Specifically, to locate the position of each trial in the "tree" of diseases, I merge the medical condition self-reported in each trial registration with NLM's Medical Subject Heading (MeSH) terms. ClinicalTrials.gov's guidance on trial registration encourages data submitters to use the MeSH terminology to report the medical condition being treated in the clinical trial. MeSH descriptors of diseases are divided by medical experts into categories and then further divided into subcategories at a consistent level of specificity.

Figure 3 provides an example of my classification of diseases into therapeutic areas. The "branch" or category of diseases in the figure is "Mental Disorders", labeled [F03]. Here, I expand one of its multiple sub-branches, Neurocognitive Disorders, labeled [F03.615], where the added level indicates greater specificity. Amnesia [F03.615.200] is the even more specific descriptor under Neurocognitive Disorders. I define a "market" as a therapeutic area with exactly three levels

[16] Throughout the empirical section I use "market", "R&D race", and "therapeutic area" interchangeably.

i.e., at the sub-sub-category level in the MeSH tree system. In this example, I assume all clinical trials studying treatment for either "Alcoholic Korsakoff Syndrome" [F03.615.200.131] or "Amnesia, Anterograde" [F03.615.200.137] are competing in the market of Amnesia [F03.615.200].

[insert Figure 3 here]

My unit of observation is firm-market-year, e.g., Pzifer-Amnesia-2015 is one observation. This level of aggregation corresponds to the level of analysis at which firms generally make budgeting decisions (Cockburn and Henderson 1995). My final sample contains an unbalanced panel of 40,461 firm-market-year observations with non-missing values for all relevant variables. I run all regressions at the firm-market-year level.

5.2 Variables and Descriptive Statistics

To measure R&D investments at the firm-market-year level, I use the number of Phase 2 trials that firms conduct and register online to comply with the FDAAA, consistent with recent studies in health economics (e.g., Finkelstein 2004; Yin 2008; Blume-Kohout and Sood 2013). Compared with patents, clinical trials present a more welfare-relevant measure of pharmaceutical innovation that is directly tied to new product launch.[17] A firm's reactions to peer disclosure, in the form of slowing down, abandoning, or accelerating its own early-stage R&D investments, will

[17] In pharmaceutical R&D, the likelihood that patents turn into products is low – firms file for patent protection on candidate drug compounds early in the drug discovery process, prior to starting clinical trials. Azoulay et al. (2019) examine the universe of 232,276 life-science patents granted to the industry by the USPTO between 1980 and 2012. Of these, only 4,718 patents (2%) are associated with advanced drug candidates (those in Phase 3 trials and beyond), and even fewer, 1,999 (<1%) are associated with FDA-approved new drugs and biologics.

ultimately result in changes in the number of its own trial initiations in the same market. My dependent variable $FocalP2_{i,k,t}$ is an indicator variable that equals one when firm *i* registers at least one Phase 2 clinical trial in market *k* in year *t*, and zero when firm *i* has registered at least one clinical trial in year *t* but none of these trials is a Phase 2 trial in market *k*.[18]

I construct my main independent variables of interest, strong and weak rivals' disclosures of interim R&D success, in two steps. First, to rank firms' R&D productivity, I measure a firm's "knowledge stock" in market *k* at year *t* using the total number of Phase 2 and Phase 3 trials in market *k* the firm has initiated in the years 2007 to *t*-1. With FDAAA requiring firms to register all Phase 2 and Phase 3 trials at trial initiation, "knowledge stock" captures the firm's accumulated experience in drug development that is specific to the therapeutic area.[19] My regression analyses (untabulated) suggest that "knowledge stock" is positively associated with the firm's subsequent initiation of Phase 3 trials in that market, consistent with prior findings that accumulated knowledge stock in the relevant therapeutic area is positively associated with gaining FDA approval for marketing a drug (Cockburn and Henderson 2001). Most prior accounting studies measure a firm's competitive position using revenue-based market shares or R&D expenses. Compared with these aggregate-level measures, my measure of "knowledge stock" exploits granular data at the R&D project level to capture the variation in technological advantage across markets within a firm.[20]

[18] This construction implicitly assumes that as long as a firm is research active in a year, it is possible/feasible for it to conduct trials in every market. I relax this assumption when I split the sample to test H4.

[19] For robustness checks, I also measure "knowledge stock" using the cumulative number of Phase 2 trials completed at the firm-market-year level, the cumulative number of Phase 3 trials initiated at the firm-market-year level, or the cumulative number of Phase 2 and Phase 3 trials at the firm-year level. The main results remain qualitatively same.

[20] One limitation of my measure is that it only captures firms' experience with drug development (i.e., the clinical trial stage) but not drug discovery (i.e., pre-clinical studies), because data on drug discovery is typically not publicly available. It is possible that a firm historically specialized in drug discovery in a market is perceived as a strong candidate in reality but is categorized as a "weak" rival under my definition. This scenario biases against my findings.

Next, I define a firm as a strong (weak) player in market *k* at year *t* if its "knowledge stock" ranks in the top (bottom) 40% within that market-year. My results are qualitatively the same if I use the top/bottom 30% or 50% to define strong/weak rivals. I compute strong (weak) rivals' disclosures of interim R&D success, denoted $RivalP1\_Strong_{i,k,t}$ ($RivalP1\_Weak_{i,k,t}$), as the total number of Phase 1 trials registered in the two years preceding *t* by firm *i*'s rivals that are strong (weak) players in market *k*. I use a two-year window to allow the focal firm sufficient time to respond to peer disclosure in a timely fashion.[21]

To control for other determinants of $FocalP2_{i,k,t}$ that might be correlated with peer disclosures of Phase 1 trial initiation, I also include the following three classes of control variables, all calculated using two lagged years. First, to measure firm *i*'s own R&D productivity in market *k*, I use the knowledge stock it recently accumulated, proxied as the number of Phase 2 and Phase 3 trials firm *i* conducted in market *k* in the two years preceding *t* ($FocalP23\_lag_{i,k,t}$). I also control for the number of Phase 1 trials firm *i* registered ($FocalP1\_lag_{i,k,t}$) to allow for the natural transition from Phase 1 to Phase 2. Second, to capture R&D productivity by firm *i*'s rivals, I use the knowledge stock recently accumulated by them, proxied as the number of Phase 2 and Phase 3 trials these rivals conducted in market *k* in the two years preceding t ($RivalP23\_lag_{i,k,t}$). Third, for each market *k*, I include the concentration of clinical-trial market shares proxied by the Herfindahl index ($HHI_{k,t}$). Appendix A provides complete descriptions of these variables.

Table 1 presents the descriptive statistics. The unit of observation is firm-market-year. To allow for two years of lagged values for explanatory variables, the sample covers years 2009 to

[21] If a firm in pre-clinical stage observes peer disclosure and decides to accelerate its drug development program, it must spend 1-3 months to plan for clinical trials and file an Investigative New Drug (IND) application to the FDA. 30 days after filing IND, the firm may begin a Phase 1 trial unless the FDA places a hold on the study. The median length of a Phase 1 trial is 291 days in my sample, and the Phase 2 trial initiation typically happens a few months after the Phase 1 trial completion. All these time periods add up to around two years.

2017. The clinical trials span 162 markets, with each market corresponding to a therapeutic area as described in Section 5.1. Within each market-year, there are on average seven Phase 2 trials registered by 12 research-active firms. A typical firm observes five (two) Phase 1 trials registered by its strong (weak) rivals in the same market in the two preceding years.

[insert Table 1 here]

The correlation matrix in Table 2 suggests that $FocalP2_{i,k,t}$ is positively associated with $RivalP1\_Strong_{i,k,t}$ and $RivalP1\_Weak_{i,k,t}$. This association can be attributed to either common market demand factors or an aggressive reaction to peer disclosure. I next analyze this relation using multi-variate regression analysis.

[insert Table 2 here]

6.0 Empirical Results

6.1 Test of H1

To test H1, I estimate the relation between firm *i*'s R&D investments in market *k* in year *t* and its strong and weak rivals' disclosures of Phase 1 trials in market *k* in the two preceding years. Specifically, I run the following logit regression at the firm-market-year level:

$$FocalP2_{i,k,t} = \beta_0 + \beta_1 RivalP1\_Strong_{i,k,t} + \beta_2 RivalP1\_Weak_{i,k,t} + \beta_3 Controls_{i,k,t} + \theta_{i,t} + \varepsilon_{i,k,t} \quad (1)$$

In all specifications, I control for firm×year fixed effects ($\theta_{i,t}$).[22] Effectively, I examine the variation across markets within a firm-year, thus controlling for unobserved factors that are firm-specific and/or time-varying, such as corporate disclosure policy, equity offering, merger and acquisition, as well as industry-level trends or shocks.[23] I report the regression results in Table 3, with robust standard errors clustered by firm.

[insert Table 3 here]

Column (1) in Table 3 presents regression results from estimating Equation (1). Consistent with H1, the coefficient for $RivalP1\_Strong_{i,k,t}$ (β_1) is significantly negative, whereas the coefficient for $RivalP1\_Weak_{i,k,t}$ (β_2) is significantly positive. In terms of economic significance, holding other variables constant, when strong (weak) rivals increase their disclosures

[22] Specifically, I estimate the model using Stata's clogit command for conditional (fixed-effects) logistic regression. The results are qualitatively similar if I use a linear probability model instead of a logit model.

[23] The regression specification with firm×year fixed effects drops all observations without within-group variance of the dependent variable, i.e., firm-years that registered Phase 2 trials in none or all of the markets. My results are similar if I use firm fixed-effects and year fixed-effects instead.

of Phase 1 trials in the two preceding years by one standard deviation, the expected log-odds of the focal firm's Phase 2 trials in the same market drop by 18.9% (increase by 15.4%). In other words, the focal firm's R&D investments are *deterred* by *strong* rivals' disclosures but *encouraged* by *weak* rivals' disclosures. Regarding control variables, firm-market-years with a larger number of recent clinical trials conducted by either the focal firm (*FocalP1_lag, FocalP23_lag*) or rivals (*RivalP23_lag*) are more likely to initiate a Phase 2 trial, while those in more concentrated markets (higher values of *HHI*) are less likely to initiate a Phase 2 trial.

To examine the overall effect of all rivals' disclosures of interim R&D success, I construct another variable $RivalP1\_lag_{i,k,t}$, which equals the total number of Phase 1 trials registered by *all* of firm *i*'s rivals in market *k* in the two years preceding *t*. Column (2) in Table 3 presents regression results from estimating Equation (1) with $RivalP1\_Strong_{i,k,t}$ and $RivalP1\_Weak_{i,k,t}$ replaced by $RivalP1\_lag_{i,k,t}$. The negative coefficient for $RivalP1\_lag_{i,k,t}$ suggests that a firm's R&D investments are, on average, deterred by its rivals' disclosures of Phase 1 trials.[24]

6.2 Test of H2

To test H2, I first identify two subsamples with the highest and lowest clinical-trial success rate at the therapeutic-area level. To do so, I rely on results from three highly-cited biostatistics studies (Hay et al. 2014; Thomas et al. 2016; Wong et al. 2019). These studies estimate the "probability of success" (POS), i.e., the overall probability of gaining final FDA approval for

[24] Additional untabulated tests suggest that a firm is more likely to register its Phase 1 trial in a market when it has a large knowledge stock in that area and when it faces greater information demands from the capital market.

marketing conditional on the drug development program entering Phase 1 clinical trial. They report an average POS of 9.6%-13.8% for all clinical trials, but large variation in POS across therapeutic areas, e.g., from a minimum of 3.4% for oncology to a maximum of 33.4% for infectious disease. Drawing on these findings, I identify a therapeutic area as having a high (low) clinical-trial success rate if all three biostatistics studies rank its POS above (below) the median cross all therapeutic areas. Observations with high and low success rate each account for about 25% of my sample.[25]

Next, I separately estimate Equation (1) for two subsamples with high and low clinical-trial success rate and report results in Table 4. In therapeutic areas with a high success rate (Column 1), the association between a firm's R&D investments and its strong rivals' disclosures, i.e., the coefficient for *RivalP1_strong*, is significantly negative, consistent with the deterrence effect of peer disclosure. In contrast, the same coefficient is insignificant in therapeutic areas with a low success rate (Column 2). Untabulated results show that the coefficients for *RivalP1_strong* in Column (1) and (2) are statistically different (p-value = 0.039), which suggests a strengthened deterrence effect when the transition from Phase 1 initiation all the way to final FDA approval is more feasible ex ante. Taken together, the results in Table 4 are consistent with H2.

[insert Table 4 here]

[25] Therapeutic areas with low success rate include neurology or central nervous system diseases, oncology, autoimmune diseases, cardiovascular diseases. Therapeutic areas with high success rate include infectious disease, eye diseases, inflammation, hematologic diseases, allergy, gastrointestinal diseases, dermatology, urology.

6.3 Test of H3

To test H3, I separately estimate Equation (1) for two subsamples partitioned on the number of research-active firms in a market. Table 5 reports the results. I define a market as "concentrated" ("dispersed") if its number of firms with at least one trial in the preceding two years is above (below) the sample median.[26] Consistent with H3, I find that the coefficient for weak rivals' disclosures (*RivalP1_weak*) is significantly positive in concentrated markets (Column 2), but insignificant in dispersed markets (Column 1). Untabulated results show these two coefficients are statistically different (p-value < 0.001). Taken together, the results suggest that the encouragement effect of peer disclosure is strengthened when the focal firm faces a limited number of rivals in the R&D race.

[insert Table 5 here]

6.4 Test of H4

To empirically measure the focal firm's flexibility in resource allocation, I consider the following two characteristics of the firm's R&D portfolio. First, within each firm-year, I capture the variation in emphasis across markets using the weight of a given market in the firm's portfolio of clinical trials. I define a market as a firm's "main focus" in a year if this market's share of the firm's total number of Phase 2 and Phase 3 trials in the last two years is above the median across all markets in that firm-year. Results in Columns (1) and (2) of Table 6 show that the focal firm is

[26] The results are similar if I split the sample using the market-year level Herfindahl index, i.e., sum of the squared term of each firm's clinical-trial market share.

only sensitive to peer disclosure when the market is *not* its main focus, presumably because firms tend to "persevere" in their core areas of business but can be more flexible adjusting investments in peripheral markets.

[insert Table 6 here]

My second measure captures the R&D diversification strategy at the firm-year level. Specifically, I calculate the squared term of a market's weight in the firm's R&D portfolio and then sum the squared terms across all markets to generate a firm-year level Herfindahl index. I define a firm-year as having a "diversified" R&D portfolio if its Herfindahl index is below the sample median in that year. Results in Columns (3) and (4) of Table 6 suggest that the competitive consequences of peer disclosure are only salient when the focal firm has a diversified R&D portfolio. Taken together, regression results in Table 6 are overall consistent with H4.[27]

[27] Regarding the statistical significance for the difference between coefficients in Columns (1) and (2) of Table 6, untabulated results show that the coefficients for *RivalP1_weak* are not statistically different (p = 0.46), and coefficients for *RivalP1_strong* are marginally statistically different (p = 0.11). Between Columns (3) and (4), the coefficients for *RivalP1_weak* are statistically different (p = 0.05), and coefficients for *RivalP1_strong* are not statistically different (p = 0.32).

7.0 Additional Analyses

7.1 Endogeneity of Peer Disclosure

My primary analyses so far treat strong and weak rivals' voluntary disclosure of Phase 1 trials as the main variables of interest. Although rivals' earlier disclosures are plausibly exogenous to the focal firm's subsequent R&D investments, a potential concern is that peer disclosures are driven by rivals' strategic considerations to shape competition (i.e., reverse causality) or by some confounding factors that influence both rivals' past disclosure and the focal firm's current R&D investments (i.e., omitted variable bias). Any alternative story needs to be able to explain why the focal firm's R&D investments are *negatively* associated with strong rivals' disclosures but *positively* associated with weak rivals' disclosures, as well as why the cross-sectional results are consistent with my theoretical predictions in H2-H4. Nevertheless, to address this potential endogeneity concern, I conduct two additional analyses to further establish causality of my key results.

First, I extend my analyses to strong and weak rivals' online registrations of *Phase 2* trial initiation, which are disclosures mandated by the FDAAA. Table 7 shows that a focal firm's R&D investments, here measured by whether the firm initiates any Phase 3 trials in a market in a year, are negatively (positively) associated with its strong (weak) rivals' *mandatory* disclosure of interim R&D success, measured by the number of Phase 2 trial registrations in the same market in the two preceding years. Therefore, results in Table 7 are consistent with H1 and qualitatively similar to the results in Table 3 – the deterrence (encouragement) effect of peer disclosure dominates when the rival is a strong (weak) player in that market, where the definitions of strong

and weak rivals remain the same as described in section 5.2. The fact that my main results continue to hold when I examine the competitive consequences of rivals' mandatory disclosure of interim R&D success alleviates the concern that these results are driven by rival firms' self-selection into voluntary disclosures.

[insert Table 7 here]

Second, market-level characteristics such as expected risk and return of R&D in that market could drive both peer firms' past R&D and the focal firm's current R&D. To address the concern of an omitted variable bias, I conduct a lead-lag analysis on the dynamic effects of peer disclosure.[28] The idea of this test is to examine the effect of peer disclosure on the focal firm's R&D investments in each year after the disclosure. If the documented peer effect is indeed driven by the focal firm's real reaction to peer disclosure, then the magnitude of peer effects (i.e., the absolute value of coefficients for *RivalP1_strong* and *RivalP1_weak*) should diminish over time, as the disclosed information about peer firms' R&D progress becomes outdated and less decision-relevant. If the documented peer effects are instead driven by inherent market characteristics, then the coefficients for peer disclosure should remain relatively stable over time. Table 8 presents the results from this lead-lag analysis. Following Beatty et al. (2013), I keep all the independent variables (all measured over the two years before year *t*), but replace the original dependent variable measuring the focal firm's Phase 2 initiation in year *t* (Column 1) with an alternative dummy variable that equals 1 if the focal firm initiates a Phase 2 trial in that market in year *t*+1 (Column 2), *t*+2 (Column 3), or *t*+3 (Column 4). Moving from Columns (1) to (4), coefficients for

[28] Note that the inclusion of firm×year fixed effects in Equation (1) already controls for time-series variations such as demographic trends. I also include control variables that vary at the market-year level. Ideally, I would further include market fixed-effects to rule out market characteristics as drivers of my main results. However, variations in my variables of interest (*RivalP1_strong* and *RivalP1_weak*) occur mostly at the market-level, so including market fixed-effects would wash away the variation that I want to capture.

RivalP1_strong and *RivalP1_weak* become increasingly insignificant in both statistical and economic senses, consistent with peer effects fading over time. In contrast, all control variables remain significant across all columns, consistent with market-level forces having a persistent influence on the focal firm's R&D decisions.

[insert Table 8 here]

7.2 Role of Disclosure Quality

Conditional on the existence of peer disclosures of interim success, the specificity of information disclosed can moderate the effects of peer disclosure. I predict that more specific disclosures enhance the credibility of Phase 1 trial registration as a (costly) signal of the disclosing rival's leadership, thus strengthening the deterrence effect of peer disclosure. To measure the specificity of peer disclosure, I use the number of words disclosed in "Outcome Measures", a data item that is required by ClinicalTrials.gov at trial initiation but is claimed to be "commercially sensitive" by the pharmaceutical trade association (IFPMA 2009).[29]

In the sample where the focal firm observes at least one peer disclosure of Phase 1 trial initiation in the two preceding years (i.e., $RivalP1\_lag_{i,k,t} > 0$), I split the sample into three subsets based on the average number of words disclosed in "Outcome Measures" of rivals' Phase 1 trial registrations. Table 9 presents the separate estimates of Equation (1) using these three subsamples. Results in Column (1) show that when peer disclosures contain the largest number of

[29] An outcome measure is the result of a treatment or intervention that is used to objectively determine the baseline function of a patient at the beginning of the clinical trial. Once the treatment or intervention has commenced, the same instrument can be used to determine progress and efficacy. Outcome measures are measurable and will be assessed by a numerical value.

words in "Outcome Measures", the coefficient for *RivalP1_strong* is significantly negative. This finding suggests that firms are deterred by the most informative disclosures of Phase 1 initiation from strong rivals. In contrast, in Columns (2)-(3), where peer disclosures reveal limited proprietary information, the coefficient for *RivalP1_strong* is less significant while the coefficient for *RivalP1_weak* becomes significantly positive, consistent with vague disclosures from weak rivals encouraging catch-up behavior.

[insert Table 9 here]

7.3 Generalizability to Other Firms

The empirical analyses so far are based on a sample of 50 firms with the largest number of trial registrations on ClinicalTrials.gov. These firms are mostly publicly-listed pharmaceutical companies and are representative in the sense that they account for 58% of all trial registrations on ClinicalTrials.gov, but whether my main results generalize to other firms is an empirical question. To address this issue, I expand my sample to all firms that have registered at least five clinical trials during the 2007-2018 sample period.[30] Table 10 presents results from two additional tests that evaluate the generalizability of my main findings.[31] First, I split the expanded sample based on the number of clinical trials the focal firm has registered during the sample period. Specifically, I classify firms with more than 100 trials as large firms, between 10 and 100 trials as medium

[30] Specifically, I follow Capkun et al. (2019) to download a comprehensive sample of all trial registrations from the AACT database (https://www.ctti-clinicaltrials.org/aact-database), a publicly available database that contains all information (protocol and result data elements) about every trial registered in ClinicalTrials.gov.
[31] The large sample size exceeds Stata's computational powers in estimating logit model with a large number of fixed effects, so I estimate a linear probability model with firm, year, and market fixed effects.

firms, and between 5 and 10 trials as small firms. Columns (1)-(3) in Table 10 show that the results in Table 3 are replicated only when the focal firm is large (Column 1), presumably because larger firms have a greater variety of alternative projects to invest in and thus are more responsive to peer disclosures.

[insert Table 10 here]

Second, I classify all firms in the expanded sample into either pharmaceutical or biotechnology firms using machine learning, following Thakor et al. (2017).[32] Prior studies find that pharmaceutical and biotechnology firms exhibit different investment strategies, due to differences in risk preferences and capital constraints (e.g., Peck et al. 2015; Thakor et al. 2017). Columns (4)-(5) in Table 10 show that my key results apply more to pharmaceutical firms than biotechnology firms, presumably because the former have more diversified R&D portfolios and hence can be more flexible in reallocating resources.

[32] Specifically, I use the "*k*-means" algorithm, a popular form of cluster analysis. This algorithm places companies into categories based on how similar they are to each other on a host of company characteristics. Following Thakor et al. (2017), my algorithm starts with prototypical "seed" companies in the pharma and biotech categories, and then places each additional company into either category by calculating a distance between that company and the seed companies based upon each company's characteristics. See the online appendix of Thakor et al. (2017) for more details.

8.0 Conclusion

This paper studies the role of peer disclosures in shaping firms' R&D investments. Drawing on game-theoretical models of R&D races in industrial organization, I hypothesize that a firm's R&D investments are *deterred* by disclosures of interim success from strong rivals but *encouraged* by disclosures from weak rivals. Using pharmaceutical firms' online registration of clinical trials in the drug development process, I find that a firm's R&D investments in a market are *negatively* associated with the disclosures of clinical trial initiation from strong rivals, but *positively* associated with disclosures from weak rivals. To my knowledge, my findings provide the first empirical evidence that a firm's reaction to peer disclosures varies with the disclosing firms' relative competitiveness in the R&D race. Thus, I contribute to the emerging literature on the effects of corporate disclosure on peer firms' real decisions.

In the U.S., the FDAAA of 2007 represents a critical advance in making clinical trials of new treatments public knowledge. Registration of clinical trials has subsequently been mandated by regulators in Europe, China, Japan, Brazil, etc. Future research can provide a more comprehensive cost-benefit analysis of FDAAA and other disclosure regulations that promote transparency in the R&D process.

Appendix A Variable Definition

variable	unit of observation	definition
FocalP2	firm-market-year	Indicator variable that equals one if the focal firm initiates at least one Phase 2 trials in a market in a given year, and zero otherwise.
RivalP1_strong	firm-market-year	Number of Phase 1 trials registered in the last two years by the focal firm's "strong rivals", i.e., rivals whose total number of Phase 2 and Phase 3 trials registered in the previous two years rank above the 60^{th} percentile within that market-year.
RivalP1_weak	firm-market-year	Number of Phase 1 trials registered in the last two years by the focal firm's "weak rivals", i.e., rivals whose number of Phase 2 and Phase 3 trials registered in the previous two years rank below the 40^{th} percentile within that market-year.
RivalP1_lag	firm-market-year	Number of Phase 1 trials registered in the last two years by all of the focal firm's rivals in a given market.
RivalP23_lag	firm-market-year	Number of Phase 2 and Phase 3 trials registered in the last two years by the focal firm's rivals in a market.
FocalP1_lag	firm-market-year	Number of a firm's Phase 1 trials registered in a market during the previous two years.

FocalP23_lag	firm-market-year	Number of a firm's Phase 2 and Phase 3 trials registered in a market during the previous two years.
HHI	market-year	Herfindahl index, calculated as the sum of squared terms of each firm's clinical trial market share (a firm's *FocalP23_lag* divided by the total *FocalP23_lag* in market-year).

Appendix B A Bayesian Updating Model of the Encouragement Effect of Peer Disclosure

In a static model, assume that the outcome of the preliminary stage is binary. Denote the event that firm i has succeeded in the preliminary stage as $S_i = 1$. Suppose the probability of success in the preliminary stage for firm i is λ_i. That is: $S_i = 1$ with probability λ_i, where $\lambda_i = \bar{\lambda} + \epsilon_i$, and $S_i = 0$ with probability $1 - \lambda_i$.

The firm-project specific success rate, λ_i, is a combination of project feasibility ($\bar{\lambda}$), which is a common uncertainty for both firms, and firm type (ϵ_i), which is idiosyncratic.[33] Without loss of generalizability, assume both $\bar{\lambda}$ and ϵ_i follow Bernoulli distributions, with probabilities p and q_i of getting a high value, respectively: $\bar{\lambda} = \lambda_H$ with probability p, and λ_L with probability $1 - p$; $\epsilon_i = \epsilon_H$ with probability q_i , and ϵ_L with probability $1 - q_i$. Assume $\epsilon_H + \lambda_H < 1$, $0 < \epsilon_L < \epsilon_H$, $0 < \lambda_L < \lambda_H$, and firms' types are independent, i.e., $\epsilon_i \perp \epsilon_j$.

Claim 1:

$E(\bar{\lambda}|S_j = 1) > E(\bar{\lambda})$.

This result suggests that a firm always revises upward its belief about project feasibility after observing a rival's disclosure of interim success. That is, peer disclosure always has a (positive) encouragement effect on the focal firm.

Proof:

$$E[\bar{\lambda}|S_j = 1] = \Pr(\bar{\lambda} = \lambda_H|S_j = 1) \cdot \lambda_H + \Pr(\bar{\lambda} = \lambda_L|S_j = 1) \cdot \lambda_L$$

$$= \frac{\Pr(\bar{\lambda} = \lambda_H, S_j = 1)}{\Pr(S_j = 1)} \lambda_H + \frac{\Pr(\bar{\lambda} = \lambda_L, S_j = 1)}{\Pr(S_j = 1)} \lambda_L$$

[33] "Project feasibility" is broad-defined here. $\bar{\lambda}$ represents the easiness of the project conditional on it being doable.

$$= \frac{A}{A+A'}\lambda_H + \frac{A'}{A+A'}\lambda_L$$

where $A = \Pr(\bar{\lambda} = \lambda_H, S_j = 1) = \Pr(\bar{\lambda} = \lambda_H) \cdot \Pr(S_j = 1 | \bar{\lambda} = \lambda_H)$, and $A' = \Pr(\bar{\lambda} = \lambda_L, S_j = 1) = \Pr(\bar{\lambda} = \lambda_L) \cdot \Pr(S_j = 1 | \bar{\lambda} = \lambda_L)$.

Recall the unconditional probabilities are $\Pr(S_j = 1) = \bar{\lambda} + \epsilon_j$, $\Pr(\bar{\lambda} = \lambda_H) = p$, and $\Pr(\bar{\lambda} = \lambda_L) = 1 - p$. Therefore,

$A = p \cdot E[\bar{\lambda} + \epsilon_j | \bar{\lambda} = \lambda_H] = p \cdot [\lambda_H + q_j\epsilon_H + (1 - q_j)\epsilon_L]$.

$A' = (1-p) \cdot E[\bar{\lambda} + \epsilon_j | \bar{\lambda} = \lambda_L] = (1-p) \cdot [\lambda_L + q_j\epsilon_H + (1 - q_j)\epsilon_L]$.

Since $E(\bar{\lambda}) = p\lambda_H + (1-p)\lambda_L$, to show $E(\bar{\lambda}|S_j = 1) > E(\bar{\lambda})$ it suffices to show that $\frac{A}{A+A'} > p$.

$$\frac{A}{A+A'} - p = \frac{p \cdot [\lambda_H + q_j\epsilon_H + (1-q_j)\epsilon_L] - p \cdot [p\lambda_H + (1-p)\lambda_L + q_j\epsilon_H + (1-q_j)\epsilon_L]}{A+A'}$$

$$\propto \lambda_H - (p\lambda_H + (1-p)\lambda_L) > 0.$$

Therefore, $E(\bar{\lambda}|S_j = 1) > E(\bar{\lambda})$.

Claim 2:

$$\frac{\partial E(\bar{\lambda}|S_j = 1)}{\partial q_j} < 0.$$

This result suggests that the extent of belief revision about project feasibility is negatively associated with the rival's perceived strength. Specifically, when the rival firm j is expected to be stronger (higher value of q_j), the focal firm's posterior belief about project feasibility is less optimistic, i.e., $E(\bar{\lambda}|S_j = 1)$ is lower. Intuitively, when the rival is expected to be stronger, the rival's interim success ($S_j = 1$) will be attributed more to the focal firm's prior belief that ϵ_j is a high value. In contrast, when the rival is expected to be weak (lower value of q_j), the rival's interim

success will be attributed to a greater extent to the alternative explanation that the project is relatively easy ($\bar{\lambda} = \lambda_H$).

Proof:

Follow the previous proof and take partial derivatives over q_j to get $\frac{\partial A}{\partial q_j} = p(\epsilon_H - \epsilon_L)$ and $\frac{\partial A'}{\partial q_j} = (1-p)(\epsilon_H - \epsilon_L)$. Therefore,

$$\frac{\partial E\left[\bar{\lambda}\middle|S_j = 1\right]}{\partial q_j} = \frac{\partial}{\partial q_j}\left(\frac{A}{A+A'}\lambda_H + \frac{A'}{A+A'}\lambda_L\right)$$

$$\propto \lambda_H \cdot [p(\epsilon_H - \epsilon_L)(A+A') - A(\epsilon_H - \epsilon_L)] + \lambda_L \cdot [(1-p)(\epsilon_H - \epsilon_L)(A+A') - A'(\epsilon_H - \epsilon_L)]$$

$$< \lambda_H \cdot [p(\epsilon_H - \epsilon_L)(A+A') - A(\epsilon_H - \epsilon_L)] + \lambda_H \cdot [(1-p)(\epsilon_H - \epsilon_L)(A+A') - A'(\epsilon_H - \epsilon_L)]$$

$$= (\epsilon_H - \epsilon_L)(A+A') - (\epsilon_H - \epsilon_L)(A+A') = 0.$$

A numerical example:

Let $\lambda_H = \epsilon_H = 0.45,\ \lambda_L = \epsilon_L = 0.05, p = 0.5$. Assume the threshold level preliminary-stage success rate is $\lambda_i^* = 0.5$. Below this level the firm should drop out. Suppose the firm's priors are: $E(\bar{\lambda}) = 0.25$ and $\epsilon_i = 0.15$.

When the rival is expected to be strong ($q_j = 0.9$), the focal firm's updated belief about project feasibility is $E\left(\bar{\lambda}\middle|S_j = 1\right) = \frac{\Pr\,(\bar{\lambda}=\lambda_H, S_j=1)}{\Pr\,(S_j=1)}\lambda_H + \frac{\Pr\,(\bar{\lambda}=\lambda_L, S_j=1)}{\Pr\,(S_j=1)}\lambda_L = 0.311$, so the focal firm's updated preliminary-stage success rate is $\lambda_i{}' = 0.311 + 0.15 = 0.461 < \lambda_i^*$. It should drop out.

When the rival is expected to be weak ($q_j = 0.1$), the focal firm's updated belief about project feasibility is $E\left(\bar{\lambda}\middle|S_j = 1\right) = \frac{\Pr\,(\bar{\lambda}=\lambda_H, S_j=1)}{\Pr\,(S_j=1)}\lambda_H + \frac{\Pr\,(\bar{\lambda}=\lambda_L, S_j=1)}{\Pr\,(S_j=1)}\lambda_L = 0.383$, so the focal firm's updated preliminary-stage success rate is $\lambda_i' = 0.383 + 0.15 = 0.533 > \lambda_i^*$. It should continue the race.

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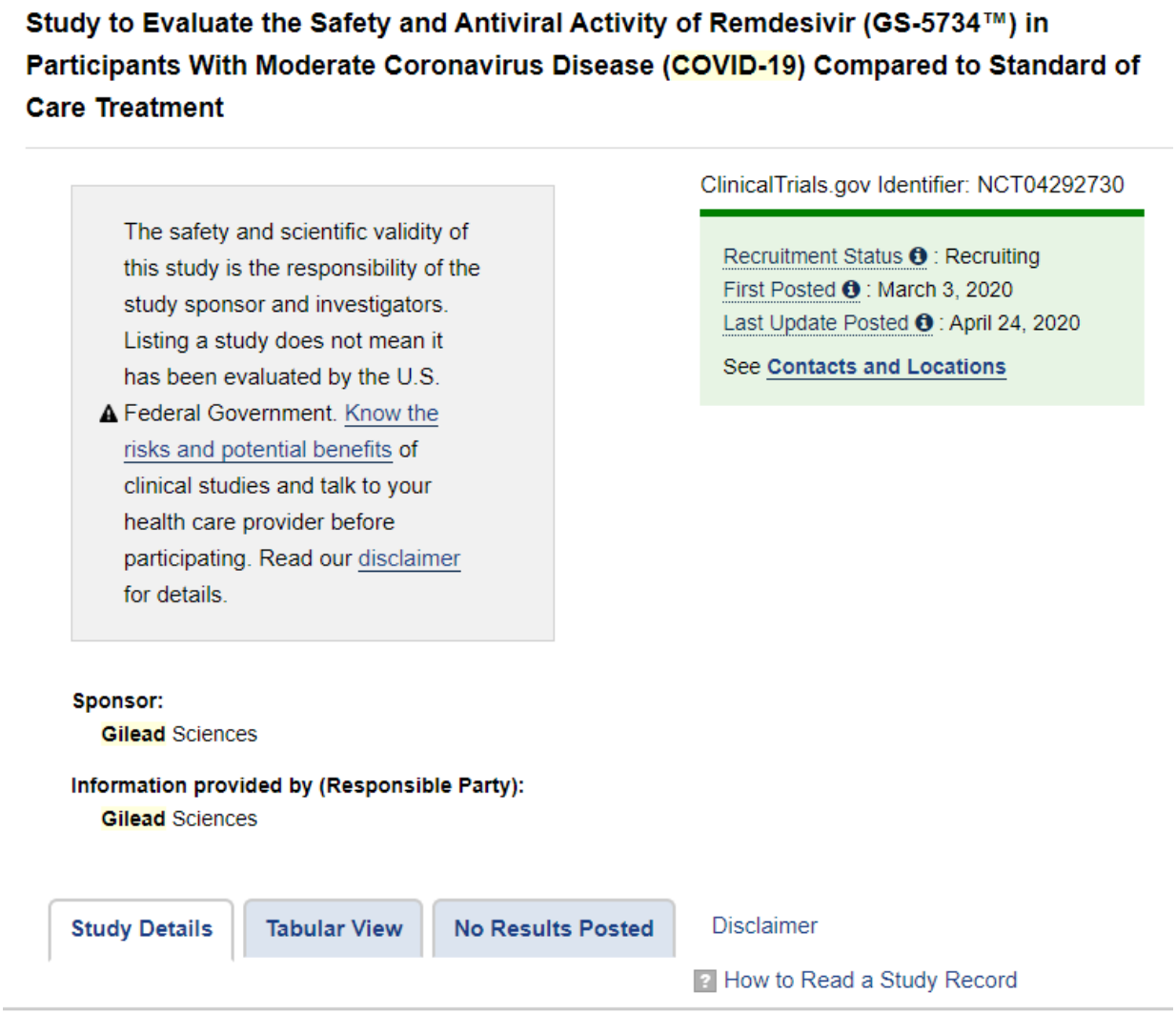
Figures & Tables

Figure 1. The Drug Development Process

Figure 2. An Example of Clinical Trial Registration on ClinicalTrials.gov (Excerpt)



Study to Evaluate the Safety and Antiviral Activity of Remdesivir (GS-5734™) in Participants With Moderate Coronavirus Disease (COVID-19) Compared to Standard of Care Treatment

The safety and scientific validity of this study is the responsibility of the study sponsor and investigators. Listing a study does not mean it has been evaluated by the U.S. Federal Government. Know the risks and potential benefits of clinical studies and talk to your health care provider before participating. Read our disclaimer for details.

ClinicalTrials.gov Identifier: NCT04292730

Recruitment Status : Recruiting
First Posted : March 3, 2020
Last Update Posted : April 24, 2020

See **Contacts and Locations**

Sponsor:
Gilead Sciences

Information provided by (Responsible Party):
Gilead Sciences

Study Details | Tabular View | No Results Posted | Disclaimer | How to Read a Study Record

Study Description

Go to

Brief Summary:

The primary objective of this study is to evaluate the efficacy of 2 remdesivir (RDV) regimens compared to standard of care (SOC), with respect to clinical status assessed by a 7-point ordinal scale on Day 11.

Condition or disease	Intervention/treatment	Phase
COVID-19	Drug: Remdesivir Drug: Standard of Care	Phase 3

Expanded Access: An investigational treatment associated with this study is available outside the clinical trial.

More info ...

Study Design

Go to

Study Type:	**Interventional**
Estimated Enrollment:	1600 participants
Allocation:	Randomized
Intervention Model:	Parallel Assignment
Masking:	None (Open Label)
Primary Purpose:	Treatment
Official Title:	A Phase 3 Randomized Study to Evaluate the Safety and Antiviral Activity of Remdesivir (GS-5734™) in Participants With Moderate **COVID-19** Compared to Standard of Care Treatment
Actual Study Start Date:	March 15, 2020
Estimated Primary Completion Date:	May 2020
Estimated Study Completion Date:	May 2020

Figure 3. An Example of the MeSH Tree of Diseases -- Branch "Mental Disorders [F3]"

Table 1. Descriptive Statistics

Variable	N	Mean	Std Dev	1st Pctl	25th Pctl	Median	75th Pctl	99th Pctl
FocalP2	40,461	0.121	0.326	0	0	0	0	1
RivalP1_strong	40,461	5.003	6.768	0	0	2	7	35
RivalP1_weak	40,461	2.192	2.446	0	0	1	3	12
HHI	40,461	0.247	0.126	0.081	0.156	0.219	0.316	0.75
FocalP1_lag	40,461	0.22	0.692	0	0	0	0	4
FocalP23_lag	40,461	0.704	1.823	0	0	0	0	11
RivalP23_lag	40,461	24.181	24.583	2	7	14	35	127

Table 2. Correlation Matrix

		(1)	(2)	(3)	(4)	(5)	(6)	(7)
(1)	*FocalP2*		**0.177**	**0.131**	**-0.186**	**0.360**	**0.457**	**0.216**
(2)	*RivalP1_strong*	**0.163**		**0.457**	**-0.462**	**0.209**	**0.197**	**0.753**
(3)	*RivalP1_weak*	**0.126**	**0.475**		**-0.337**	**0.162**	**0.145**	**0.472**
(4)	*HHI*	**-0.156**	**-0.352**	**-0.291**		**-0.171**	**-0.260**	**-0.660**
(5)	*FocalP1_lag*	**0.362**	**0.218**	**0.173**	**-0.136**		**0.463**	**0.221**
(6)	*FocalP23_lag*	**0.484**	**0.244**	**0.187**	**-0.174**	**0.567**		**0.236**
(7)	*RivalP23_lag*	**0.208**	**0.862**	**0.484**	**-0.460**	**0.236**	**0.279**	

Numbers below the diagonal indicate Pearson correlation coefficients. Numbers above diagonal indicate Spearman correlation coefficients. Numbers in bold indicate p-value <1%.

Table 3. The Effects of Rivals' Disclosure of Phase 1 Trials on the Focal Firm's R&D Investments (Test of H1)

VARIABLES	pred. sign	(1) FocalP2	(2) FocalP2
RivalP1_strong	-	**-0.023*** **	
		[0.001]	
RivalP1_weak	+	**0.022** **	
		[0.041]	
RivalP1_lag	**?**		**-0.011** **
			[0.034]
FocalP1_lag		0.346***	0.348***
		[0.001]	[0.001]
FocalP23_lag		0.331***	0.333***
		[0.001]	[0.001]
RivalP23_lag		0.013***	0.012***
		[0.001]	[0.001]
HHI		-2.860***	-2.966***
		[0.001]	[0.001]
Observations		36,668	36,668
Cluster SE		firm	firm
Fixed effects		firm×year	firm×year

This table presents results from logit regressions at the firm-year-market level. The dependent variable is *FocalP2*, an indicator variable that equals one if the focal firm initiates at least one Phase 2 trials in a market in a year, and zero otherwise. All other variables are defined in Appendix A. All regressions include firm×year fixed effects. Standard errors are clustered by firm. P-values are in brackets. *, **, *** indicate significance at the 10%, 5%, and 1% levels, respectively, for a two-tailed *t*-test.

Table 4. Sample Split by Clinical Trial Success Rate (Test of H2)

		(1)	(2)
	pred.	clinical-trial success rate	
VARIABLES	sign	high	low
RivalP1_strong	**-**	**-0.040****	**-0.001**
		[0.019]	**[0.953]**
RivalP1_weak	**+**	**0.034**	**0.030***
		[0.177]	**[0.057]**
FocalP1_lag		0.276***	0.380***
		[0.001]	[0.001]
FocalP23_lag		0.392***	0.381***
		[0.001]	[0.001]
HHI		-1.293**	-2.626***
		[0.024]	[0.001]
RivalP23_lag		0.026***	0.016***
		[0.001]	[0.001]
Observations		8,388	8,094
Cluster SE		firm	firm
Fixed effects		firm×year	firm×year

This table presents results from logit regressions at the firm-year-market level. The dependent variable is *FocalP2*, an indicator variable that equals one if the focal firm initiates at least one Phase 2 trials in a market in a year, and zero otherwise. All other variables are defined in Appendix A. Columns 1-2 are based on two subsamples partitioned by the "probability of success" (POS), i.e., the overall probability of gaining final FDA approval for marketing conditional on the drug development program entering Phase 1 clinical trial. Specifically, I identify a therapeutic area as having a high (low) clinical-trial success rate if all three biostatistics studies (Hay et al. 2014; Thomas et al. 2016; Wong et al. 2019) rank its POS above (below) the median cross all therapeutic areas. All regressions include firm×year fixed effects. Standard errors are clustered by firm. P-values are in brackets. *, **, *** indicate significance at the 10%, 5%, and 1% levels, respectively, for a two-tailed *t*-test.

Table 5. Sample Split by Number of Competing Firms in a Market (Test of H3)

VARIABLES	pred. sign	(1) Dispersed market (n_firm >8)	(2) Concentrated market (n_firm <=8)
RivalP1_strong	**-**	**-0.004**	**-0.043****
		[0.564]	**[0.033]**
RivalP1_weak	**+**	**-0.011**	**0.079*****
		[0.289]	**[0.002]**
FocalP1_lag		0.278***	0.448***
		[0.001]	[0.001]
FocalP23_lag		0.279***	0.499***
		[0.001]	[0.001]
HHI		-2.236***	-0.621
		[0.003]	[0.160]
RivalP23_lag		0.005**	0.013
		[0.020]	[0.161]
Observations		15,115	17,515
Cluster SE		firm	firm
FE		firm×year	firm×year

This table presents results from logit regressions at the firm-year-market level. The dependent variable is *FocalP2*, an indicator variable that equals one if the focal firm initiates at least one Phase 2 trials in a market in a year, and zero otherwise. All other variables are defined in Appendix A. Columns 1-2 are based on two subsamples partitioned by number of research-active firms (firms with at least one trials in the two preceding years) in a market. All regressions include firm×year fixed effects. Standard errors are clustered by firm. P-values are in brackets. *, **, *** indicate significance at the 10%, 5%, and 1% levels, respectively, for a two-tailed *t*-test.

Table 6. Sample Split by Focal Firm's Diversification Strategy (Test of H4)

		(1)	(2)	(3)	(4)
		Is this market the focal firm's main focus?		Is the focal firm diversified?	
VARIABLES	pred. sign	yes	no	no	yes
RivalP1_strong	**-**	**-0.014***	**-0.040*****	**-0.015**	**-0.028*****
		[0.088]	**[0.008]**	**[0.115]**	**[0.002]**
RivalP1_weak	**+**	**0.017**	**0.059****	**-0.007**	**0.037*****
		[0.104]	**[0.018]**	**[0.724]**	**[0.002]**
FocalP1_lag		0.261***	0.543***	0.389***	0.313***
		[0.001]	[0.001]	[0.001]	[0.001]
FocalP23_lag		0.192***	0.212***	0.632***	0.466***
		[0.001]	[0.001]	[0.001]	[0.001]
RivalP23_lag		0.009***	0.010***	0.019***	0.008***
		[0.001]	[0.001]	[0.001]	[0.001]
HHI		-2.069***	-2.405***	-3.238***	-2.609***
		[0.001]	[0.001]	[0.001]	[0.001]
Observations		11,742	19,028	17,402	18,839
Cluster SE		firm	firm	firm	firm
Fixed effects		firm×year	firm×year	firm×year	firm×year

This table presents results from logit regressions at the firm-year-market level. The dependent variable is *FocalP2*, an indicator variable that equals one if the focal firm initiates at least one Phase 2 trials in a market in a year, and zero otherwise. All other variables are defined in Appendix A. Columns (1)-(2) are based on two subsamples partitioned by whether the market is the focal firm's focused area, i.e., with share of Phase 2 and Phase 3 trials above median among all markets for that firm-year. Columns (3)-(4) are based on two subsamples partitioned by whether the focal firm is diversified, i.e., with a firm-year level Herfindahl index (sum of the squared term of each market's share of Phase 2and Phase 3 trials) below median in a given year. All regressions include firm×year fixed effects. Standard errors are clustered by firm. P-values are in brackets. *, **, *** indicate significance at the 10%, 5%, and 1% levels, respectively, for a two-tailed *t*-test.

Table 7. Effects of Rivals' Mandatory Disclosure of Phase 2 Trials

VARIABLES	pred. sign	(1) FocalP3	(2) FocalP3
RivalP2_strong	**-**	**-0.014*** **	
		[0.002]	
RivalP2_weak	**+**	**0.098*** **	
		[0.001]	
RivalP2_lag	**?**		**-0.002**
			[0.571]
FocalP1_lag		0.518***	0.539***
		[0.001]	[0.001]
FocalP2_lag		0.385***	0.374***
		[0.001]	[0.001]
HHI		-2.840***	-2.949***
		[0.001]	[0.001]
Observations		41,005	37,752
Cluster SE		firm	firm
FE		firm×year	firm×year

This table presents results from logit regressions at the firm-year-market level. The dependent variable is *FocalP3*, an indicator variable that equals one if the focal firm initiates at least one Phase 3 trials in a market in a year, and zero otherwise. All other variables are defined in Appendix A. All regressions include firm×year fixed effects. Standard errors are clustered by firm. P-values are in brackets. *, **, *** indicate significance at the 10%, 5%, and 1% levels, respectively, for a two-tailed *t*-test.

Table 8. Lead-Lag Analysis of the Dynamic Effects of Peer Disclosure

VARIABLES	(1) FocalP2	(2) FocalP2_lead1	(3) FocalP2_lead2	(4) FocalP2_lead3
RivalP1_strong	**-0.022*** **	**-0.023** **	**-0.016**	**-0.014**
	[0.001]	**[0.013]**	**[0.131]**	**[0.229]**
RivalP1_weak	**0.022** **	**0.005**	**0.007**	**-0.007**
	[0.043]	**[0.708]**	**[0.631]**	**[0.663]**
FocalP1_lag	0.342***	0.300***	0.260***	0.251***
	[0.000]	[0.000]	[0.000]	[0.001]
FocalP23_lag	0.325***	0.265***	0.213***	0.176***
	[0.000]	[0.000]	[0.000]	[0.000]
HHI	-2.845***	-2.743***	-2.901***	-3.300***
	[0.000]	[0.000]	[0.000]	[0.000]
RivalP23_lag	0.013***	0.014***	0.012***	0.012***
	[0.000]	[0.000]	[0.000]	[0.000]
Observations	36,668	32,406	27,956	23,482
Cluster SE	firm	firm	firm	firm
FE	firm×year	firm×year	firm×year	firm×year

This table presents results from logit regressions at the firm-year-market level. From Column 1 to 4, the dependent variables are dummy variables that equal to 1 if the focal firm initiates a Phase 2 trial in that market in year *t* (Column 1), in year *t*+1 (Column 2), in year *t*+2 (Column 3), or in year *t*+3 (Column 4). All other variables are defined in Appendix A. All regressions include firm×year fixed effects. Standard errors are clustered by firm. P-values are in brackets. *, **, *** indicate significance at the 10%, 5%, and 1% levels, respectively, for a two-tailed t-test.

Table 9. Sample Split by Disclosure Quality

	(1)	(2)	(3)
	Average amount of sensitive information disclosed		
VARIABLES	high	medium	low
RivalP1_strong	**-0.020****	**-0.012***	**-0.000**
	[0.044]	**[0.060]**	**[0.986]**
RivalP1_weak	**-0.044***	**0.051*****	**0.057****
	[0.067]	**[0.004]**	**[0.041]**
FocalP1_lag	0.305***	0.402***	0.611***
	[0.001]	[0.001]	[0.001]
FocalP23_lag	0.274***	0.332***	0.485***
	[0.001]	[0.001]	[0.001]
HHI	-2.517***	-2.881***	-2.964***
	[0.001]	[0.001]	[0.001]
RivalP23_lag	0.009***	0.015***	0.021***
	[0.002]	[0.001]	[0.001]
Observations	10,300	10,621	8,412
Cluster SE	firm	firm	firm
FE	firm×year	firm×year	firm×year

This table presents results from logit regressions at the firm-year-market level. The dependent variable is FocalP2, an indicator variable that equals one if the focal firm initiates at least one Phase 2 trials in a market in a year, and zero otherwise. All other variables are defined in Appendix A. Columns 1-3 are based on three subsamples partitioned by amount of sensitive information disclosed in Phase 1 trial registration, defined as the number of words disclosed in the data item "Outcome Measures" averaged across all rivals' Phase 1 trial registrations. All regressions include firm×year fixed effects. Standard errors are clustered by firm. P-values are in brackets. *, **, *** indicate significance at the 10%, 5%, and 1% levels, respectively, for a two-tailed t-test.

Table 10. Generalizability to Other Firms

	(1)	(2)	(3)	(4)	(5)
	focal firm's number of trial registrations			*k*-means classification	
	Large	Small	Medium	Pharmaceutical	Biotechnology
RivalP1_strong	**-0.001***	**-0.000**	**0.000**	**-0.001*****	**0.000**
	[0.070]	**[0.712]**	**[0.492]**	**[0.004]**	**[0.924]**
RivalP1_weak	**0.002*****	**0.001****	**0.001*****	**0.001****	**0.000***
	[0.001]	**[0.010]**	**[0.001]**	**[0.012]**	**[0.070]**
FocalP1_lag	0.119***	0.073***	0.061***	0.133***	0.066***
	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]
FocalP23_lag	0.039***	0.027***	0.060***	0.039***	0.067***
	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]
HHI	-0.173***	-0.033***	-0.034***	-0.156***	-0.035***
	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]
RivalP23_lag	0.001***	0.000***	0.000***	0.000***	0.000***
	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]
Observations	122,424	95,948	315,559	97,697	106,369
Cluster SE	firm	firm	firm	firm	firm
Fixed effects	firm, year, market	firm, year, market	firm, year, market	firm, year, market	firm, year, market

This table presents results from OLS regressions at the firm-year-market level. The dependent variable is FocalP2, an indicator variable that equals one if the focal firm initiates at least one Phase 2 trials in a market in a year, and zero otherwise. All other variables are defined in Appendix A. Columns (1)-(3) are based on three subsamples partitioned by number of clinical trials registered by the focal firm, with 10 and 100 being the cutoff values. Columns (4)-(5) are based on two subsamples partitioned by whether the focal firm is a pharmaceutical firm or biotechnology firm, classified using a k-means algorithm following Thakor et al. (2017). All regressions include firm, year, market fixed effects. Standard errors are clustered by firm. P-values are in brackets. *, **, *** indicate significance at the 10%, 5%, and 1% levels, respectively, for a two-tailed t-test.