Rival Signals and Project Selection: Insights from the Drug Development Process

Panos Markou
UVA Darden School of Business, Charlottesville, VA, USA, markoup@darden.virginia.edu

Stylianos Kavadias
University of Cambridge Judge Business School, Cambridge, UK, s.kavadias@jbs.cam.ac.uk

Nektarios Oraiopoulos
University of Cambridge Judge Business School, Cambridge, UK, n.oraiopoulos@jbs.cam.ac.uk

Project selection decisions are complex because they must balance not only financial returns, project risk, and fit with strategy, but also competitive circumstances. A rival's project development efforts provide two pieces of information: a *market rivalry* signal, indicating potentially heightened competition in a market, and a *technological* signal, indicating a possible solution to a problem in that market. We hypothesize that these signals affect a firm's likelihood of project selection in opposite directions, and that the timing of the signals matters for selection. We examine the drug development pipelines of the top 15 pharmaceutical companies from 1999–2016 to examine how rival projects drive the decision to progress a drug from pre-clinical laboratory trials to clinical trials in humans. Early-stage rival projects provide a stronger market rivalry signal, and they are associated with a decreased likelihood of the firm selecting its own project to compete in the same market. Late-stage rival projects signal technological feasibility and are associated with an increase in the likelihood of selection. We then exploit heterogeneity in market potential (i.e., disorder prevalence/incidence) and a molecular compound's technology (i.e., therapeutic modality) to independently manipulate the salience of the two signals. Finally, we provide evidence on how selection based on rival signals informs project success. Information from rival projects prompts the selection of more successful drugs, but only after a threshold when sufficient uncertainty has been resolved.

Key words: project selection; new product development; spillovers; competition; R&D management; pharmaceutical industry; empirical

1. Introduction

Effective research and development (R&D) is essential for the creation of new products and greater overall firm competitiveness. However, improving R&D productivity requires overcoming two key challenges: (i) consistently coming up with promising new ideas and (ii) systematically selecting and supporting ideas that deliver value. While the generation of new ideas is necessary for success and has attracted substantial attention (Osborn 1960,

Stevens and Burley 1997, Girotra et al. 2010, Sommer et al. 2020), it is not sufficient. In many industries, the question of how to effectively allocate scarce resources across different projects has become a pressing concern and key challenge to achieving success (Kavadias and Chao 2007, Ding et al. 2014).

Project selection decisions are challenging because of the uncertainty and complexity inherent in making those decisions (Drakeman and Oraiopoulos 2020). Management often needs to consider multiple dimensions, such as financial returns, project risk, and fit with strategy, but also competitive circumstances, which is the focus of this paper. Resource allocation decisions often must be made against a backdrop of fierce competition: rivals continuously develop and introduce new product offerings, and technological and competitive environments constantly evolve (Jain and Ramdas 2005, Chan et al. 2007). In such environments, the investments of rivals may also reveal potentially useful information (Griliches 1979, Jaffe 1989, Griliches 1992, Bloom et al. 2013). The firm may then use this information to supplement its own knowledge and improve its decision-making.

In this paper, we ask: *How do rival project decisions inform a firm's own project selection?* We theorize that rival projects provide the firm with two distinct types of information signals: a *market rivalry* signal, indicating potentially heightened competition with subsequent rent effects, and a *technological* signal, indicating a possible solution to a problem in that market. On the one hand, as rivals develop their own projects, there is a higher likelihood that the firm will face strong market competition, and therefore lower rents, if it pursues its own project in the same market. On the other hand, the firm may learn from rival project developments and improve upon them, increasing its own project's chance of success. Therefore, the decision to allocate resources to a project ultimately requires the firm to balance a negative, market rivalry signal with a positive, technological signal.

We assess the existence, strength, and implications of these two signals for project selection within the context of pharmaceutical R&D. In this industry, decision-makers face the challenging task of selecting projects that exhibit highly uncertain payoffs and that encompass all the complexities discussed earlier. Simultaneously, rivals make observable project decisions and investments into treating the same disorders. The industry also offers a distinct characterization of project selection decisions. Drug development involves pre-clinical research and the highly regulated clinical trial phases. In the pre-clinical stage,

firms explore the feasibility of a compound through a series of experiments that are initially lab-based (*in vitro*) and subsequently performed on living organisms (*in vivo*). After pre-clinical testing, firms face the decision to either progress the compound to a sequence of phases of clinical trials in humans (Phases I, II, and III), or cease further development.

The Phase I selection decision must balance economic considerations against the likelihood of failure. Initiating Phase I trials requires fulfilling a long list of requirements set by regulatory agencies, ranging from pre-clinical safety testing, to detailed clinical testing plans, to detailed manufacturing rules to prevent impurities.[1] Therefore, the transition to human testing involves a significant investment not only in monetary terms, but also in terms of launching a complex and highly regulated process. As such, projects selected for Phase I must have cleared numerous pre-clinical hurdles and offer strong evidence about their potential. This makes the Phase I decision an ideal setting for our study.

We test how rival signals affect the decision to select a project for Phase I trials by tracking the drug development pipelines and decisions of the top 15 pharmaceutical companies (by sales) from 1999–2016. We theorize and empirically demonstrate that rivals' project choices play an important role in a firm's Phase I selection decision. Project selection depends on the *type* and *timing* of the two contending information signals received from these rival investments. Rival *pre-clinical*-stage projects provide weak technological signals, in that they are relatively uninformative about a project's feasibility in treating a clinical indication. At that stage, very little of the technological uncertainty has been resolved. Still, such early-stage investments indicate market entry intentions into a specific therapeutic domain. We find that firms are less likely to send a project targeting the same market as their rivals into clinical trials. Ceteris paribus, we estimate that a one-standard deviation increase in the number of rival pre-clinical-stage projects is associated with an 18.3 percentage point (pp) decrease (95% confidence interval [CI]: 16.4–20.2pp) in the probability of selection.

Rival *clinical*-stage projects provide more reliable information about technological feasibility: they reveal potential approaches and mechanisms to treat a disorder. This information enhances the expectations of a successful result and may overshadow worries about heightened competitive intensity. Ceteris paribus, we find that a one-standard deviation increase in the number of rival clinical-stage projects is associated with a 11.1pp increase (95% CI: 8.9–13.3pp) in the probability of selection.

Finally, we examine whether these signals also provide *useful* information, in that they permit better selection decisions. Specifically, we analyze whether project choices that are contingent on specific rival signals are more likely to receive regulatory approval. Conditional on selection, we find that projects following earlier-stage rival signals do not exhibit higher success rates. However, signals from rival projects that have surpassed a level of uncertainty resolution (specifically, drugs that have passed Phase II trials) are associated with significantly higher likelihood of success for the focal project. As such, we show that one manner by which managers can directly impact the success of an R&D program is to carefully assess and act on the different information signals they receive.

2. Literature Review

Our work draws on two literature streams: one on the relationship between competition and innovation, and another that examines the project selection decision in the context of the new product development process.

2.1. Competition and Innovation

Theoretical work has modeled how firms invest in R&D as they preempt and race each other to be the first to introduce an innovation (Gilbert and Newbery 1982, Reinganum 1983, Harris and Vickers 1987). Yet, empirical support for theoretical predictions that firms' R&D strategies are reactions to rivals' investments has been mixed. On the one hand, Khanna (1995), Lerner (1997), Czarnitzki and Kraft (2004) find evidence of a "followership" dynamic, whereby firms invest more in R&D and try to innovate more than technological leaders. On the other hand, Cockburn and Henderson's (1994) and Zizzo's (2002) findings do not broadly support predictions from the racing literature.

Interestingly, the above work generally does not account for the possibility that firms *learn* from their rivals' efforts. Returns to R&D and the knowledge generated by one firm may spill over to another, essentially allowing the other firm to achieve results with less effort or lower cost (Griliches 1979, Jaffe 1986, Griliches 1992). Indeed, the empirical literature generally sees spillovers as key, positive drivers of firm productivity (Cockburn and Henderson 1994, Henderson and Cockburn 1996), the introduction of innovative products (Leiponen and Helfat 2010), and firm financial performance (Gu 2016).

A more recent line of inquiry, however, shows that knowledge spillovers may also present negative externalities on firm-level R&D investment and productivity. Furman et al. (2005)

analyze worldwide journal publications by both public and private institutions at the level of the firm-therapeutic area (TA). Their key finding is that patent output is positively correlated with publicly authored work, but negatively correlated with private-sector work. They ascribe this result to two possibilities: R&D and knowledge generation by the focal firm (i) renders it more difficult for rivals to generate subsequent, novel discoveries and (ii) signals future competition, reducing the attractiveness of pursuing further R&D in the same TA.

Bloom et al. (2013) formalize this tension between productivity-increasing technological spillovers and market rivalry spillovers. They develop firm level, patent- and industry-based measures that identify the effects of technology and market rivalry spillovers and empirically estimate the effects of both on measures of firm performance, such as market value, patent output, and productivity. They find that R&D by rivals in the same technology space is associated with higher market value, patenting, and productivity, whereas rival R&D in a similar product market space is associated with lower market value only.

We follow Furman et al. (2005) and Bloom et al.'s (2013) lead and recognize the importance of the tension between the two types of spillovers. However, our study deviates from the prior work by studying informational spillovers at the granular, project level instead of the aggregate, firm level. This allows us to make the following two contributions. First, we are able to speak to the ability of spillovers to impact *technological* success, as measured by an external performance threshold such as regulatory approval. This is because project-level technological success involves a much more specific set of decisions than overall firm performance. Therefore, our results expand our knowledge of R&D spillovers by shedding light on how managers leverage technological and competitive information signals to drive project decisions, and how this information affects project success.

Second, we uncover a temporal dimension to spillovers at the project level. Prior work, such as Krieger (2021), has examined the pharmaceutical industry and has shown that signals about rivals' project failures influence the firm's own termination decision, and that market and technology overlap moderates this effect. We extend this work by accounting explicitly for the timing of these signals (e.g., early vs. late; pre-clinical vs. Phase III). We show that a signal's role in project selection depends on when it was generated.

This temporal dimension is important because, as we also show, signal timing has implications for the eventual *success* of a project. As we highlight, it is those signals that are

generated by late-stage rival projects that seem to correlate with a project's technical success. In other words, primarily late-stage signals facilitate learning and the resolution of uncertainty. Early-stage signals have no effect on success, and they may even be misleading. Therefore, whereas prior work can tell us the value of an extra R&D dollar, our analysis's focus on the timing of the signal highlights that it matters *when* that R&D dollar is spent.

2.2. Project Selection and NPD

How firms select projects is a fundamental question in the new product development (NPD) and R&D management literatures (Krishnan and Ulrich 2001, Shane and Ulrich 2004, Kornish and Hutchison-Krupat 2017, Kavadias and Hutchison-Krupat 2020, Kavadias and Ulrich 2020). Research on this topic has examined, for example, how to direct R&D budgets and how to allocate resources across multiple projects (Kavadias and Chao 2007, Chao et al. 2014, Hutchison-Krupat and Kavadias 2014, Schlapp et al. 2015, Pennetier et al. 2019). Little work, however, has analyzed project selection given rival choices.

Ali et al. (1993) assess how competitive pressures affect project selection, and they identify conditions that render investments into highly innovative products optimal. They show that similar time-to-market development capabilities across competitors lead to investments into novel technological domains. Bhaskaran and Ramachandran (2011) examine a firm's decision to invest in an incremental, technologically safe product or an advanced, risky project. They show that, under a wide range of conditions, firms benefit by diversifying efforts and pursuing products opposite to their competitors' choices; moreover, product investments may alter competitors' product choices and deter them from pursuing a similar product. Zschocke et al. (2014) show that market competition drives firms to direct R&D budgets to incremental (i.e., close to past efforts) project improvements. Closer to our work, Oraiopoulos and Kavadias (2014) model the tension between followership due to technological learning, and diversification due to market competition. They show that *where* a rival directs R&D efforts, and *what* information these efforts reveal, affect the decision to undertake a project in a previously explored technological domain.

Overall, the vast majority of this literature has offered a theoretical treatment of competition's role in the project selection decision, but it does not empirically describe how firms actually decide to direct project efforts. As such, one contribution of our paper is to offer specific metrics that one can use to measure some of the key drivers of project selection proposed by the prior theoretical models (e.g., signals, technological relatedness).

Additionally, our work empirically validates the theoretical findings from Oraiopoulos and Kavadias (2014) motivated by a microelectronics R&D setting: greater competition leads to a diversification of R&D efforts, yet the possibility to effectively learn may induce firms to follow each other into a technological domain. However, whereas they also propose that learning may cause firms to diversify (due to the fact that future improvements may exhibit only marginally better outcomes), we do not find such an occurrence. In the context of pharmaceutical R&D, not only may learnings be harder to transfer across technological domains, but such domains may also offer greater potential to capture value. We therefore demonstrate that theory motivated from a different setting, such as microelectronics, might not necessarily apply to the biopharmaceutical context.

3. Theory & Hypothesis Development

In this section, we motivate hypotheses concerning how firms select projects. Complementing the theoretical exposition below, we develop a simple analytical model of drug selection and rival signals in Appendix E, which also supports the hypotheses articulated hereafter.

3.1. Selection in Drug Development

After discovering a compound and evaluating its properties through pre-clinical research, pharmaceutical firms must decide whether to send the compound through to clinical trials involving humans. These clinical trials test the safety and efficacy of the compound in treating a disorder and are necessary before the drug may be approved to be marketed and become available to patients.

The decision to select a compound for clinical trials is informed by both *technological* and *market* considerations (Chan et al. 2007, Arora et al. 2009, Ding et al. 2014). Selecting a compound is in part driven by the likelihood that it will be able to clear clinical trials and ultimately receive regulatory approval. Therefore, a firm engages in internal research and pre-clinical testing in order to uncover and learn about the various properties of a compound. Pre-clinical trials ascribe some probability to a compound that it will successfully target and treat a disorder. At the same time, the firm must weigh the potential revenue of the project against potential development costs, and it will select the compound only if its expected profitability exceeds some threshold (Arora et al. 2009).

3.2. Technological and Market Rivalry Signals

Besides conducting scientific and market research, a firm may gain knowledge about its own project's potential from its rivals. In uncertain environments with incomplete information, knowledge is heterogeneously dispersed. Rivals may therefore have additional (or superior) knowledge regarding the potential of a specific technology or market. This knowledge is reflected through the rivals' development activities, which (in addition to the firm's private information) can be used to guide the firm's own decision-making process.

Rival projects act as information signals that provide two insights (Bloom et al. 2013, Furman et al. 2005): (i) a rival's beliefs that they are able to develop a potential technological solution and (ii) a rival's beliefs that a specific market offers sufficient rents to be captured. With respect to the former, a rival development effort signals *technological feasibility*. It is well established that knowledge spillovers play a significant role in diffusing knowledge across firms in R&D-intensive industries (Jaffe 1986, Griliches 1992). In such contexts, scientists generally have a well-informed view of the research being conducted by rival firms and the wider scientific community (Henderson and Cockburn 1996, Cockburn and Henderson 1998). Many firms draw on the same industry databases, and face-to-face knowledge transfer can happen between individual scientists attending conferences or over informal coffee meetings (Bloom et al. 2013).

In the pharmaceutical context, as a rival sends its drug candidate through the progressive phases of pre-clinical and clinical development, it indirectly communicates its underlying knowledge about the compound's potential to target and treat a particular disorder. A rival's project development activity, therefore, generates a signal that manifests in knowledge about a specific technological domain or molecular compound. The focal firm, then, can account for the information from this signal when selecting which compounds to develop, thus benefiting from the knowledge generated by its rival and better assessing its own uncertainty about the technological potential of its drug. In many cases, the knowledge gained from rivals' R&D efforts is used to guide the development and manufacture of follow-up compounds, leading to drugs that are often more efficacious (Ma and Zemmel 2002). This suggests positive returns to the industry from a productivity point of view, and that such "positive" technological signals from rivals' projects should be associated with an increased likelihood to select a project in the same domain as a rival project.

Yet, developing a new product also represents a significant commitment on the part of a rival to enter a market (Ettlie et al. 1984, Semadeni and Anderson 2010). Rival developments in a market therefore signal *market entry intentions*. One feature of pharmaceutical R&D is that the clinical indication defines the market. A drug indicated for a particular disorder may only be approved for that same disorder, and manufacturers are strictly prohibited from marketing the drug for non-approved indications or otherwise deviating from the drug label or package insert. As such, a rival's investment in a drug to treat a given disorder signals a willingness to compete in that specific market for patients. Considerable financial expenses and opportunity costs for time and capital further mean that a project choice is a *credible* commitment to pursue a market (DiMasi et al. 2016). A rival's project investment decision therefore signals an increased likelihood of eventual product market entry, manifesting in higher possible competitive intensity and less revenues in expectation. In anticipation of potential downstream competition, rival choices may lead the firm to diversify its own efforts to other markets (Oraiopoulos and Kavadias 2014). Such "negative" market rivalry signals should be associated with a decreased likelihood to select a project in the same indication as a rival project.

3.3. Rival Project Stage and Signal Strength

Given the opposing theoretical arguments that stem from rival projects' information signals, we hypothesize that which effect dominates depends on the strength of the signals. In turn, the strength of either signal depends on the relative timing of the rival actions, vis-à-vis the selection decision of a focal firm. Early-stage projects are mired by considerable uncertainty and are akin to experimentation and the exploration of a domain (Thomke and Kuemmerle 2002). As far as technological feasibility is concerned, early-stage rival projects send uninformative, relatively weak technological signals. For example, pre-clinical results are typically poor predictors of clinical success (Landis et al. 2012). Thus, the technological knowledge that may be gained from a rival's pre-clinical research project is minor.

However, early-stage rival projects signal credible market entry intentions, and the potential for eventual, heightened product-market competition. Even though the technical success of an early-stage project may be uncertain, pre-clinical research is still cost-, resource-, and time-expensive. Firms conduct pre-clinical research with the intention that the compound will be developed and eventually succeed (LaMattina 2011), requiring further investments in marketing channels, salesforce training, and developing other expensive

downstream capabilities. Moreover, drug discovery and development is not a winner-take-all race (Cockburn and Henderson 1994), and there are several instances where follower drugs generate greater sales than the drugs of early movers (Ma and Zemmel 2002).[2] Thus, although early-stage rival projects still face an uncertain development path, they do send salient market rivalry signals.

Hypothesis 1a *Early-Stage Rival Project Signals. Early-stage rival project signals are associated with a decreased likelihood of a firm selecting its own project targeting the same indication.*

In contrast to pre-clinical projects, rivals' decisions to proceed with clinical trials signal more information about the technological potential of these compounds. Success rates for drugs in clinical trials are substantially higher than for those in the pre-clinical stage (Paul et al. 2010). Having cleared the pre-clinical hurdle, some uncertainty has been resolved and the compound has demonstrated reasonable promise. Compared to early-stage projects, late-stage rival projects are more informative with regard to technological feasibility. Hence, a firm should be more inclined to follow such rival project choices.

However, late-stage rival projects also signal competitive intentions. It is intuitive that the market for patients with a given disorder is finite. Any two drugs that target the same patient population will therefore face fierce competition. Once again, all else equal, the negative, market rivalry signal from a rival project should decrease the likelihood that a firm selects a project in the same domain.

Whether the technological signal or market rivalry signal from a late-stage rival project dominates is not straightforward upfront. It is therefore uncertain whether late-stage rival projects should be positively or negatively related to project selection. Rather than speculate on the direction of selection, we pose the following competing hypotheses.

Hypothesis 1b *Late-Stage Rival Project Signals. Late-stage rival project signals are associated with a* decreased *likelihood of a firm selecting its own project targeting the same indication.*

Hypothesis 1c *Late-Stage Rival Project Signals. Late-stage rival project signals are associated with an* increased *likelihood of a firm selecting its own project targeting the same indication.*

To summarize, rival projects send both a technological signal and a market rivalry signal. These signals have opposing effects on project selection, and the net direction of selection ultimately depends on the relative strengths of these signals. Early-stage rival projects send a technological signal that is weaker relative to the market rivalry signal, so we expect firms to diversify their efforts away to other domains. Late-stage projects send both strong market rivalry and technological signals: their effects on selection are, a priori, ambiguous.

3.4. Technological Relatedness and Technological Signals

The strength of the technological signal's effect on selection depends on how relevant this technological signal is for the firm's own project (Bloom et al. 2013, Paci et al. 2014). Technologies evolve and advance because scientists and engineers draw on and better understand the bodies of knowledge and information underlying said technologies. Being able to draw on scientific underpinnings is especially important in science-based industries (Mansfield 1995, Fleming and Sorenson 2004).

In such contexts, scientists are better able to incorporate knowledge spillovers because the projects on which they are working draw on similar technological and scientific principles as their rivals' projects (Oraiopoulos and Kavadias 2014). Firms operating in the same technological landscape or developing projects that utilize similar technologies will be familiar with and better able to draw on this knowledge. Indeed, knowledge spillovers (and therefore gains in R&D productivity) are stronger among "technological neighbors" (Jaffe 1986), that is, firms that operate closer in a technological space and generate knowledge and patents in related classes.

In short, technological relatedness will affect the technological component of the signals received from rivals' projects. We propose that as rivals progress more technologically related projects through clinical development, the effect of the technological signal from these projects on the likelihood of selection should increase.

Hypothesis 2 *Technological Relatedness. The impact of the stage of a rival's project on the firm's likelihood of selecting its own project is stronger when these projects are more technologically related.*

3.5. Market Potential and Market Rivalry Signals

At the same time, the effect of a market rivalry signal will depend on the competitive structure of the downstream market being targeted (Hsieh and Vermeulen 2014). A critical determinant of the level of innovative activity is the potential of the targeted market

(Schmookler 1966, Pakes and Schankerman 1984). A market with greater potential means that there will be more demand to be fulfilled and, therefore, higher revenues can be realized. Larger markets also allow firms to differentiate themselves better, thus reducing competition intensity and increasing profits (Deephouse 1999). In contrast, projects launched in low potential markets face greater competition and are less likely to recover their costs of investment. Indeed, the degree of competition and market potential are significant drivers of market entry (Martin et al. 1998, Acemoglu and Linn 2004).

Against this backdrop, we expect market potential to be a contingent factor in the relationship between the market rivalry signal from a rival project and selection. In high-potential markets, the size of the market is large enough to accommodate more than one company. As such, market rivalry signals are less likely to deter a firm from entering the market and seeking an alternative market. On the other hand, in regimes of low market potential, the market rivalry signal becomes more salient since the pool of potential patients is reduced. We expect that as market potential decreases, the tendency to diversify efforts away to a different market will increase, and the likelihood of selection will decrease.

Hypothesis 3 *Market Potential. The impact of the stage of a rival's project on the firm's likelihood of selecting its own project is stronger in markets with low market potential.*

4. Data and Econometric Specification

We describe here our data set and the specifications of the econometric models used to test our hypotheses. A detailed description of our systematic approach to preparing the database for the ensuing analysis is provided in Appendix C, along with a comparison of several metrics from our data set to those from popular press and industry reports.

4.1. Data and Sample

Our study draws upon the Clarivate Analytics Cortellis database, which contains a near-exhaustive amount of information for the entirety of the industry. We restrict our analysis to the top 15 pharmaceutical companies by sales in 2016 (see Appendix C).

We begin by first identifying the drug-indication projects that the top 15 were working on between 1999 and 2016. Prior to this time period, data quality is very poor: coverage of the industry is very thin and biased toward drugs that were selected for clinical trials and successfully launched. We select 1999 as the starting year to allow enough time for a more representative sample to be formed. We discard projects which were in-licensed after

Phase I (representing selection decisions of other firms), but retain in-licensed pre-clinical projects. Of these remaining 10,281 projects, 1,240 projects were still ongoing in the pre-clinical phase in 2016 (when our data collection ended) and are not considered in the analysis. Among the rest, 4,981 projects were selected for Phase I and 4,060 projects were terminated in the pre-clinical phase. Our working sample consists of the 9,041 projects that were or were not selected for Phase I. Of the 4,981 projects that entered clinical trials, 1,545 were still ongoing, 3,096 failed in clinical trials, and 340 were approved.

There are three types of projects in our data: projects that were selected for clinical trials, projects that were not selected, and projects that were ongoing at the end of our data collection period. For the first two types, a selection decision was made that led to a project being "selected in" or "selected out."[3] For the third type, we cannot measure the number of rival projects at the time of selection since, by definition, the selection decision has not happened yet. Selection is undefined for these projects, and they are not included in our estimation sample. As such, each observation in our data set is a unique project that is observed at one point in its development, when a selection decision was made.

4.2. Variable Definitions

This section presents definitions for the main variables in our analysis. Descriptive statistics are presented in Table 1. Some variables have a lower number of observations due to timing effects (*Carryover*, *Strength*, and *SelectionRatio*), because we observe success only if a project has finished trials and either been launched or terminated (*Success*), or due to a focus on the oncology TA (*Incidence*). More complete definitions for control variables are presented in Appendix A, along with a correlation matrix.

4.2.1. Project Selection. We define selection by capturing whether the firm sent the project to clinical trials. Our dependent variable *Selected* takes on a value of 1 if the focal drug-indication project was selected to enter the Phase I Clinical stage or further; 0 if the project was terminated before reaching Phase I trials.[4]

4.2.2. Signals from Rival Projects. Cortellis includes timestamps of when projects enter (or not) clinical development and as they are eventually launched or development ends. Although we cannot know exactly when a firm's management team makes decisions, we do know when projects entered and exited pre-clinical and clinical trials. We assume that these timestamps correspond to decision points, and we use these to capture the

Table 1 Descriptive Statistics

Variable	Description	n	Mean	SD	5%	Median	95%
Selected	Project selected (1) or not (0)	9,041	0.551	0.497	0	1	1
Success	Project received approval (1) or not (0)	3,436	0.099	0.299	0	0	1
PreClinSignal	# rival pre-clinical projects	9,041	21.243	43.468	0	4	150
TrialSignal	# rival clinical projects	9,041	13.544	21.001	0	5	69
PreClinSignal_Bio	# rival pre-clinical, biologics	9,041	3.486	11.800	0	0	29
PreClinSignal_NonBio	# rival pre-clinical, non-biologics	9,041	17.757	33.661	0	4	117
TrialSignal_Bio	# rival clinical stage, biologics	9,041	2.383	6.083	0	0	16
TrialSignal_NonBio	# rival clinical stage, non-biologics	9,041	11.161	16.918	0	4	52
Biologic	Project is biologic (1) or chemical (0)	9,041	0.232	0.422	0	0	1
Rare	Project targets rare disease (1) or not (0)	9,041	0.067	0.250	0	0	1
Incidence_Reverse	*ln* of indication incidence (reverse coded)	1,537	-10.239	1.697	-13.064	-10.384	-7.374
Inlicensed	Project was in-licensed (1) or not (0)	9,041	0.190	0.392	0	0	1
Acquired	Project obtained from M&A (1) or not (0)	9,041	0.111	0.315	0	0	1
Multiple	Launched for >1 indication (1) or not (0)	9,041	0.062	0.241	0	0	1
Extension	Extension/cocktail drugs (1) or not (0)	9,041	0.063	0.244	0	0	1
Carryover	# successes in last 3 years in indication	8,193	0.176	0.645	0	0	1
stdRD	R&D spend (standardized)	9,041	0.000	1.000	-1.353	-0.215	1.775
IndScope	Indication scope	9,041	0.024	0.020	0.012	0.020	0.045
IndScale	Indication scale	9,041	6.010	7.647	1	3	22
FirmScale	Firm scale	9,041	286.894	145.683	57	269	553
Deals	Yearly change in in-licensing deals	9,041	0.167	2.483	-3	0	4
Strength	Pipeline strength	8,576	1.072	6.174	-7.603	0.949	13.801
SelectionRatio	Proportion of projects selected each year	8,576	0.271	0.156	0.101	0.225	0.523
PriceShock	Sharpest daily %-age drop in stock price	9,041	0.062	0.036	0.027	0.052	0.122

signals that the firm had at the time regarding rivals' activities. $PreClinSignal$ is defined as the number of ongoing, rival pre-clinical projects targeting the same indication in the same calendar year the selection decision is made. $TrialSignal$ is defined as the number of ongoing, rival projects in any phase of clinical trials targeting the same indication in the same calendar year the selection decision is made. For each focal firm's project, we capture the number of concurrent rival pre-clinical or clinical projects, respectively.[5]

For comparison, we also define $PreClinSignalTA$ and $TrialSignalTA$. These capture signals at the higher, TA level of aggregation. We measure these variables similarly as above, except we sum all signals from rival projects across all indications within the same TA as the focal project. We thus compare effect sizes of signals on selection at different levels of analysis. We expect indication-level effects to be stronger than TA-level ones.

4.2.3. Technological Relatedness and Market Potential. To test H2 and H3, we require measures that manipulate the salience of the technological and market rivalry signals independently. If our measures simultaneously influence both signals, then there will be confounding effects on the relationship between the two signals and selection.

We exploit heterogeneity in drugs' therapeutic modalities and in market potential driven by population demographics. Our identifying assumption here is that the size of the patient base suffering from a disorder is orthogonal to the technology used to treat that population (Acemoglu and Linn 2004). In other words, we expect drugs' scientific underpinnings to be exogenous to patient demographics. We explain our measures in turn.

Technological Relatedness. At the highest level, therapeutics fall into two distinct categories: chemical drugs that are produced from chemical synthesis (also known as "small" molecules in the industry) and biologics that are produced from living organisms ("large" molecules). Chemical drugs and biologics differ in many ways, including their physical size (biologics are orders of magnitude heavier), complexity and molecular structure (chemicals are relatively simple while biologics are typically complex proteins), and manufacture (small molecule drugs are created through the synthesis of chemicals, whereas large molecule drugs are protein-based and extracted from biological sources and/or produced by biological processes). These two therapeutic modalities represent fundamentally different approaches to developing drugs and treating disorders. This means that the technological signal received from a rival project with a different modality should be markedly less salient than a signal from a project with the same modality.

We first create the variable *Biologic*, which takes on value 1 if the focal project technology is coded as "Biological therapeutic" in Cortellis, and 0 if it is coded as "Small molecule." Yet, we are not concerned with whether biologic projects *per se* are more likely to be selected than chemical drugs. Rather, we are interested in whether selection of a biologic drug differs according to the (biologic vs. non-biologic) rival signals received. We therefore decompose our rival signal measures $PreClinSignal$ and $TrialSignal$ into their biologic and non-biologic constituents. We specify $PreClinSignal\_Bio$, $TrialSignal\_Bio$, $PreClinSignal\_NonBio$, and $TrialClinSignal\_NonBio$ to capture the pre-clinical and clinical trial signals from biologic and non-biologic rival projects.[6]

Market Potential. We specify two variables to capture market potential. The first measure is based on whether a project is indicated for a rare disease. Rare diseases affect a small enough portion of the population that it is unlikely that the costs of R&D and commercialization will be recuperated.[7] As such, rare diseases provide one clear measure of market potential based on patient population. We construct the variable *Rare* by matching indication names in our data set to the directory of all rare diseases composed by Orphanet.[8]

Rare dichotomizes indications into those with either high or low market potential. The advantage of this variable is that it allows us to easily assign a measure of market potential to every project in our data set. The drawback is that it is coarse due to its binary nature.

We deal with this by also measuring disease incidence: a continuous measure of the number of new patients diagnosed with a disease. We focus on incidence rates for cancer indications, as oncology drugs make up the largest TA in our data set and, importantly, cancer statistics are rigorously tracked by the National Cancer Institute's Surveillance, Epidemiology, and End Results (SEER) Program. SEER collects and provides cancer data and information from several cancer registries across the country. We obtain data on cancer indication incidence rates through SEER*Stat and match indications in Cortellis and SEER by hand, based on the indication name. We create the reverse-coded variable $Incidence\_Reverse$ by multiplying the ln-transformed incidence rates by -1. This measure is decreasing in market potential and is comparable with *Rare*. We estimate different models with either variable to ensure that our results are not driven by sample size.

4.2.4. Controls. We provide here a brief exposition of our control variables. Table 1 and Appendix A provide further details and references.

We first control for several drug- and project-level factors that may be correlated with selection. $Inlicensed$ captures whether the drug was in-licensed (1) or originated in-house (0), and *Acquired* captures whether a drug entered the development pipeline through an M&A (1) or began development in-house (0). We also control for project "quality" through the variables $Multiple$ (whether a drug is able to successfully treat multiple indications) and $Extension$ (line extensions and "cocktail" combinations). Finally, as returns from prior R&D investments may carry over to future projects and affect the selection decision, we control for prior successes in developing an indication with the variable $Carryover$.

We also include several firm-level control variables. We control for a firm's R&D expeditures using *stdRD* (a standardized measure of R&D spend with mean 0 and standard deviation 1). $IndScope$ measures the level of scope across indications in a firm's pipeline, and $IndScale$ and $FirmScale$ capture indication- and firm-level economies of scale, respectively. $Deals$ proxies for the possibility of industry herding by capturing the amount of deal-making activity surrounding an indication. As firms may be more likely to select projects for development if their pipelines are thinning and they become more desperate, *Strength* controls for the strength of a firm's pipeline. $SelectionRatio$ controls for the

proportion of pre-clinical projects sent to clinical trials in a year: i.e., how "wide" each firm's gate between pre-clinical and clinical trials is. In addition to firm indicators, this allows us to control for differing selection protocols among firms. Finally, unanticipated "bad news" may also affect selection if withdrawals and failures lead to an acceleration of other compounds into the pipeline. We rely on changes in market valuation to capture the magnitude of such bad news (Girotra et al. 2007). *PriceShock* measures the most acute day-on-day percentage drop in a firm's stock price in a year. Larger values of *PriceShock* correspond to larger drops in share price.

All our models also include a set of firm, year, and TA indicators (see Appendix D).

4.3. Model Specification

We specify binary choice models to estimate whether a project will be selected for clinical trials. We explain the particular models we estimate to test each hypothesis in later sections, but they are variants of the following probit model:

$$\begin{aligned} Selected_j^* &= \alpha_0 + \alpha_j \mathbf{X}_j + \epsilon_{1j} \\ Selected_j &= \mathbb{1}[Selected_j^* > 0] \end{aligned} \tag{1}$$

For each project j, $Selected^*$ is a latent variable, $\mathbf{X}$ is the set of all variables and controls, and $\epsilon_1 \sim \mathcal{N}(0,1)$. *Selected* is the observed dichotomous variable that denotes whether a project was selected for development, and $\mathbb{1}$ is the indicator function. Unless otherwise noted, all models include robust standard errors clustered at the drug level.

5. Rival Signals and Project Selection

Before presenting our results, we note that all ensuing estimates (unless otherwise noted) are *average marginal effects*.[9] We interpret these as, ceteris paribus, the change in the probability of selection from a one-unit increase in the value of a variable: e.g., the marginal increase or decrease in the likelihood of selection stemming from one extra rival signal.

5.1. General Insights

Table 2 displays the estimates of our probit models testing Hypotheses 1a–1c. Models I–II estimate signals from rival projects targeting the same indication as the focal project; Models III–IV estimate signals from rival projects targeting all indications in the same TA.

Examining the control variables, we find that project-level (as opposed to firm-level) characteristics are primarily the strongest predictors of project selection. The estimates in

Table 2 Probit Models for Project Selection

Notes: The dependent variable is *Selected*. Reported estimates are average marginal effects. Robust standard errors clustered by drug are in parentheses. $^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$; $^{+}p < 0.10$

	(I) Indication-level	(II) Indication-level	(III) TA-level	(IV) TA-level
$PreClinSignal(TA)$	-0.0053***	-0.0042***	-0.0002	-0.0008**
	(0.0002)	(0.0002)	(0.0002)	(0.0003)
$TrialSignal(TA)$	0.0062***	0.0053***	-0.0001	0.0001
	(0.0006)	(0.0005)	(0.0001)	(0.0001)
$Biologic$		0.0902***		0.0957***
		(0.0152)		(0.0160)
$Rare$		0.0886***		0.1143***
		(0.0242)		(0.0246)
$Multiple$		0.2735***		0.2991***
		(0.0269)		(0.0256)
$Extension$		0.1586***		0.1743***
		(0.0241)		(0.0253)
$Inlicensed$		-0.0370*		-0.0462**
		(0.0160)		(0.0169)
$Acquired$		-0.1717***		-0.1819***
		(0.0232)		(0.0250)
$Carryover$		0.0190*		0.0559***
		(0.0079)		(0.0091)
$stdRD$		-0.0268+		-0.0241+
		(0.0138)		(0.0145)
$IndScope$		-0.0463		0.1987
		(0.4856)		(0.5295)
$IndScale$		-0.0018		-0.0120***
		(0.0011)		(0.0008)
$FirmScale$		0.0002		0.0003*
		(0.0001)		(0.0002)
$Deals$		0.0004		-0.0027
		(0.0020)		(0.0020)
$Strength$		-0.0017+		-0.0021*
		(0.0010)		(0.0011)
$SelectionRatio$		0.3684***		0.4084***
		(0.0511)		(0.0539)
$PriceShock$		1.4306***		1.5747***
		(0.1807)		(0.1888)
TA Indicators	Yes	Yes	Yes	Yes
Firm Indicators	Yes	Yes	Yes	Yes
Year Indicators	Yes	Yes	Yes	Yes
# Projects	9,041	8,024	9,041	8,024
Pseudo R^2	0.199	0.257	0.104	0.206
Log-likelihood	-4,980	-4,078	-5,576	-4,355

Model II suggest that projects from multi-indication compounds are approximately 27.4 percentage points (pp) more likely to be selected, extension-line projects are 15.9pp more likely to be selected, and biologics are 9.0pp more likely to be selected for development.

In-licensed projects are around 3.7pp less likely to be sent to clinical trials. In other words, although firms commit substantial effort to identify and bring promising, early-stage compounds into the pipeline, these are less likely to be sent to trials than in-house projects. This may be indicative of extra monetary and non-monetary costs associated with in-licensed projects that render them less likely to be developed (Taneri and De Meyer 2017, Crama et al. 2017). Similarly, projects acquired through M&As are also less likely

to be selected, perhaps because acquisitions in the industry are typically "targeted": firms acquire biotechs or other pharmaceuticals with an eye to bringing one or a few specific compounds into the pipeline or portfolio, while suspending most other projects.

We find some evidence that firms with more late-stage projects and therefore stronger pipelines are more selective ($Strength < 0$). Conversely, firms with weaker pipelines are more likely to send a project to clinical trials. We also find that as firms "widen the gate" between the pre-clinical and clinical phases, the likelihood of any individual project being selected for clinical trials increases ($SelectionRatio > 0$). Finally, we document that more acute drops in firm market value are associated with an increase in the likelihood that a project is selected ($PriceShock > 0$).

5.2. Selection and Signals from Rival Projects

We now turn to our hypotheses regarding how early- and late-stage signals from rivals inform the firm's selection decision. We find strong support for Hypothesis 1a: early-stage projects by rivals are negatively associated with selection ($PreClinSignal < 0$). Rival pre-clinical projects signal an intention to enter a market, but they are relatively uninformative signals about the technological potential of the drug. As such, the market rivalry signal dominates the technological signal. In anticipation of future competition, the marginal rival pre-clinical project increases the likelihood of project termination. This effect is also strong: Model II estimates that a one-standard-deviation increase in the number of rival projects in pre-clinical trials is associated with an 18.3pp decrease (95% confidence interval [CI]: 16.4–20.2pp) in the probability that the firm will select a project for the same indication.[10]

Hypotheses 1b and 1c posit that late-stage investments by rivals provide the firm with both strong market rivalry and strong technological signals. Accordingly, the firm's decision to either follow its rivals or to avoid targeting the same domain depends on whether the market rivalry signal or technological signal dominates. We find evidence for the latter (H1c): signals from rivals' late-stage projects are significantly, positively associated with the likelihood of a firm sending its own project into clinical trials ($TrialSignal > 0$). A one-standard-deviation increase in the number of rival projects in clinical trials increases the probability of selection by 11.1pp (95% CI: 8.9–13.3pp).

In Models III and IV, we find much weaker evidence that signals matter at the overall TA level. $PreClinSignalTA$ is several times smaller in magnitude than $PreClinSignal$,

and $TrialSignalTA$ is non-significant. We conclude that signals are more salient at more granular levels of a technological and competitive domain.

Altogether, the results suggest that firms are less likely to pursue projects in the same indication the more early-stage signals they receive about their rivals initiating efforts into those indications. In contrast, late-stage rival signals are associated with an increased likelihood of selecting a project and following a rival into the domain.

5.2.1. Signals and Technological Relatedness. To test Hypothesis 2, we estimate:[11]

$$\begin{aligned} Selected^* = \beta_0 + \beta_1 Biologic + & \\ & \beta_2 PreClinSignal\_Bio + \beta_3(PreClinSignal\_Bio \times Biologic) + \\ & \beta_4 TrialSignal\_Bio + \beta_5(TrialSignal\_Bio \times Biologic) + \\ & \beta_6 PreClinSignal\_NonBio + \beta_7(PreClinSignal\_NonBio \times Biologic) + \\ & \beta_8 TrialSignal\_NonBio + \beta_9(TrialSignal\_NonBio \times Biologic) + \\ & \beta \mathbf{X} + \epsilon_2 \\ Selected = \mathbb{1}[Selected^* > 0] & \end{aligned} \tag{2}$$

where $\mathbf{X}$ is the set of all controls and $\epsilon_2 \sim \mathcal{N}(0,1)$.

Through a series of interaction terms, Equation (2) estimates how signals from rival (non-)biologic project affects selection when the firm's own project is a (non-)biologic, that is, when technologies are related or not. H2 posits that technological signals should be more salient when the technologies of the firm's and rivals' projects are related. We expect the technological signal's effect on selection to be greater when a biologic project receives late-stage biologic signals ($(\beta_4 + \beta_5) > \beta_4$) and when a non-biologic project receives late-stage non-biologic signals ($\beta_8 > (\beta_8 + \beta_9)$). Moreover, if early-stage rival projects are indeed technologically uninformative (as posited in H1a), then the effects of pre-clinical signals should be the same, regardless of similar or different technologies ($\beta_3 = 0$ and $\beta_7 = 0$).

In Table 3, we find that the interactions of $PreClinSignal\_Bio \times Biologic$ (β_3) and $PreClinSignal\_NonBio \times Biologic$ (β_7) are not statistically different from zero. Regardless of whether focal and rival project technologies are related, the effects of early-stage signals are the same. This is further evidence that pre-clinical projects provide little or no information about technological viability.

Table 3 Signals and Technological Relatedness

Notes: The dependent variable is *Selected*. Reported estimates are coefficients from a probit model. Robust standard errors clustered by drug are in parentheses. $^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$; $^{+}p < 0.10$

		Coeff. from Eqn 2
Biologic	β_1	0.3684***
		(0.0643)
PreClinSignal_Bio	β_2	-0.0080*
		(0.0032)
PreClinSignal_Bio × *Biologic*	β_3	0.0014
		(0.0073)
TrialSignal_Bio	β_4	0.0135*
		(0.0058)
TrialSignal_Bio × *Biologic*	β_5	0.0371**
		(0.0115)
PreClinSignal_NonBio	β_6	-0.0168***
		(0.0012)
PreClinSignal_NonBio × *Biologic*	β_7	0.0033
		(0.0026)
TrialSignal_NonBio	β_8	0.0217***
		(0.0022)
TrialSignal_NonBio × *Biologic*	β_9	-0.0241***
		(0.0045)
All Controls		Yes
TA, Firm, Year Indicators		Yes
# Projects		8,024
Pseudo R^2		0.262
Log-likelihood		-4,050

In support of H2, we find that both interactions on late-stage signals are statistically significant. Clinical-phase signals from rival biologics are stronger when the firm's own project is a biologic ($\beta_5 > 0$), and clinical-phase signals from rival non-biologics are stronger when the firm's own project is a non-biologic ($\beta_8 > (\beta_8 + \beta_9)$). Late-stage signals alter the selection decision, and this depends on whether the underlying technologies are related.

Figure 1 visualizes these results and plots the marginal effect of a signal on the probability of selection. The left chart plots pre-clinical and clinical *biologic* signals against the focal project being a biologic or not. Technological relatedness does not influence selection when rival pre-clinical efforts are undertaken; yet late-stage signals significantly affect selection.

Selection is more likely when firms receive late-stage signals from rival projects utilizing the same technology (vs. a different technology). In the left chart, rival biologic projects have a strong effect on the firm's project if it is a biologic, but this effect is much weaker when the firm's own project is a non-biologic. Similarly, in the right chart, non-biologic rival signals only have an effect on the focal project when it is also a non-biologic. In other words, the pattern that emerges suggests that late-stage signals only affect those projects that are using a related technology.

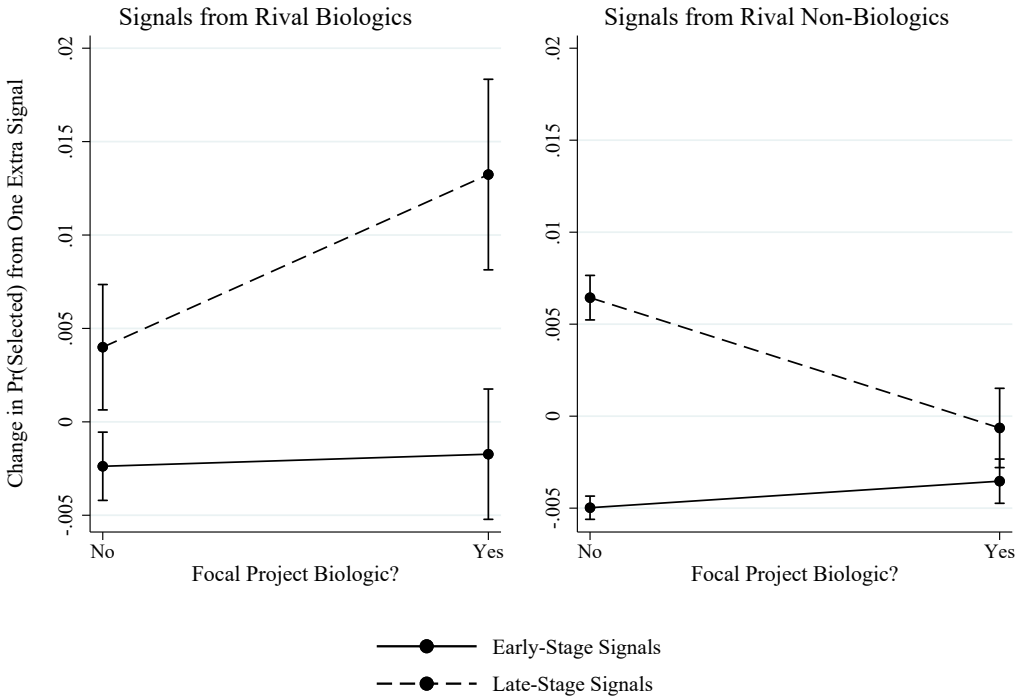

Figure 1 Signals from Rival Biologic and Non-Biologic Projects

5.2.2. Signals and Market Potential. We test H3 by estimating the following model:

$$\begin{aligned} Selected^* =& \gamma_0 + \gamma_1 PreClinSignal + \gamma_2 TrialSignal + \gamma_3 \mathbf{Market} + \\ & \gamma_4 \left(PreClinSignal \times \mathbf{Market}\right) + \gamma_5 \left(TrialSignal \times \mathbf{Market}\right) + \\ & \gamma \mathbf{X} + \epsilon_3 \\ Selected =& \mathbb{1}[Selected^* > 0] \end{aligned} \tag{3}$$

where $\mathbf{X}$ is a set of controls and $\epsilon_3 \sim \mathcal{N}(0,1)$. In Equation (3), **Market** refers to either variable *Rare* or *Incidence_Reverse*. Table 4 displays the estimation results.

Model I in Table 4 first shows that rare diseases are more likely to be selected for clinical trials. This may reflect the fact that institutions often provide incentives for drugmakers to target rare diseases. In line with H3, we find that for projects targeting rare diseases, signals from rival pre-clinical projects are associated with a lower likelihood of selection ($\gamma_4 < 0$). For smaller markets, the potential for greater competition leads to a greater diversification effect away from that market. This is because the eventual possibility of competition reduces the expected value of the focal project (see also Appendix E, where our simple model provides additional intuition behind this result). Model II in Table 4

Table 4 Signals and Market Potential

Notes: The dependent variable is *Selected*. *Rare* captures rare diseases, and *Incidence_Reverse* is a reverse-coded measure of indication incidence. Reported estimates are probit coefficients. Robust standard errors clustered by drug are in parentheses. $^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$; $^{+}p < 0.10$

		(I)	(II)
		Coeff. from Eqn 3	
PreClinSignal	γ_1	-0.0146***	-0.8389***
		(0.0009)	(0.1180)
TrialSignal	γ_2	0.0181***	0.0843**
		(0.0019)	(0.0280)
Rare	γ_3	0.6593***	0.3508*
		(0.1131)	(0.1549)
PreClinSignal × *Rare*	γ_4	-0.2956***	
		(0.0501)	
TrialSignal × *Rare*	γ_5	0.0014	
		(0.0128)	
Incidence_Reverse	γ_3		-0.0553
			(0.0442)
PreClinSignal × *Incidence_Reverse*	γ_4		-0.0597***
			(0.0097)
TrialSignal × *Incidence_Reverse*	γ_5		0.0056*
			(0.0023)
All Controls		Yes	Yes
TA Indicators		Yes	No
Firm Indicators		Yes	Yes
Year Indicators		Yes	Yes
# Projects		8,024	1,424
Pseudo R^2		0.263	0.215
Log-likelihood		-4,047	-407.1

shows a similar pattern among cancer indications. Projects targeting indications with lower incidence rates are less likely to be selected for clinical trials.

We do not document a consistent change in the effect of market potential on the relationship between late-stage signals and selection ($\gamma_5 = 0$). This suggests that after a rival has sent its project to clinical trials, the firm primarily pays attention to the technological signal. This is because the marginal effect on the selection decision is driven by the learning effect rather than the size of the market. Thus, although a late-stage rival project sends both kinds of signals, the technological signal dominates for the project selection decision.

This is also shown in Figure 2, which plots the marginal effect of an extra rival project signal on the probability of selection, depending on the potential of the target market. In both plots, the effect of pre-clinical rival signals on selection are stronger (more negative) in low-market-potential regimes than in high-market-potential regimes, supporting H3. Conversely, late-stage signal effects do not differ by market potential.

5.2.3. Robustness. We perform a series of robustness checks and discuss the most salient ones here. Readers are referred to Appendix B for a complete exposition.

Phase II Selection. Whereas Phase I is the first test in humans, Phase II is another milestone in the drug development process as it establishes the efficacy of the compound.

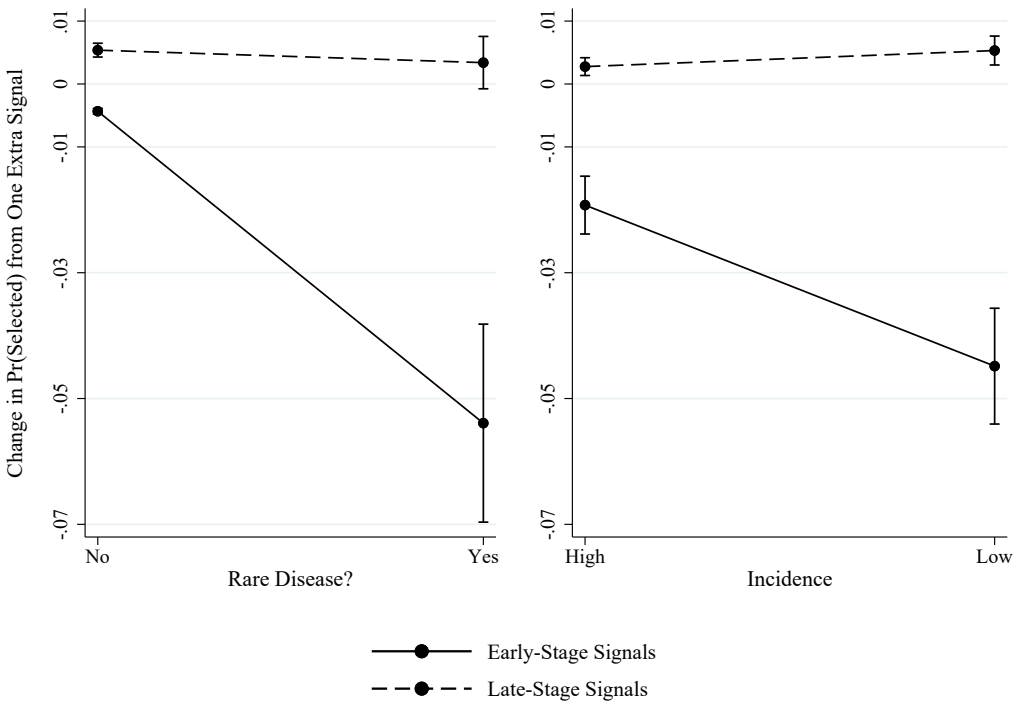

Figure 2 Rival Project Signals and Market Potential

We test whether the above analysis is robust to selection defined as entry into Phase II trials and find that our results are largely unchanged to this alternative specification.

Multiple Selection Decisions. Drug development can be modeled as a process of multiple stages and gates rather than a "one-shot" selection. We consider the "nestedness" of the selection process by estimating a trivariate probit model with selection into Phases I and II. The results are consistent with our main findings.

Endogeneity from Breakthrough Technologies. In many industries, the emergence of new, breakthrough technologies may render older solutions obsolete, conceivably leading to a simultaneous increase in new rival projects. In our context, this would mean that pre-clinical projects would be endogenous to the emergence of a technology. Yet, although there may indeed be industries whereby a new, superior technology renders an older one obsolete, such dynamics do not accurately characterize the pharmaceutical industry (see also Appendix B.8 for a more full explanation). Nevertheless, our results are robust to controlling for drugs' "Breakthrough Therapy" status as a proxy for technological superiority.

6. Extension: Signals and Project Success

Given that rival project signals affect project selection, we now ask: Are these rival project signals meaningfully informative? In other words, do rival projects carry *useful* knowledge

to lead to eventual regulatory approval? Over the last two decades, industry-wide R&D expenses and regulatory stringency on the number of trials have increased, while the numbers of approved compounds have barely kept up. Therefore, understanding the drivers of technical success and improving R&D productivity has been dubbed the industry's "grand challenge" (Paul et al. 2010).[12]

We investigate whether rival signals are associated with a higher likelihood of regulatory approval. We create *Success* to capture whether a project received approval from a regulatory body. This variable is set to 1 if a project's development status is "Launched;" and 0 if a project was "Discontinued," "Divested," "No Development Reported," "Outlicensed," "Suspended," or "Withdrawn," denoting that the firm ceased developing the project.[13]

Our model for success takes the form

$$Success^* = \delta_0 + \mathbf{W}\delta + \epsilon_4 \tag{4}$$
$$Success = \mathbb{1}[Success^* > 0]$$

where $Success^*$ is a latent variable, $\epsilon_4 \sim \mathcal{N}(0,1)$, and $\mathbf{W}$ is a set of controls.

Estimating the drivers of project success is complicated by the fact that firms endogenously decide which projects to pursue or abandon. We thus account for potential selection bias by estimating bivariate probit models with sample selection (Van de Ven and Van Praag 1981). The "heckprobit" model simultaneously estimates probits of Equations (1) and (4) using maximum likelihood estimation. To improve identification, we leverage two variables that plausibly satisfy criteria for instruments: *SelectionRatio* and *PriceShock* (see Appendix A for variable definitions).[14]

SelectionRatio measures the proportion of a firm's pre-clinical projects that are sent to clinical trials in a given year, and it captures how "wide" each firm's gate between pre-clinical and clinical trials is. As a firm's *SelectionRatio* increases, the likelihood of any one project being selected increases, so we expect this variable to be strongly, positively correlated with selection. One potential issue with this variable is that as internal productivity rates deteriorate and pipelines dry up, firms may deliberately relax their standards for selecting compounds for development, thereby leading to a higher rate of selection of "poor" projects. In this case, *SelectionRatio* would be negatively correlated with success. To account for this and to be more confident that the selection ratio is not correlated with success, we control for whether firms are "scraping the bottom of the barrel" in the pursuit

of an approval. After controlling for pipeline strength (*Strength*), a wider funnel between pre-clinical and clinical should not imply a lower selection threshold or the selection of lower-quality drug candidates. Conditional on pipeline strength, we expect *SelectionRatio* to be uncorrelated with the error term in Equation 4.

We also include *PriceShock* as an instrument. Significant drops in firms' market values should be strongly correlated with selection, but they should not affect a project's eventual success. Drops in market value in this industry are often driven by the announcement of a late-stage clinical failure (see, e.g., Girotra et al. 2007), rejection of a promising drug by a regulatory body, or expiration of a key patent. We expect *PriceShock* to be positively correlated with a project's likelihood of selection as the firm may attempt to replenish its pipeline after a negative pipeline shock (Hermosilla 2020). However, we have no reason to believe that such shocks correlate with a different project's future success probability, especially since we measure price shocks before projects have even entered clinical trials.

Before we present our results, we note a potential limitation of this approach. Barring an exogenous shock such as an unanticipated regulatory change, any instrument's validity may be questioned. This is also true in our context, where selection and success are tightly linked.[15] To this extent, we have taken special care to explicitly control for as many confounding factors as possible and eliminate the possibility of a residual correlation between ϵ_4 and *SelectionRatio* or *PriceShock*.

Proceeding to the analysis, we recalculate late-stage rival signals to account for signals from rival projects in Phase I, Phase II, Phase III, and Pre-registration, and we tabulate estimates from our heckprobit models in Table 5. Model I evaluates signals at the fine-grained indication level, whereas Model II evaluates signals at the broader TA level.

We first note that ρ_{14} is statistically significant in Model I, implying the existence of some unobserved factors driving both selection into Phase I trials and regulatory approval, and justifying the estimation of a heckprobit model. Moreover, we find that it is signals at the *narrow*, *indication*-level that matter for selection and success. Signals from projects within the TA are broadly non-significant or have weak effect sizes. Similar to Section 5.2, this supports the idea that information from within the same scientific domain is useful.

The estimates from Model I are displayed in Figure 3. Once again, pre-clinical signals are associated with a decreased likelihood of a project's Phase I selection, and late-stage

Table 5 Signals, Project Selection, and Success

Notes: Model I measures signals within the same indication as the focal project (e.g., *PreClinSignal*), and Model II within the same TA (e.g., *PreClinSignalTA*). Reported estimates are average marginal effects. Robust standard errors clustered by drug are in parentheses. $^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$; $^{+}p < 0.10$

	(I) Indication-Level Signals		(II) TA-Level Signals	
	Selected	*Success*	*Selected*	*Success*
$PreClinSignal(TA)$	-0.0042***	-0.0009*	-0.0010***	-0.0001
	(0.0003)	(0.0004)	(0.0003)	(0.0002)
$PISignal(TA)$	0.0050***	-0.0025**	-0.0001	0.0001
	(0.0011)	(0.0010)	(0.0003)	(0.0002)
$PIISignal(TA)$	0.0075***	-0.0010	0.0001	0.0001
	(0.0012)	(0.0008)	(0.0002)	(0.0002)
$PIIISignal(TA)$	0.0092**	0.0047**	0.0010+	0.0002
	(0.0032)	(0.0018)	(0.0006)	(0.0004)
$RegSignal(TA)$	0.0016	0.0232**	-0.0006	0.0009
	(0.0211)	(0.0086)	(0.0011)	(0.0006)
$Strength$	-0.0012	-0.0000	-0.0014	0.0001
	(0.0011)	(0.0006)	(0.0012)	(0.0007)
$SelectionRatio$	0.3928***		0.4288***	
	(0.0554)		(0.0590)	
$PriceShock$	1.5226***		1.7246***	
	(0.1962)		(0.2035)	
ρ	-0.593**		-0.475*	
$Wald\ \chi^2(1)\ \rho = 0$	10.71		6.55	
All Controls	Yes		Yes	
TA, Firm, Year Indicators	Yes		Yes	
# Projects	6,506	3,040	6,506	3,040
Log-pseudolikelihood	-3963.0		-4217.8	

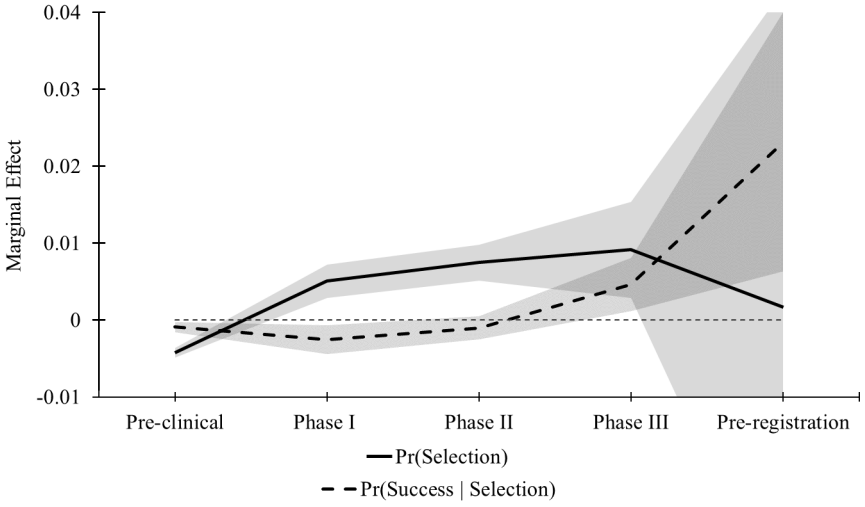

Figure 3 Project Selection and Success

Notes: Marginal effects from Models I and II in Table 5. Shaded areas are 95% confidence bands around the point estimates.

rival signals are overall associated with an increased likelihood of selection. These results corroborate those from Section 5.2.

Regarding success, we find that following rival project signals is not necessarily associated with an increased likelihood of success, and we even find some evidence that following these signals may be misleading. The estimates for $PreClinSignal$, $PISignal$, and $PIISignal$

are negative, and the coefficient for Phase I signals is statistically significant. Information from Phase II and earlier seems to be uninformative at best. Once rival projects have successfully passed Phase II trials, however, information signals are increasingly valuable. Conditional on selection, one extra Phase III signal is associated with a 0.47pp increase (95% CI: 0.12pp–0.81pp) in the likelihood of success, and one extra signal from a rival project that successfully completed Phase III is associated with a 2.32pp (95% CI: 0.63pp–4.00pp) increase. Given that the average conditional probability of success in our data set is 9.9 percent, in relative terms, these correspond to a 4.7 percent and 23.4 percent increase in the probability of success, respectively.[16] Signals from Phase III and later seem to be useful and economically significant.

7. Conclusion

Rival project choices convey two opposing types of information: a *technological signal*, and a *market rivalry signal*. We unpack how competitive product development efforts affect not only the level of R&D investment and productivity, but also the direction of innovation. We find that the development stage of a rival's project plays a significant role in the firm's decision of *where* to allocate its product development resources. As our results show, the potential for future market competition makes it more likely that a firm will diversify development efforts *away from* a market. This diversification is more pronounced in the absence of knowledge spillovers, or for smaller markets (e.g., rare diseases). However, advanced rival efforts signal the feasibility of a potential solution, and they may reverse project selection toward investment *into* a market.

Are the selection decisions that emerge from these signals justified? In other words, does following the rival signals translate to a higher likelihood of regulatory approval? Only in some cases can we record such an effect. Specifically, we document a threshold with respect to the development stage at which the rival effort takes place: information from rival projects that have successfully completed Phase II significantly improves the likelihood of success for the focal firm's project. Yet the information from rival projects still in Phase II or prior is not associated with an increase in the focal project's probability of approval. In fact, following these signals may even adversely affect the likelihood of success.

The latter result indicates that firms may overestimate the information conveyed by rival actions: while the information from rival projects in Phase I and II influences a

firm's selection decision, it proves irrelevant for the project's success (see Figure 3). This distinction between information signals on which firms *act* and those on which they *should act* bears a direct managerial implication from our analysis.

Project selection decisions require senior executives to prioritize among and weigh multiple criteria in the presence of significant uncertainty. Thus, it is not surprising that their decisions end up being influenced by all possible bits of information, including the headlines that a rival commits tens of millions for a Phase II clinical trial of a drug that targets the same indication. Yet, according to our analysis such information should be weighted less (or not at all) in their list of criteria. Firms should beware of introducing bias in their process by reading too much into the information conveyed by their rivals' advanced projects (those in Phase I and II). The focal firm might have perfectly solid reasons to select a given drug for further development, but signals from rivals should not be one of them, at least until the rivals have successfully completed Phase II.

Our analysis also yields insights regarding the extent to which knowledge accumulation in the pharmaceutical industry can improve the likelihood of success of a new product. As discussed earlier, biopharmaceutical R&D is an environment wherein substantial knowledge spillovers occur across rivals. Given the sheer volume of this knowledge, it is important for executives to know when such information improves their chances of success. For example, in estimating the likelihood of success for a given compound, firms often use industry success rates at the level of a TA (DiMasi et al. 2010). Our analysis suggests that such anchors are likely to be uninformative, unless they are at the indication level. We find that signals from rival efforts carry informational value only when they concern projects that target the same indication. Rival signals from projects targeting different indications, even when these indications belong to the same TA, do not affect the chances of success of the a firm's project. Thus, when assessing how to factor in information from "comparable" projects, senior executives should draw a clear distinction between projects that target the same indication and those that do not.

Finally, our findings corroborate the narrow effectiveness of knowledge spillovers in the drug development process, which also illustrates the highly uncertain and complex nature of this process. A departure from the narrow boundary of a specific indication drastically limits the predictive power gained from rival signals. A drug that is highly effective for one disease can be completely ineffective for one that seems closely related. In such an

environment, where building upon existing knowledge has been and will remain a key driving force, the role of serendipity cannot be overemphasized. Simply put, despite the monumental progress of scientific research in the past few decades, when it comes to therapeutic pathways, the unknown parameters still vastly outnumber the known ones. That is why, in their pursuit of drug discoveries, firms need to appropriately assess and act upon the signals that carry informational value, while acknowledging that for many of their development projects such information simply does not exist. We are hopeful that our research study will help firms improve these challenging selection decisions.

Acknowledgments

The authors would like to thank attendees at the European TOM Day at INSEAD, and the 2018 M&SOM Annual Meeting, as well as Dr. David Brown and Dr. Hitesh Sanganee for their insights in the pharmaceutical drug discovery and development context.

References

Acemoglu D, Linn J (2004) Market size in innovation: Theory and evidence from the pharmaceutical industry. *The Quarterly Journal of Economics* 119(3):1049–1090.

Ali A, Kalwani MU, Kovenock D (1993) Selecting product development projects: Pioneering versus incremental innovation strategies. *Management Science* 39(3):255–274.

Arora A, Gambardella A, Magazzini L, Pammolli F (2009) A breath of fresh air? Firm type, scale, scope, and selection effects in drug development. *Management Science* 55(10):1638–1653.

Bhaskaran SR, Ramachandran K (2011) Managing technology selection and development risk in competitive environments. *Production and Operations Management* 20(4):541–555.

Bloom N, Schankerman M, Van Reenen J (2013) Identifying technology spillovers and product market rivalry. *Econometrica* 81(4):1347–1393.

Chan T, Nickerson JA, Owan H (2007) Strategic management of R&D pipelines with cospecialized investments and technology markets. *Management Science* 53(4):667–682.

Chao RO, Lichtendahl KC, Grushka-Cockayne Y (2014) Incentives in a stage-gate process. *Production and Operations Management* 23(8):1286–1298.

Cockburn I, Henderson R (1994) Racing to invest? The dynamics of competition in ethical drug discovery. *Journal of Economics & Management Strategy* 3(3):481–519.

Cockburn IM, Henderson RM (1998) Absorptive capacity, coauthoring behavior, and the organization of research in drug discovery. *The Journal of Industrial Economics* 46(2):157–182.

Cook D, Brown D, Alexander R, March R, Morgan P, Satterthwaite G, Pangalos MN (2014) Lessons learned from the fate of astrazeneca's drug pipeline: A five-dimensional framework. *Nature Reviews Drug Discovery* 13(6):419–431.

Crama P, De Reyck B, Taneri N (2017) Licensing contracts: Control rights, options, and timing. *Management Science* 63(4):1131–1149.

Czarnitzki D, Kraft K (2004) An empirical test of the asymmetric models on innovative activity: who invests more into r&d, the incumbent or the challenger? *Journal of Economic Behavior & Organization* 54(2):153–173.

Deephouse DL (1999) To be different, or to be the same? It's a question (and theory) of strategic balance. *Strategic Management Journal* 20(2):147–166.

DiMasi JA, Feldman L, Seckler A, Wilson A (2010) Trends in risks associated with new drug development: success rates for investigational drugs. *Clinical Pharmacology & Therapeutics* 87(3):272–277.

DiMasi JA, Grabowski HG, Hansen RW (2016) Innovation in the pharmaceutical industry: New estimates of R&D costs. *Journal of Health Economics* 47:20–33.

Ding M, Dong S, Eliashberg J, Gopalakrishnan A (2014) Portfolio management in new drug development. *Innovation and Marketing in the Pharmaceutical Industry*, 83–118 (Springer).

Drakeman D, Oraiopoulos N (2020) The risk of de-risking innovation: Optimal R&D strategies in ambiguous environments. *California Management Review* 62(3):42–63.

Ettlie JE, Bridges WP, O'Keefe RD (1984) Organization strategy and structural differences for radical versus incremental innovation. *Management Science* 30(6):682–695.

Fleming L, Sorenson O (2004) Science as a map in technological search. *Strategic Management Journal* 25(8-9):909–928.

Furman JL, Kyle MK, Cockburn I, Henderson RM (2005) Public & private spillovers, location and the productivity of pharmaceutical research. *Annals of Economics and Statistics* 79/80:165–188.

Gilbert RJ, Newbery DM (1982) Preemptive patenting and the persistence of monopoly. *The American Economic Review* 514–526.

Girotra K, Terwiesch C, Ulrich KT (2007) Valuing R&D projects in a portfolio: Evidence from the pharmaceutical industry. *Management Science* 53(9):1452–1466.

Girotra K, Terwiesch C, Ulrich KT (2010) Idea generation and the quality of the best idea. *Management Science* 56(4):591–605.

Griliches Z (1979) Issues in assessing the contribution of research and development to productivity growth. *The Bell Journal of Economics* 92–116.

Griliches Z (1992) The search for R&D spillovers. *Scandinavian Journal of Economics* 94:S29–S47.

Gu L (2016) Product market competition, R&D investment, and stock returns. *Journal of Financial Economics* 119(2):441–455.

Harris C, Vickers J (1987) Racing with uncertainty. *The Review of Economic Studies* 54(1):1–21.

Henderson R, Cockburn I (1996) Scale, scope, and spillovers: The determinants of research productivity in drug discovery. *The RAND Journal of Economics* 32–59.

Hermosilla M (2020) Rushed innovation: Evidence from drug licensing. *Management Science* Forthcoming.

Hsieh KY, Vermeulen F (2014) The structure of competition: How competition between one's rivals influences imitative market entry. *Organization Science* 25(1):299–319.

Hutchison-Krupat J, Kavadias S (2014) Strategic resource allocation: Top-down, bottom-up, and the value of strategic buckets. *Management Science* 61(2):391–412.

Jaffe AB (1986) Technological opportunity and spillovers of R&D: Evidence from firms' patents, profits, and market value. *The American Economic Review* 76(5):984–1001.

Jaffe AB (1989) Characterizing the "technological position" of firms, with application to quantifying technological opportunity and research spillovers. *Research Policy* 18(2):87–97.

Jain S, Ramdas K (2005) Up or out—or stay put? Product positioning in an evolving technology environment. *Production and Operations Management* 14(3):362–376.

Kavadias S, Chao RO (2007) Resource allocation and new product development portfolio management. Loch CH, Kavadias S, eds., *Handbook of New Product Development Management*, chapter 6, 135–163 (Elsevier).

Kavadias S, Hutchison-Krupat J (2020) A framework for managing innovation. *INFORMS TutORials in Operations Research* 202–228.

Kavadias S, Ulrich KT (2020) Innovation and new product development: Reflections and insights from the research published in the first 20 years of *Manufacturing & Service Operations Management*. *Manufacturing & Service Operations Management* 22(1):84–92.

Khanna T (1995) Racing behavior technological evolution in the high-end computer industry. *Research Policy* 24(6):933–958.

Kornish LJ, Hutchison-Krupat J (2017) Research on idea generation and selection: Implications for management of technology. *Production and Operations Management* 26(4):633–651.

Krieger JL (2021) Trials and terminations: Learning from competitors' R&D failures. *Management Science* 67(9):5301–5967.

Krishnan V, Ulrich KT (2001) Product development decisions: A review of the literature. *Management Science* 47(1):1–21.

LaMattina J (2011) Why taking "shots on goal" matters to R&D. *Drug Truths* URL `https://johnlamattina.wordpress.com/2011/05/26/why-taking-shots-on-goal-matters-to-rd/`, Accessed November 11, 2019.

Landis SC, Amara SG, Asadullah K, Austin CP, Blumenstein R, Bradley EW, Crystal RG, Darnell RB, Ferrante RJ, Fillit H, et al. (2012) A call for transparent reporting to optimize the predictive value of preclinical research. *Nature* 490(7419):187–191.

Leiponen A, Helfat CE (2010) Innovation objectives, knowledge sources, and the benefits of breadth. *Strategic Management Journal* 31(2):224–236.

Lerner J (1997) An empirical exploration of a technology race. *The Rand Journal of Economics* 228–247.

Ma P, Zemmel R (2002) Value of novelty? *Nature Reviews Drug Discovery* 1(8):571–572.

Mansfield E (1995) Academic research underlying industrial innovations: Sources, characteristics, and financing. *Review of Economics and Statistics* 77(1):55–65.

Martin X, Swaminathan A, Mitchell W (1998) Organizational evolution in the interorganizational environment: Incentives and constraints on international expansion strategy. *Administrative Science Quarterly* 566–601.

Oraiopoulos N, Kavadias S (2014) The path-dependent nature of R&D search: Implications for (and from) competition. *Production and Operations Management* 23(8):1450–1461.

Osborn AF (1960) *Applied Imagination: Principles and Procedures of Creative Problem-solving.* (New York: Scribner), revised edition.

Paci R, Marrocu E, Usai S (2014) The complementary effects of proximity dimensions on knowledge spillovers. *Spatial Economic Analysis* 9(1):9–30.

Pakes A, Schankerman M (1984) An exploration into the determinants of research intensity. Griliches Z, ed., *R&D, Patents and Productivity*, chapter 9, 209–232 (University of Chicago Press).

Paul SM, Mytelka DS, Dunwiddie CT, Persinger CC, Munos BH, Lindborg SR, Schacht AL (2010) How to improve R&D productivity: The pharmaceutical industry's grand challenge. *Nature Reviews Drug Discovery* 9(3):203–214.

Pennetier C, Girotra K, Mihm J (2019) R&D spending: Dynamic or persistent? *Manufacturing & Service Operations Management* 21(3):636–657.

Reinganum JF (1983) Uncertain innovation and the persistence of monopoly. *The American Economic Review* 73(4):741–748.

Schlapp J, Oraiopoulos N, Mak V (2015) Resource allocation decisions under imperfect evaluation and organizational dynamics. *Management Science* 61(9):2139–2159.

Schmookler J (1966) *Invention and Economic Growth* (Harvard University Press).

Semadeni M, Anderson BS (2010) The follower's dilemma: Innovation and imitation in the professional services industry. *Academy of Management Journal* 53(5):1175–1193.

Shane SA, Ulrich KT (2004) 50th anniversary article: Technological innovation, product development, and entrepreneurship in Management Science. *Management Science* 50(2):133–144.

Sommer SC, Bendoly E, Kavadias S (2020) How do you search for the best alternative? Experimental evidence on search strategies to solve complex problems. *Management Science* 66(3):1395–1420.

Stevens GA, Burley J (1997) 3,000 raw ideas = 1 commercial success! *Research-Technology Management* 40(3):16–27.

Taneri N, De Meyer A (2017) Contract theory: Impact on biopharmaceutical alliance structure and performance. *Manufacturing & Service Operations Management* 19(3):453–471.

Thomke S, Kuemmerle W (2002) Asset accumulation, interdependence and technological change: Evidence from pharmaceutical drug discovery. *Strategic Management Journal* 23(7):619–635.

Van de Ven WP, Van Praag BM (1981) The demand for deductibles in private health insurance: A probit model with sample selection. *Journal of Econometrics* 17(2):229–252.

Williams R (2012) Using the margins command to estimate and interpret adjusted predictions and marginal effects. *The Stata Journal* 12(2):308–331.

Zizzo DJ (2002) Racing with uncertainty: A patent race experiment. *International Journal of Industrial Organization* 20(6):877–902.

Zschocke MS, Mantin B, Jewkes EM (2014) The effect of competition on R&D portfolio investments. *Production and Operations Management* 23(8):1439–1449.

Endnotes

[1]For more details on the IND application process see: `https://www.fda.gov/drugs/types-applications/investigational-new-drug-ind-application`, accessed May 1, 2021

[2]For example, in the market for type 2 diabetes, there have been 13 drugs launched since 2000 that achieved over $1B in annual sales in 2020 alone. Six of these were biologics and seven were chemical formulations, highlighting that there does not seem to be one superior or inferior technology; rather, there are multiple ways (some based on chemicals and others on biologics) to arrive at a solution. (Source: Evaluate Pharma.)

[3]For a project that was not selected, our measures are not merely capturing the last observable point in time. Rather, Cortellis notes that a particular project has ceased being further developed. Such projects are not lost due to an inability to observe them or "follow up," which would lead to right censoring. Rather, development has ended, and these projects have been selected out.

[4]Given the high failure rates in the industry, pharmaceutical firms initiate many exploratory projects, well aware that most will fail. As such, the drug development process can be described as a state-gate process—essentially, a series of real options, where the firm may exercise the option to abandon a project at any stage. However, given the substantial effort and investment required for initiating clinical trials , it is unlikely that a firm would initiate such a process without strong hopes of seeing the project through. In other words, at the time of the selection decision, the case for the project is made based on the assumption that the product will make it to the market (rather than being terminated in future stages). In Appendix B.1, we relax this assumption and estimate a multi-stage model.

[5]Projects that are still ongoing at the end of 2016 are included in the calculation of $PreClinSignal$, since they are ongoing projects when the focal firm is making its selection decisions.

[6]In other words, we specify that $PreClinSignal = PreClinSignal\_Bio + PreClinSignal\_NonBio$ and $TrialSignal = TrialSignal\_Bio + TrialSignal\_NonBio$.

[7]In 1999, the European Commission defined an orphan disease as one that affects no more than five people per 10,000. In the United States, the Rare Diseases Act of 2002 legally acknowledges rare diseases as those affecting populations smaller than 200,000 individuals.

[8]Orphanet is a global network of resources and information on rare diseases coordinated by the French National Institute of Health and Medical Research. (https://www.orpha.net/consor/cgi-bin/Disease_Search.php?lng=EN&search=Disease_Search_List; accessed Feb. 15, 2020).

[9]We report the Average Marginal Effects which estimate a marginal probability by using the observed values for each observation (rather than the variable means). See Williams (2012).

[10]From Table 1, the standard deviation of $PreClinSignal$ is 43.468. So, $-0.0042 \times 43.468 = -0.183$.

[11]We omit subscripting on project j for ease of exposition.

[12]Although various measures of R&D productivity exist (for example, dollars-per-drug or sales-over-R&D), one oft-cited measure of productivity in this industry is the number of projects needed for one eventual success (Paul et al. 2010, Cook et al. 2014). Our analysis of technical success and the likelihood of regulatory approval speaks to this latter metric.

[13]In Appendix B.6, we test the robustness of our results by considering the cases where a project was outlicensed but nevertheless successfully developed by the licensee.

[14]In Appendix B.3 we estimate additional models to show that the heckprobit estimation is not adversely affecting our analysis.

[15]Even with a change in the regulatory landscape, it would be difficult to convince oneself that such a shock would affect only selection, but not the process and criteria by which drugs are evaluated and approved (i.e., success). Moreover, such external shocks would likely affect all firms and provide no/very little variation across or within firms.

[16]$0.0047/0.099 \times 100\% = 4.7\%$ and $0.0232/0.099 \times 100\% = 23.4\%$.