Firm Boundaries and Incentives:
Evidence from the Biopharmaceutical Industry

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Abstract

How do the choice of firm boundaries and contractual incentives within firms interact to shape innovation outcomes? We address this question using granular data on drug development projects submitted for FDA approval and hand-collected data on managerial compensation. We find that, when a company introduces drug project progression goals as a component of managerial compensation, it creates an agency problem that induces managers to advance to clinical trials more and less promising internally developed drug projects, controlling for possible sources of heterogeneity across drug projects and across companies. This novel mechanism, which reduces innovation efficiency and results in suboptimal firm-boundary decisions as reflected in the choice between internal development and licensing, does not occur with in-licensed drug projects. It is also distinct and coexists with selection effects and contractual inflexibility.

1. INTRODUCTION

The way R&D activities are organized within and across firms has long been identified as an important driver of the successful development of innovations (e.g., Aghion and Tirole, 1994). This makes the design of innovation mode an important element for both corporate strategy and economic growth (Arora, Fosfuri, and Gambardella, 2001).

Over the years many studies have documented the importance of organizational design for effective R&D investment. Two aspects have been shown to play an important role in innovation mode design. First, whether innovation projects are performed within a company or through strategic alliances, which shapes company-level contractual boundaries and incentives. Second, how incentives are designed within the company, which determines the behavior of innovation managers.

The first aspect has been developed in a large literature on internal capital markets, starting with the seminal contribution of Stein (1997). This literature studies the trade-offs implied by the choice of firms' boundaries (Seru, 2014). Research projects performed internally can be better controlled by headquarters. These allocate capital among competing projects and nurture success by shifting resources from low-performing to high-performing projects ('winner picking') using soft information that would be difficult to contract upon with external parties. Moreover, internal project development is often financially more cost-effective as it is often internally funded, which is cheaper than raising debt or equity. However, internal capital markets also have a 'dark side' because they cannot contractually commit to an efficient 'winner picking' when they face a soft-budget constraint, as first argued by Scharfstein and Stein (2000). Sourcing R&D projects outside the firm boundaries, typically through strategic alliances, including licensing, allows firms to engage in a wider variety of projects than would be possible to develop internally. Such contracts, however, make it more difficult to terminate a project for non-technical reasons, limiting headquarters'

ability to engage in winner-picking. Within this context, Robinson (2008) showed that strategic alliances, in a situation where winner-picking is non-contractible, provide an efficient way to pursue innovative R&D projects.

The second aspect relevant to innovation mode design has also been studied extensively, but largely in isolation from the first one. An important assumption of the literature on firms' boundaries is that the agents involved in research projects act in sync with their principal, the firm that employs them. However, several studies document the pervasive presence of agency problems within hierarchies that may tilt incentives on the wrong side (see Mookherjee, 2013, for a survey). This adds an important dimension to the choice of firm boundaries that can lead to different conclusions than those the internal capital markets literature has reached.

In this study, we consider these two aspects jointly, and analyze empirically how contractual incentives provided by managerial compensation affect the efficiency of the innovation process in a situation where companies license some R&D projects to improve the quality of their innovation output. We argue that asymmetric information about the success probability of drug projects creates an agency problem between the firm and its managers. We then provide evidence that managerial compensation based on drug project progression goals leads to inefficient firm-boundary decisions, as reflected in the choice between internal development and licensing.

We therefore provide empirical evidence on how the joint effect of contractual incentives and institutional design affects firm performance, more specifically the success rate of innovative projects, in the context of R&D by biopharma companies. This allows us to address the theoretical contract literature started by Holmström (1984) and later advanced by Dessein (2002), which discusses under which conditions a principal can motivate an agent who possesses private information to act on its behalf, and the literature on organizational

structure and internal capital markets in R&D intensive firms, as exemplified by Robinson (2008). We provide evidence that innovation mode design may become ineffective, and lead to inefficient decisions when the interaction between its components fails to align.

We do so by looking at the biopharmaceutical industry, where established companies develop their pipeline of new drugs to advance through clinical trials towards regulatory approval by relying both on in-licensing of drug projects developed by specialized start-ups and on internally developed drug projects.

Several characteristics of the biopharmaceutical ('biopharma') industry make it an excellent ground for studying how the interplay between contracting and incentives affects innovation. First, this industry has since long relied on several modes of innovation, where large incumbents engage in internal R&D, cooperate with other incumbents in R&D joint ventures, or delegate exploration of new drug compounds to specialized start-ups from which they license. We focus on the comparison between internally developed and in-licensed drugs since in both modes of innovation incumbents have control over project development. This allows us to compare these two different modes of organization of R&D activities in a homogeneous industry environment. Drug projects are also inherently risky, as only a very small percentage of those that enter clinical development eventually receive regulatory approval. Second, clinical trials provide a suitable structure to compare the success of internal and in-licensed innovation by mandating standardized development phases. Third, the standardized regulatory processes result in data on clinical trials at a granular level, which allows us to control for different effects and for alternative mechanisms that may drive our results.

We build on the work of Robinson (2008), who develops a model in which contractual rigidity explains why companies choose to in-license some innovation development projects. Licensing contracts limit a company's flexibility to reduce funding or terminate an in-

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licensed project (winner picking), compared to internally developed projects. Robinson theorizes that incumbents select alliances to overcome internal incentives to divert resources away from risky innovative projects, which he calls 'longshots.' Longshot projects are those with a low probability of success but high value if successful: high risk and high reward. These projects are therefore a natural choice to organize as alliances – since it is more likely that resources would be diverted away from risky longshot projects organized internally. Drug projects fit perfectly the longshot characterization of high-risk and high-reward projects.

We build on Robinson's empirical analysis, which uses industry-level data, in two major ways. First, and most important, we consider that firm managers respond to incentives, which shape their decisions on the continuation of drug development projects. Second, we exploit the detail of our data to analyze potentially competing explanations for the observed outcomes of different innovation modes.

Our study also provides the first large-scale rigorous documentation that internally developed drug projects have a significantly lower success rate than in-licensed ones: innovation mode therefore matters for the success of innovation projects. This is a well-documented stylized fact in the trade literature on R&D alliances in biopharma (Kola and Landis, 2004; DiMasi et al., 2010; Smietana et al., 2016; Markou et al., 2023). We exploit drug project-level data to show that this result holds not just at a descriptive level, but even when controlling for possible sources of heterogeneity across drug projects, including the phase, the therapeutic area, and several other drug project characteristics. This allows us to rule out drug-level effects as possible alternative explanations. In particular, drug development involves separate phases: Phase 1 tests the safety of a drug in a small group of participants; Phase 2 tests the drug for dosing and efficacy in a larger group of patients with the disease to be treated; Phase 3 tests the safety and efficacy of the new drug in a much

larger group of patients; and the Review phase involves the approval from a regulatory agency (in our case the US Food and Drug Administration, FDA). We show that the higher success rate of in-licensed drug projects cannot be explained simply by the trial phase at which projects enter the incumbents' pipeline. Indeed, we find that most in-licensed deals are concluded by the start of Phase 2 of clinical trials.

We then explore three potential mechanisms that could drive the pattern we document. First, incumbents could be particularly good at selecting promising drug project candidates to license, an explanation that builds on the 'absorptive capacity' literature (Cohen and Levinthal, 1990; Nerkar and Roberts, 2004). Second, incumbents could use in-licensing contracts to commit not to terminate 'longshot' projects; such contractual arrangements may prevent in-licensors from terminating projects due to strategic reasons unrelated to the drugs' quality, and thus contribute to the higher success rate of in-licensed drug projects (Robinson, 2008). Third, we posit that one also needs to consider the interaction between contractual arrangements and the incentives provided by the incumbent to its R&D managers, because managerial incentives could mitigate or amplify the productivity differential of internal and in-licensed projects. Therefore, we explore the possibility that the interaction between licensing and incentives may lead internal R&D teams to bring forward less promising drug projects due to monetary and career incentives within the incumbent. This interaction between contracting and incentives creates an agency problem within the firm, which has not yet been studied in the literature and could contribute to lowering the success rate of internally developed drug projects vis-à-vis externally sourced ones.

Our focus on the role of managerial incentives within incumbent firms comes from the observation that, for biopharma companies, these incentives have been changing since the beginning of the century. Attempting to contrast the secular decline in R&D productivity (DiMasi et al., 2010; Paul et al., 2010; Pammolli et al., 2011; Schuhmacher et al., 2023),

since the early years of this century biopharma companies have increasingly adopted compensation schemes that reward managers for achieving annual R&D goals, often measured by the number of pipeline projects that are advanced to the next phase of clinical trials. It is common practice to set R&D goals at the corporate level and then cascade down through the R&D organization to team and individual goals to create alignment with corporate annual goals (Loch, 2008). Roche provides an example of how corporate goals connect to managers' variable compensation in their 2020 annual report: "Firstly, the variable components are intended to create additional financial incentives to achieve corporate goals and to keep innovation at a consistently high level while increasing the value that the company creates for all stakeholder groups. Secondly, in order to allow employees and managers to participate in the company's business success, adequate compensation measures are key. Both objectives are incentivised by annual bonus payments and long-term securities-based programmes." We document that the fraction of biopharma companies in our sample adopting R&D-based incentive compensation schemes increased from 14% in 2000 to 69% in 2020. While the stated goal of these schemes is to increase R&D productivity by rewarding employees based on drug project performance, they can have the unintended effect of reducing the success rate of internally developed drug projects by giving R&D managers private incentives to advance the development of even lower-quality projects. By contrast, we expect agency issues to be less pressing for in-licensed projects because of close pre-licensing managerial scrutiny due to the higher costs of in-licensing compared to those of internal projects, and also due to milestone payments typical with progressing in-licensed projects to the next phase (Edwards, 2019; Markou et al., 2023).

This agency problem is likely to emerge in drug development phases in which R&D teams hold private information regarding the underlying quality and prospects of drug projects. In Section 2.1, we argue that this is the case for Phase 2 of drug project trials, which

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has the lowest success rate among all phases. We also bring anecdotal evidence that industry executives and observers are aware of agency issues in a way that corroborates our conjecture.

Our results paint an interesting picture of how incentives interact with the effects of in-licensing. The key finding is that the data confirm the importance of considering both the contracting and incentives aspects of innovation modes. We show that when information asymmetries are minor, R&D-based managerial compensation has either no effect or a positive effect on the success rate of internal drug projects vis-à-vis in-licensed drug projects. This is the case with Phase 1 and Phase 3 of clinical trials. By contrast, in Phase 2, characterized by the presence of more private information held by R&D teams, R&D-based managerial compensation has the effect of reducing the success rate of internal vis-à-vis in-licensed drug projects. Indeed, we find that the difference in success rate between internal and in-licensed drug projects is mostly driven by firms that adopted R&D-based managerial compensation.

We also find evidence for other mechanisms that build on previous results in the literature. First, consistent with a selection effect, we find that in-licensed drug projects have a higher likelihood of approval (LOA), than similar internally developed drug projects as assessed by industry analysts at the time of the licensing deal. We also find that in-licensed drug projects have higher sales potential than internally developed ones. This suggests that biopharma companies are selecting in-licensed drug projects that are more likely to be successful–both technically and commercially–than similar internally developed projects. Consistent with an absorptive capacity argument, we also find that companies that invest more in R&D select better in-licensing projects, pointing to a role of internal R&D beyond that of discovering and developing new drugs. Yet, we do not find evidence that this "winner-picking" is significantly different for firms that adopt R&D-based managerial compensation,

which suggests that the two mechanisms are distinct. Second, consistent with Robinson (2008), we find that contractual arrangements prevent licensees from terminating projects due to strategic reasons unrelated to the drug, and thus contribute to the higher success rate of in-licensed drugs. Yet, our results continue to hold when we exclude projects terminated for non-technical reasons, and therefore we conclude that contractual inflexibility does not entirely explain our results.

Overall, we document that, given the presence of private information regarding the quality of R&D projects, R&D-based managerial compensation can impose large agency costs on biopharma companies (Jensen and Meckling, 1976) and decrease the relative efficacy of licensing as an innovation mode. Documenting the negative incentives that contracting under asymmetric information creates when they interact with licensing of R&D contracts contributes a new perspective on how organizational design affects innovation efficiency.

Our paper contributes to several streams of research on the organization of innovation activities within and across firms. First, we contribute to the literature on internal capital markets as a form of capital allocation mechanism (e.g., Gertner and Scharfstein, 2013). Second, we contribute to the literature on devising optimal innovation modes, particularly on the choice between in-licensing and internal R&D (e.g., Robinson, 2008). Third, we contribute to the literature on agency problems and incentives in R&D and their effect on R&D productivity (e.g., Arora et al., 2009).

The rest of the paper is organized as follows. We present our sample in Section 2, and our methodology in Section 3, and report our results in Section 4. The paper closes with a conclusion in Section 5. An Online Appendix reports further results.

2. SAMPLE AND DATA

In this section, we describe our sample and data to illustrate why biopharma is an ideal testing ground for our study. We start with a description of the regulatory context in which biopharma companies innovate and of the way decisions about drug project management take place. We then describe our data sources and how we built our sample, and discuss the variables we use in the analysis.

2.1 Institutional context

R&D is considered the lifeblood of the biopharmaceutical industry (Szustek, 2015; Masson, 2023), as the success of a biopharma company depends on a steady stream of new drugs (Kola and Landis, 2004; Schuhmacher et al., 2023). Developing a new drug, however, is a long, costly, and uncertain endeavor. It takes over 13 years to develop a new drug from discovery to regulatory approval (Martin et al., 2017), with an estimated cost of $2.6 billion, including the costs of drug candidates that fail during development (DiMasi et al., 2016).

Drug development is a highly regulated process that is structured into preclinical research followed by three separate clinical trial phases, with each phase increasing in the number of participants and cost ((Scott Morton and Kyle, 2012)). Developing a new drug begins in the discovery phase. Thousands of compounds are screened against a disease target before finding a promising candidate (Hughes et al., 2011). About half of potential drug candidates fail even prior to preclinical testing (Paul et al., 2010). Preclinical research tests drug candidates for biological activity and potential toxicity in animals before clinical trials in humans. Each phase of clinical trials is then designed to answer specific questions related to the benefits and risks of a new drug. Phase 1 tests the safety of a drug in a small group of participants, usually healthy volunteers, and measures safe dosage ranges and the metabolism of the drug. Phase 2 tests the drug for dosing and efficacy in a larger group of patients with the disease to be treated. Phase 2 is sometimes split into two trials: Phase 2a to study dose

ranging and Phase 2b to assess efficacy. Phase 2 is considered 'proof of concept' for new drug safety and efficacy and has the lowest clinical phase success rate. Phase 3, which on average takes longer than the previous phases, is pivotal for regulatory approval and multiple clinical trials can test thousands of patients to demonstrate the treatment benefit and safety of a new drug. After successful clinical studies, approval from a regulatory agency, like the US FDA, is required to obtain permission to market a new drug (FDA, 2018) through the Review phase.

Overall, roughly 90% of drug candidates that make it to Phase 1 clinical testing fail prior to approval (Hay et al., 2014; Thomas et al., 2016; Dowden and Munro, 2019). An analysis of 9,704 development projects developed by 1,779 companies between 2011 and 2020 reported the following average phase success rates: 52% for Phase 1, 29% for Phase 2, 58% for Phase 3, 91% for Review, and therefore just 8% for overall success across all phases (Thomas et al., 2021).

Biopharma firms typically adopt a stage-gate ("go/no-go") governance process to evaluate which compounds should advance to the next phase of development (Bode-Greuel and Nickisch, 2008). Most projects are terminated due to technical reasons, such as lack of drug efficacy or safety. However, project attrition is also due to non-technical reasons such as commercial potential, strategic fit in the firm's portfolio, strategic realignment, or budget constraints. An analysis of 30 biopharma firms between 2013 to 2018 found that 20% of project terminations were due to non-technical issues (Dowden and Munro, 2019). Similarly, Hay et al. (2014) report that 20% of 359 Phase 3 terminations between 2003 and 2011 were due to commercial reasons, and Waring et al. (2015) report that 21% of Phase 1 and Phase 2 drug candidates at four large biopharma companies between 2000 and 2010 were terminated due to rationalization of the portfolio and 7% for commercial reasons.

The standardized structuring of the drug development process into clinical trial phases is useful to understand the configuration of the agency problems we explore empirically since each phase is characterized by a different level of uncertainty and of private information held by R&D managers. Agency problems between shareholders and R&D managers are likely to be highest for projects entering Phase 2 of clinical trials, which has the lowest success rate, as R&D teams and management know that the failure of an occasional weak project will unlikely lead to finger-pointing. Industry analyses support the existence of such agency issues. Peck et al. (2015), for instance, note that "even when weak projects are eventually terminated, it is accepted as part of the high risk of drug development, and team members may be praised for their perseverance." A project team may advocate for a "go to Phase 2" decision to R&D managers, even if they suspect evidence of activity or efficacy could be lacking. Compensation linked to phase progression goals could therefore nudge R&D managers—those with close knowledge of achievement against annual R&D goals—to approve advancing a less promising project into Phase 2 instead of requesting additional data collection or terminating the project. The amount of private information held by R&D teams is likely to be lower in Phase 1, Phase 3, and Review Phase. Projects entering Phase 1 generally have standard preclinical data for evaluating safety and enabling an Investigational New Drug (IND) application to the FDA to start clinical studies in human subjects. Projects entering Phase 3 have robust safety and efficacy data to support End-of-Phase-2 meetings with the FDA and enable Phase 3 clinical study designs with statistical power. Moreover, the large investments required during Phase 3 are likely to increase scrutiny of projects' quality and reduce the scope for pursuing lower-quality projects for private benefits (DiMasi et al., 2016). Finally, projects entering the Review Phase have little or no information asymmetry

due to the large body of evidence generated by Phase 3 clinical studies and documentation required by the FDA for submission for approval.[1]

Our proposed mechanism, which looks at the potentially negative interaction of managerial contracts with incentives provided by licensing of R&D projects, is corroborated by anecdotal evidence. For instance, an AstraZeneca publication on their own productivity stated: "A surprising factor contributing to project failure was the transitioning of projects to the next phase in the absence of sufficiently robust data. For example, 18% of projects that failed in Phase II owing to a lack of clinical efficacy (5 out of 28) were identified as having transitioned into this phase based on weak clinical evidence, which is indicative of inadequate project governance. One potential reason for this observation might be that […] the use of volume-based metrics encouraged project teams and leadership groups to progress projects to the next phase in order to meet yearly goals" (Cook et al., 2014). A Pfizer evaluation of its success rates also noted that it advanced projects into Phase 2 that lacked sufficient data, "Something that came as a surprise was the observation that a significant number of programs failed to gather a compelling body of evidence to demonstrate a thorough understanding of the degree of modulation of the pharmacological target by the NME [new molecular entity, i.e., a novel drug] under investigation. As a consequence, a team in this situation was unable to deduce whether lack of efficacy in the clinical POC [proof of concept, i.e., Phase 2] study was caused by the NME not achieving pharmacologically relevant activity or whether the target was not relevant for the chosen indication" (Morgan et al., 2012). A joint publication by Boston Consulting Group and Bristol Myers Squibb provided this summary: "It is not unusual for R&D staff to progress candidate assets even when continuation may, for strategic reasons, be unwarranted. This 'progression-seeking' tendency is a rational response to the

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[1] Fernando et al. (2022) estimates the average development costs as about $30 million for Phase 1, $70 million for Phase 2, and $310 million for Phase 3. DiMasi et al. (2016) reports similar estimates.

organizational context - rewards such as raises, job security and prestige are associated with progressions - but is clearly misaligned with a company's overall goals" (Tollman et al., 2016). Hal Barron, the R&D chief of GSK at the time, provided a simple explanation: "If you reward progression, you will get progression" (Terry, 2018).

2.2 Data sources

We build our data mainly from three databases: Biomedtracker, Cortellis, and Evaluate Pharma, which are global providers of data and analysis of the biopharmaceutical industry. Each database provides accurate historical data on clinical trials, current drug project status, and licensing deals. These databases are extensively used by investors, companies, and researchers (e.g., Hermosilla, 2018; Krieger, Li, and Thakor, 2022). The Biomedtracker database, published by Citeline, is our main source for drug project data, as it contains information on drug development history and attributes, likelihood of approval (LOA) estimates of drug projects, and clinical trial, regulatory, and partnering events. The Cortellis Competitive Intelligence database, published by Clarivate, provides data on the reasons for project discontinuation. Evaluate Pharma, published by Evaluate, has an extensive archive of annual sales, financial, and pipeline data for biopharmaceutical firms. For drug projects for which these databases do not contain information on whether they are internally developed or in-licensed, we use AdisInsight, another provider of data and analysis for the biopharmaceutical industry, published by Springer, to identify the originator of the project. Finally, we hand-collect information on managerial compensation schemes from firms' annual reports and proxy statements. In the following sections, we describe the datasets we created for our analyses from these databases.

2.3 Sample construction

We build our sample through the following procedure. First, we identify the top 50 biopharmaceutical companies measured by pharmaceutical sales in 2020 (Christel, 2021). We exclude two private companies that do not disclose executive compensation details and six firms that did not develop investigational drugs for the US market. The resulting set of 42 companies represents an estimated 70% of 2020 global biopharma R&D spending (see Table A1 in the Online Appendix). We then search the Biomedtracker database for all the drug projects developed by each company. A drug development project (or simply drug project) is defined as the combination of a drug candidate and a therapeutic indication that Biomedtracker uniquely identifies by a drug indication ID.[2] We focus on drug projects intended for eventual FDA approval that are developed to treat diseases, symptoms, or medical conditions. These include New Molecular Entities (NMEs), which are novel small molecule drugs that are chemically synthesized; biologics, which are novel drugs derived from living organisms; and non-NME line extensions, which are drugs that have been previously approved by the FDA and have been reformulated or tested in new indications. We exclude generic drugs and biosimilar drugs that copy a previously approved drug since these do not require the standard clinical trial phases for FDA approval. Following previous literature (Kola and Landis, 2004; DiMasi et al., 2010; Smietana et al., 2016; Dowden and Munro, 2019), we also exclude vaccines since these are primarily preventative agents.

For our analysis, we measure drug development project phase success events over a 15-year period between 2006 and 2020. An observation is defined by drug project i at development phase t, where the development phase can be Phase 1, Phase 2, Phase 3, and Review. Our sample contains 3,802 drug development projects for 2,245 drugs tested in 456 therapeutic indications across 18 therapeutic areas. Table 1 provides definitions for all

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[2] Therefore, if a drug targets two (or more) diseases, this will result into two (or more) separate drug development projects, whose outcomes are independent.

variables; it is divided into four panels that correspond to the four datasets that we use for our analyses.

2.4 Phase success dataset variables

For each drug project, we determine whether it successfully progressed to the next phase or failed to do so. Phase transition success is defined as advancement to the next development phase. For example, Phase 2 success would be achieved upon initiation of Phase 3, and Phase 3 success upon FDA submission for approval. Phase transition failure of a clinical phase is defined as a suspension event for the drug project or as elapsing of more than 1.5 times the median phase duration since the start of the current phase (Martin et al., 2017).[3] We use a 1.5 multiplier to be conservative and account for projects in therapeutic areas that take longer than average (e.g., see Smietana et al., 2016; Wong et al., 2019). Wong et al. (2019) report that the durations of terminated projects are similar to those of successful ones in Phase 1, eight months shorter in Phase 2, and three months longer in Phase 3. The 1.5 multiplier is conservative since it exceeds the 95th percentile of clinical phase durations reported in Wong et al. (2019). We define Review phase failure as the receipt of an FDA complete response letter (CRL) that informs a company that the drug will not be approved in its current form or as the passing of more than 1.5 times the standard 12-month FDA review time since the date of submission. To ensure that we only include phases where the incumbent licensee has full control over the process, we exclude from the phase success calculation drugs that were licensed after the start of that phase. For example, a drug that was acquired midstream during Phase 1 would not be included in Phase 1 success calculation, but would be included in success calculations for later phases. Some drug projects can occasionally be allowed by the FDA to skip phases and these are considered successes.

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[3] See Table B1 in the Online Appendix for data on phase duration benchmarks.

Next, we research the drug project's originator in Biomedtracker, Cortellis, and AdisInsight. Internal drug projects are originated by incumbent biopharma companies themselves. In-licensed drug projects are originated by another company, typically a specialized start-up, and later in-licensed by a biopharma company. Since there was considerable consolidation of the biopharma industry over the sample period (Thomas et al., 2024), we also include drug projects that were in-licensed by companies that later merged with, or were acquired by, a company in our sample. For example, Merck & Co inherited in-licensing agreements made by Schering-Plough before their 2009 merger. However, we do not include projects internally developed by a company later acquired by a focal biopharma company through a merger or acquisition since, unlike in-licensing, mergers typically are not decisions regarding individual drug projects. Moreover, we exclude out-licensing deals and in-licensing deals where the biopharma company was not the lead partner since our focus is on projects in which the focal biopharma company had decision rights.

Table 2 shows that the overall success rate for in-licensed projects is 13.6%, which is more than twice the success rate of internally developed projects (5.3%). Moreover, Table 2 shows that in-licensed projects have a higher average success rate in each Phase. The phase success rates reported in Table 2 are comparable to studies and industry reports covering a similar time period (Hay et al., 2014; Hermosilla, 2021; Smietana et al., 2016; Thomas et al., 2021). Table 3 further shows that most licensing deals occur in the early phases of development. Hence, the difference in overall success rate is not simply driven by incumbent firms in-licensing projects at a later phase of development.

From Biomedtracker we further obtain drug project-level characteristics. Table 4 reports the distribution of these characteristics in our sample. First, drug classification captures drug project novelty and includes NMEs, biologic, and non-NMEs as categories. Novel drug projects have lower success rates than non-NME line extensions. Table 4 shows

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that nearly two-thirds of the drug projects in Phase 1 are NMEs, and almost one-third are biologics. A therapeutic area is a grouping of diseases with common characteristics into 18 groups, usually aligned with a medical specialty, such as oncology or neurology. Phase success rates vary markedly by therapeutic area (Danzon, Nicholson, and Pereira, 2005; Thomas et al., 2021). Historically, oncology, neurology, and cardiovascular drugs have the lowest success rates; Table 4 shows that they are also among the therapeutic areas with the most drug projects. Biomedtracker also divides therapeutic areas into 67 sub-categories, for example, solid tumor is a sub-therapeutic area of oncology, and neurodegenerative is a sub-therapeutic area of neurology. Indication is the disease that the drug is intended to treat, such as Alzheimer's disease, which has a notoriously low success rate (Kim et al., 2022); there are 456 in our sample. A drug can be tested for many therapeutic indications, the lead indication is the one the firm believes has the strongest scientific rationale and higher likelihood of approval. We see from Table 4 that, depending on the phase, between 40 to 60% of the drug projects are lead indications. Molecule type groups drug projects into 19 categories such as small molecule, monoclonal antibody, natural protein, etc. Molecule type can influence phase success rates; for example, monoclonal antibodies generally have higher success rates than traditional small molecule-based drugs due to their targeted mechanism of action and specificity. Finally, the FDA regulatory designations can significantly impact the likelihood of approval by offering various benefits to facilitate development and streamline the regulatory review process. Table 4 shows that the most common regulatory designation is rare disease, which is given to almost one out of five drug projects in Phase 1.

2.5 Managerial compensation variables

For each firm and year in the sample, we manually collect information on managerial compensation schemes from firms' annual reports and proxy statements between 2000 and

2020. In particular, we record if a firm included R&D-based performance metrics, such as achieving a certain number of development phase progressions, regulatory submissions, or approvals, in the goals used for determining variable executive compensation. We then record if R&D performance metrics were used to determine short-term incentives pay (i.e., annual cash bonus) and/or long-term incentives pay (i.e., grants of stock-based compensation that vest over time) for managers. We measure each of these corporate policies building dummy variables for whether they are present or not. We also measure the intensity of incentive compensation as the fraction of variable executive compensation determined by R&D-based performance metrics. For example, R&D goals accounted for 30% of Amgen's 2020 executive short-term annual incentive compensation: this included a 10% weight for "Advance Early Pipeline" performance metrics and a 20% weight for "Execute Key Clinical Studies and Regulatory Filings" performance metrics, as reported in their 2021 proxy statement and notice of annual meeting of stockholders. Table 5 reports descriptive statistics for these variables, both by year and for the whole sample period. R&D performance metrics are used in about 42% of the company-year observations, and are more common for short-term compensation than for long-term compensation. We also observe an increasing use of both types of compensation, as shown in Figure 1. The intensity of R&D-based managerial compensation appears to be relatively stable over time around, with a weight of about 25% of variable pay, which provides a substantial incentive for managers to achieve the target performance metrics.

2.6 Additional data

To test the selection and contractual inflexibility mechanisms, we employ additional datasets, as described below. Panels B–D of Table 1 provide the definitions of the variables in

these datasets. We report the descriptive statistics for these datasets in Section 3.3, where we bring them into the analysis. There, we also discuss their role in the analysis.

Likelihood of Approval. Biomedtracker maintains estimates of drug projects' Likelihood of Approval (LOA), which is the estimated probability of reaching FDA approval from the current phase. Analysts with advanced degrees in life sciences or medicine adjust LOA estimates up or down in real time using information from press releases, analyst calls, and presentations at investor and medical meetings, as these become available. We use these data to determine whether in-licensed drug projects have a significantly higher LOA than internally developed projects at the time of the licensing deal.

Peak sales forecasts. From Evaluate Pharma's archive of consensus sales forecasts, we collect sales forecasts between 2006 and 2020 for drug projects developed by sample firms from Phase 1 through Review. We then build the peak annual sales forecast variable by taking, for each firm, the mean of consensus peak sales forecasts by phase and year. We use these data to determine whether in-licensed drug projects have a significantly higher estimated commercial potential than internally developed projects.

Project discontinuation reason. We collect data on the reasons for the discontinuation of projects in our sample from the Cortellis database.

3. METHODOLOGY

We begin our analysis of what factors determine clinical trial phase success by focusing on the role of the choice of firm boundaries through the internal development versus in-licensing of new drugs. We estimate the difference in the success rate between internally developed and in-licensed drug projects in each clinical trial phase with the following linear probability model:

$$Y_{ijt} = \beta\, Internal_j + X_j' \cdot \gamma + \delta_i + \eta_t + \varepsilon_{ijt} \qquad (1)$$

where i denotes firms, j drug projects, and t years. Our unit of observation is a drug project j by firm i, which started the clinical trial phase in year t. We estimate Equation (1) separately for each of the four clinical trial phases. The dependent variable Y_{ijt}, is *Phase Success*, which is a dummy variable that equals 1 if the drug project succeeds in transiting to the next clinical trial phase, and 0 if it was suspended or did not advance within 1.5 times the mean phase duration. The coefficient of main interest is β, which represents the difference in phase success probability between internal and in-licensed drug projects, where we use a dummy indicating whether the project was internally developed (*Internal*) as the main independent variable. The vector X_j' includes variables that vary at the level of the drug project, and γ is the associated vector of coefficients. The terms δ_i and η_t represent firm and phase start year fixed effects, respectively; we also test a specification where these two terms enter as an interaction, as well as a specification where we further interact them with a set of molecule type dummies. Finally, ε_{ijt} represents the error term.

To rule out the possibility that differences in success rates are simply driven by drug characteristics, we exploit the granularity of our data and deploy a rich set of drug-project-level variables (X_j'), including the drug project's classification, its indications and lead indication, its regulatory designations, therapeutic or sub-therapeutic areas, and its molecule type. The structure of our data also allows us to account for differences in success rates being driven by firm-level factors with firm fixed effects and vectors of interaction effects. Firm fixed effects account, for instance, for firms' portfolio strategy, technological and commercial capabilities, orientation towards licensing, and ability to perform screening, due diligence, and management of in-licensed drug projects, which are important elements for post-licensing success (Palermo et al., 2019). Moreover, we use year fixed effects to account for industry-wide variations in success rates and for other time-varying factors, like variations in scientific discoveries. We employ also firm × year fixed effects to further address concerns

about unobserved factors and control for effects that vary across both companies and time. Additionally, we employ a specification where we interact sub-therapeutic areas with year to control for time-varying market-level effects, where we identify a market with a sub-therapeutic area (Brooks, 1995). Finally, we estimate a specification with a triple interaction of molecule, firm, and year to control for firm-level time variation in the 'science' the firm is developing, which we define at the level of the molecule (Drews, 2000; Sarantos and Cleo, 2013). We further discuss these fixed effects when presenting our results. Finally, since the error term of projects within the same drug project pipeline may not be independent, we cluster standard errors by firm.

We then move to testing whether the difference in success rate between internal and in-licensed projects is partly driven by agency problems internal to the biopharma company. For this, we study whether the effect of the *Internal* dummy is affected by the use of R&D-based managerial compensation, using a variation of Equation (1) where we interact the *Internal* dummy with one of our four measures of R&D-based managerial compensation:

$$Y_{ijt} = \beta_1\, Internal_j + \beta_2\, Internal_j \cdot Compensation_{it} +$$

$$\beta_3\, Compensation_{it} + X_j' \cdot \gamma + \delta_i + \eta_t + \varepsilon_{ijt} \qquad (2)$$

Next, we run an event study to further examine the dynamics of the effects of R&D-based managerial compensation. Given the changes in the institutional and competitive contexts over time, the effect of R&D-based managerial compensation on the phase success rate of internal projects is likely to differ among cohorts of firms that introduced these compensation schemes in different years. Hence, we run the event study using the methodology of Sun and Abraham (2021), which is robust to treatment effects heterogeneity. As a first step, we estimate the following model:

$$Y_{ijt} = \beta_1\, Internal_j + \sum_e \sum_{l \neq -1} \beta_2^{el}(\mathbf{1}\{E_i = e\} \cdot \mathbf{1}\{t - E_i = l\} \cdot Internal_j) +$$

$$\sum_{l \neq -1} \beta_3^l\, \mathbf{1}\{t - E_i = l\} + X_j' \cdot \gamma + \delta_i + \eta_t + \varepsilon_{ijt} \qquad (3)$$

where E_i is the calendar year in which firm i introduced the R&D-based managerial compensation, $\mathbf{1}\{E_i = e\}$ is an indicator for firm i being in cohort e of firms that introduced the R&D-based compensation in the same year, $\mathbf{1}\{t - E_i = l\}$ is an indicator for firm i in year t being l periods away, backward or forward, from the introduction of the R&D-based compensation.[4] The treated cohorts include all internal drug projects of firms that introduce the R&D-based compensation during the sample period. Firms that never introduced R&D-based compensation packages (i.e., with $\infty \in supp\{E_i\}$) constitute the control cohort of "never treated". Firms that already had R&D-based compensation packages at the beginning of the sample period (i.e., with $0 \in supp\{E_i\}$) are "always-treated," and their internal drug projects are excluded from the estimation as in Sun and Abraham (2021). The coefficient β_1 captures the average phase success rate difference between internal and in-licensed projects (e.g., among the never treated firms). Coefficients β_2^{el} measure, for firms in cohort e, the success rate difference between internal and in-licensed projects l years away from the introduction of R&D-based compensation, where the year before the introduction ($l = -1$) serves as the baseline category and is omitted. Coefficients β_3^l measure the phase success rate of in-licensed projects l years away from the introduction of R&D-based compensation. In more restrictive specifications with firm × year fixed effects, these coefficients are absorbed by the fixed effects.

The second step of the procedure estimates the sample shares of each cohort e in each relative time period l. Finally, the interaction-weighted (IW) estimator of Sun and Abraham (2021) is the weighted average of the estimates of β_2^{el} from Equation (3), with weights set to the estimated cohort shares.

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[4] We assume that the R&D-based managerial compensation is introduced if the firm did not report it in the previous year but did so in the current and following year. E_i is the year in which the firm introduced the compensation.

Lastly, to test alternative theoretical mechanisms, we run OLS models similar to (1), which we describe in Section 4.3.

4. RESULTS

4.1 Difference in phase success rate between internal and in-licensed projects

We now move to study what determines the differences in success rates between internal and in-licensed drug projects within phases that we document in Table 2. Specifically, our next step is to study whether these differences remain when comparing similar drug projects. We estimate several specifications of the linear probability model of Equation (1), where the dependent variable is a dummy indicating whether the drug project has progressed to the next phase. In Table 6, we consider drug project success in Phase 1, 2, 3, and Review, respectively. In each case, the key independent variable is a dummy indicating whether the drug project is internally developed.

The granularity of our data allows us to compare internally developed drug projects with in-licensed drug projects along several dimensions, using a variety of fixed effects. All specifications include controls for Drug Classification, Lead Indication, and a vector of Regulatory Designations (see Table 1 for definitions). Drug classification accounts for basic differences in compound type; lead indication notes that the project is pursuing the indication that the firm believes has the highest likelihood of success; and regulatory designations control for a variety of specific project characteristics that may affect its clinical development. Specification (1) adds Therapeutic Area, which controls for the market size, medical challenges, and the typical likelihood of success of a specific set of diseases; these characteristics affect the likelihood of licensing (Hermosilla and Wu, 2018) and innovating (Acemoglu and Linn, 2004). Specification (1) also adds firm fixed effects to account for firm-specific commercial, scientific, and technological capabilities, as well as licensing strategy

and capabilities. Specification (2) employs more fine-grained sub-therapeutic areas and adds year fixed effects to account for any cyclical and year-specific factors that may affect the drug project success. Specification (3) adds Molecule Type which controls for variation in the specific molecular nature of the drug project (the 'science behind it'); it also substitutes firm and year fixed effects with their interaction. Firm × year fixed effects are a particularly powerful control that allows us to account for firm-level variation in factors such as size, pipeline, commercial success, financial strength, and competitive positioning that may affect the choice between internal development and in-licensing (Hermosilla, 2021; Krieger, Li, and Thakor, 2022). Firm × year fixed effects also account for changes in external or internal business conditions that affect a specific firm in a specific year (Hermosilla, 2021). Specification (4) replaces the 67 Sub-Therapeutic area fixed effects with a vector of 456 Indication fixed effects, which are a much more granular control for the targeted disease. Finally, specifications (5) and (6) employ interaction effects that control for changes in the 'market,' interacting sub-therapeutic area with year, and for changes in the 'science,' by interacting molecule with firm and year.

Notice that our choice of excluding singletons (Correia, 2015) reduces the number of observations in specifications (3), (4), (5), and (6). Notice also that the number of observations slightly increases when moving from Phase 1 to Phase 2 to the next, which might seem puzzling. This is because firms may test a drug in multiple indications after it has been shown to be safe in Phase 1. Firms may also in-license drug projects at any Phase, though this becomes much less common after Phase 2.

The results reported in Table 6 clearly show that internal drug projects are less likely to experience phase success than in-licensed projects, even once we control for drug project characteristics. Specifically, the success rate from Phase 1 to Phase 2 is 12 to 17 percentage points higher for in-licensed drug projects than for internal ones, depending on the

specification. This difference is not trivial, considering that the average success rate for Phase 1 is about 50% (see Table 2). In-licensed projects are also about 6–8 percentage points more likely to successfully transition from Phase 2 to Phase 3, against an average success for that phase of about 30%. For Phase 3 the probability of going to the Review phase is 11 to 18 percentage points higher for in-licensed drugs, against an average success rate of about 62%. Finally, we see that the success rate difference in the Review Phase, while keeping its negative sign, is significant only in one specification. Overall, these results indicate that in-licensed projects are substantially more successful than internally generated ones, with a phase success probability between 20% and 30% higher.

4.2 The effect of R&D-based managerial compensation

Next, we explore the role of R&D-based managerial compensation. Table 5 shows that, out of the total firm-year observations in our sample, 42.1% adopted R&D-based managerial compensation, including 37.9% with short-term compensation and 12.8% with long-term compensation (see Panel A of Table 1 for definitions). The average weight of R&D-based managerial compensation, given by the fraction of variable compensation dependent on R&D targets, for firms that have such schemes, is 26.4%. Figure 1 shows that the fraction of companies utilizing R&D-contingent compensation increased substantially over the analysis period, rising from about 14% in 2000 to 69% in 2020.

Table 7 reports the results of different specifications of the linear probability model in Equation (2), which adds a variable capturing the firm's R&D-based managerial compensation and interacts it with *Internal*, our key explanatory variable. The structure of the table is similar to that of Table 6, but we build a different Panel for each clinical trial phase. In each Panel, we report results for the four measures of incentive compensation that may motivate the choices of biopharmaceutical companies' R&D managers. This model allows us

to test whether the difference in success rate between internal and in-licensed projects varies across firms with and without R&D-based managerial compensation.

Panel A of Table 7 focuses on Phase 1. The first set of regressions, using the *R&D-based Managerial Compensation* dummy, provides some evidence that the use of incentive pay attenuates the difference in the success rate of internally developed projects vis-à-vis in-licensed projects. This result may suggest that R&D-contingent compensation achieves the desired effect of increasing R&D productivity in Phase 1. Alternatively, it may indicate that the introduction of the R&D-based managerial compensation leads managers to terminate internal projects at a lower rate in this phase. Yet, this result does not hold any longer when we measure R&D-contingent compensation with short-term incentives (*R&D STMC*), long-term incentives (*R&D LTMC*), or with its weight on managerial variable pay (*R&D-based Managerial Compensation Intensity*).

Panel B of Table 7 reports results from the regressions for Phase 2. Here we find that the presence of R&D-contingent managerial compensation significantly reduces the success rate of internal projects vis-à-vis in-licensed projects. This result holds when considering both the *R&D-based Managerial Compensation* dummy and the *R&D-based Managerial Compensation Intensity*. Interestingly, when looking at the distinct effect of short-term incentives (*R&D STMC*) and long-term incentives (*R&D LTMC*), we see that the effect is largely driven by short-term incentives. Overall, these results are in line with our hypothesis that the presence of R&D-based managerial compensation creates an agency problem by providing R&D managers with a monetary incentive to bring forward lower-quality projects in Phase 2. We further explore this mechanism in the rest of our analysis.

Panel C of Table 7 reports results from the regressions for Phase 3. Specifications (3) and (4) provide some evidence that the success rate of internal projects vis-à-vis in-licensed projects improves with R&D-based managerial compensation, particularly with short-term

incentives. However, this result is not robust across all specifications. Finally, Panel D of Table 7 shows that there is no significant difference in the Review Phase.

A possible explanation for the result that R&D-based managerial compensation leads to a lower success rate for internal drug projects entering Phase 2 is one of reverse causality: companies with a lower success rate in Phase 2 may react by introducing R&D-contingent compensation to stimulate R&D productivity. To test this possibility, we examine the dynamics of the effects of R&D-based managerial compensation, using the event study methodology of Sun and Abraham (2021), as described in Section 3. We estimate Equation (3) for projects in Phase 2 up to seven years before and after the introduction of R&D-based compensation.[5] Figure 2 reports the estimates for each of models (1)-(6) of Tables 6 and 7. Overall, the graphs indicate that the phase success rate difference between internal and in-licensed projects does not exhibit a clear trend before the introduction of R&D-based compensation, and that it increases after these monetary incentives are introduced. Figure C1 in Online Appendix C complements these findings by showing that the success rate of in-licensed drug projects remains largely constant before and after the introduction of R&D-based compensation.

These results align with our hypothesis that R&D-based managerial compensation reduces the phase success rate of internal drug projects by rewarding managers for holding in the pipeline lower-quality projects. To further explore this mechanism, we test whether the number of internal drug projects in the pipeline increases after the introduction of these compensation schemes. To do so, we create a dataset consisting of a panel of firm-year observations measuring the number of internal projects in the firm's pipeline among all phases for each year between 2001 and 2020. We build this dataset using data from

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[5] We bin more distant leads and lags into those at +/– 7 years, respectively, due to the scarcity of these observations.

Evaluate Pharma. While our main analysis suggests that the agency problem manifests in Phase 2, we lack data on the number of internal projects by phase, so this analysis remains at the firm level.

We apply the event study methodology of Sun and Abraham (2021) to this dataset, using never-treated firms as the control cohort and excluding always-treated firms from the estimation. Aggregating data across phases allows us to extend to ten the number of leads and lags from the introduction of the R&D-based compensation. Figure 3 shows that the number of internal projects remains stable before the introduction of the compensation schemes, increases by about one unit around four years after the introduction, and by two around nine years after the introduction. Since the median number of internal projects is 6 (the mean is about 15), these increases are economically meaningful.

4.3 Alternative mechanisms

After establishing our main results, that adopting R&D-based managerial pay creates an agency conflict that leads to a lower Phase 2 success rate, we now explore two other, alternative, mechanisms that could also explain the difference in success rate between internally developed and in-licensed drug projects. First, it could be that firms have R&D absorptive capacity (Cohen and Levinthal 1989, 1990) that allows them to select, and in-license externally developed projects that are more likely to be successful (the 'selection' mechanism). Second, following the findings by Robinson (2008) that contractual obligations create costs in terminating licensing agreements, it could be that in-licensed drugs are less likely to be discontinued due to non-technical reasons and therefore are more likely to reach FDA approval (the 'contractual' mechanism). We now examine both mechanisms in turn.

Selection. The first mechanism that we examine is that some firms develop superior absorptive capabilities that allow them to scout for, screen, and select externally developed drugs that are more likely to be successful. Cohen and Levinthal (1989, 1990) introduced the concept of absorptive capacity as a firm's ability to recognize the value of new information, assimilate it, and apply it to commercial ends. The authors suggested that absorptive capacity is a function of the firm's level of prior related knowledge and is cumulative. Developing absorptive capacity is thus considered a major factor in a firm's innovation performance. Building on Cohen and Levinthal's work, Cockburn and Henderson (1998) argue that the combination of internal and external sources of knowledge is an important factor in innovation performance for pharmaceutical companies. Firms with more absorptive capacity are likely to be better at screening external drug projects and therefore may be able to better select promising drugs (Cohen and Levinthal, 1989, 1990; Arora and Gambardella, 1994; Arora et al., 2009; Fernald et al., 2017). We bring absorptive capacity into our analysis in three steps.

First, we use firms' R&D intensity as a proxy for their absorptive capacity and ability to select promising external projects (Arora and Gambardella, 1994). R&D intensity is measured as the ratio of annual pharmaceutical R&D spending divided by annual pharmaceutical sales. Evaluate Pharma provides estimates of annual R&D spending and sales specifically for pharmaceuticals, which makes R&D intensity ratios comparable between pure-play biopharma firms and conglomerates like Johnson & Johnson. In Table C1 in the Online Appendix, we report the results of regressions testing how the difference in success rate between internal and in-licensed drug projects is moderated by the firm's absorptive capacity. The results in specifications (2) to (4) and (6) reflect a moderating role of R&D intensity, whose coefficient is negative and significant in several specifications. These results

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point to the selection mechanism (via absorptive capacity) being relevant for understanding the differential success rate between internal and in-licensed drug projects.

Second, we provide a more direct test of the selection mechanism by comparing the Likelihood of Approval (LOA) of similar in-licensed and internally developed projects. For this, we employ a different dataset that reports the LOA estimate of drug projects on the dates of certain events.

As described in the Sample and Data section, the LOA measures the probability of reaching FDA approval from the current phase as determined by industry analysts with advanced degrees in life sciences or medicine. Our data include 938 in-licensing deal announcements. Table 8 reports summary statistics for the LOA of internal and in-licensed projects. For the former, LOA is measured at a phase initiation event, for the latter, LOA is measured at the licensing deal announcement date. The LOA of internal and in-licensed drug projects appear to be extremely close and exhibit a very similar variation, suggesting that there is no selection mechanism at play. However, we analyze the role of LOA further in a regression setting. Table 9 shows the regression results of a variation of Equation (2) where we add a control for clinical trial Phase, on top of the controls we use in all similar specifications in previous regressions: drug characteristics, and combinations of firm and year fixed effects. Since we do not have sub-therapeutic area information for LOA data, we do not include a specification interacting sub-therapeutic area with year fixed effects. We also do not include the triple interaction of molecule type with year and firm fixed effects. Since Biomedtracker analysts base their LOA estimate of a drug project on the LOA benchmark for a particular therapeutic area and phase and then adjust the estimate up or down based on new information, the triple interaction is unlikely to be relevant.

The results in Table 9 show that LOA at the time of the licensing deal is significantly higher than similar internal drug projects across all specifications. This suggests that firms

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possess private information and/or scouting and screening capabilities that allow them to select in-licensed projects with a higher expected likelihood of approval (Alcacer et al., 2010; Davies, 2013). This brings further support for a selection mechanism to be at work.

Third, we test whether in-licensed projects are not only more likely to be approved, but also more likely to be commercially successful, and therefore potentially less likely to be terminated for commercial reasons. We match the Biomedtracker data with the Evaluate Pharma's archive of consensus sales forecasts to collect sales forecasts for the drug projects in our sample for each phase. Excluding projects that do not match across the two datasets, we obtain a new dataset of peak sales forecasts for 1,032 drug projects across trial phases (544 internal and 488 in-licensed), for a total of 12,573 observations of mean peak sales forecasts by phase and year: 5,698 for internal drug projects and 6,875 for in-licensed drug projects.[6] Table 10 reports the descriptive statistics. Peak sales are higher for in-licensed drug projects in Phase 1 and Phase 2, and higher for internal drug projects in Phase 3 and Review. We then employ the same variation of Equation (1) that we used in the LOA regressions, which includes a control for Phase, where we now use the log of Peak Sales as the dependent variable. Table 11 shows that the peak consensus sales forecasts for in-licensed projects, after controlling by phase, are 15 to 20 percent higher than for internally generated drug projects, depending on the specification. Thus, the higher success rate of in-licensed drugs is at least partly driven by a selection effect.

As a last step, in Table 12, we verify whether the results from Panel B of Table 7, which suggest the presence of agency problems in Phase 2, can be explained by a difference in selection ability between firms with and without R&D-based managerial compensation. In particular, Table 12 tests whether the difference in LOA between licensed and internal

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[6] The observation is mean peak sales forecast by phase and year, so there can be many observations for each drug project. Analysts forecast sales throughout the year but most forecasts are in months when quarterly earnings are reported: January, April, July, and October.

projects at the time of the licensing deal in Phase 2 is significantly different between firms with and without R&D-based managerial compensation. The results clearly indicate that the selection effect is not significantly different for firms with R&D-based managerial compensation. Overall, the agency problem we document is therefore a mechanism that is distinct from the selection effect.

Contractual inflexibility. Robinson (2008) proposes another reason why in-licensed projects may have a higher success rate than internally developed projects: contractual inflexibility. Robinson argues that contractual arrangements create costs for the termination of in-licensed projects, which then become less likely to be discontinued due to non-technical reasons (i.e., pipeline prioritization) and thus have a higher success rate. He argues that licensing contracts contain clauses that limit the flexibility of a firm to reduce funding or terminate an in-licensed project. This is true in particular for "commercially reasonable effort" clauses. Most licensing deals are structured with milestone payments upon advancement of the project, which reduces risk to the licensee, but also incentivizes the originating company to push for the project to advance to the next phase. Originators may take legal action if they think the licensee did not spend enough effort to advance the project. Robinson (2008) theorizes that large in-licensing firms select alliances to overcome internal incentives to divert resources away from risky innovative projects, which he called 'longshots.' Longshot projects have a low probability of success but high value if successful: high risk and high reward. Robinson (2008) argues that longshot projects are a natural choice to organize as alliances – since it is more likely that resources would be diverted away from risky longshot projects organized internally. To test this hypothesis, we collect data on the reasons for the discontinuation of projects in our sample from the Cortellis database. The resulting sample, which is naturally smaller than our main sample, contains 377 discontinued

drug projects with known discontinuation reasons: 165 internal and 212 in-licensed. Table 13 reports descriptive statistics for the discontinuation reasons, by clinical trial Phase. Adverse Event and Lack of Activity or Efficacy (see Panel D of Table 1 for the definitions) are the two technical discontinuation reasons that would not be affected by contractual clauses; they are more common for in-licensed projects, and account for about 65% of all discontinuations. On the other hand, Pipeline Prioritization implies a business-based discretionary decision that may be more difficult to implement under an in-licensing agreement; they account for nearly 19% of all discontinuations and are more common for internally developed drug projects. We then formally test Robinson's (2008) hypothesis by regressing the Pipeline Prioritization reason for project discontinuation on the dummy for internally developed drug projects and the usual controls. Table 14 reports the results, which indicate that Pipeline Prioritization is more common for internally developed drug projects, 15% to 19% more than for in-licensed projects.[7]

Overall, we find evidence of the contractual inflexibility mechanism in our data. Lastly, we verify whether this mechanism could explain our results from Table 7, Panel B, which highlights that the difference in success rate between internal and in-licensed projects in Phase 2 is largely driven by firms that adopted R&D-based managerial compensation (in line with our proposed 'agency problem' mechanism). Specifically, we run the same regressions of Table 7, Panel B, excluding from the sample all drug projects that are discontinued due to pipeline prioritization. Our results, reported in the Online Appendix (Table C2), do not change. Thus, the results of Table 7, Panel B, appear to be largely driven by drug projects that fail or progress due to technical reasons, which suggests that internal projects brought forward by R&D managers due to their monetary incentives are inherently

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[7] In unreported robustness regressions, we excluded the "other" discontinuation category and obtained similar results.

of lower quality. We therefore conclude that contractual inflexibility, while being an active mechanism in drug project management, does not fully account for the difference in phase success between internally generated and in-licensed projects.

5. CONCLUSIONS

We provide large-scale evidence that internally developed drug projects have a significantly lower success rate than in-licensed drug projects. The granularity of our data allows us to show that this result holds after controlling for several drug-level characteristics– including the phase, the drug classification, the regulatory designations, the therapeutic or sub-therapeutic area, the molecule type, and the indication–as well as firm-level idiosyncratic effects in each year. Next, we examine different potential mechanisms that could explain this pattern.

First, we provide novel evidence that this difference in success rate is at least partly driven by agency problems internal to the biopharma firms. Biopharma companies increasingly adopted compensation schemes that reward managers based on the number of pipeline projects that are advanced to the next phase. In 2020, 69% of the firms in our sample had adopted these incentive schemes, compared with just 14% in 2000. These schemes give R&D managers monetary incentives to advance the development of even lower-quality projects to achieve volume-based pipeline progression goals. We show that this agency problem emerges in Phase 2, which is characterized by the lowest success rate and the presence of more private information held by R&D teams. While this mechanism is consistent with anecdotal evidence (e.g., Cook et al., 2014; Morgan et al., 2012; Tollman et al., 2016), to the best of our knowledge this study is the first to document it empirically. In line with our hypothesis that managers hold in the pipeline lower-quality internal projects to increase the pipeline volume to their benefit, we also find that the introduction of the R&D-

based managerial compensation schemes increases the number of internal projects in the firm's pipeline.

Second, consistent with a selection effect, we find that in-licensed drug projects have a higher LOA at the time of the licensing deal and have higher sales potential than internally developed ones. This suggests that biopharma companies are selecting in-licensed drug projects that are more likely to be successful–both technically and commercially–than similar internally developed projects. Consistent with an absorptive capacity argument, we also find that companies that invest more in R&D select better in-licensing projects. Third, consistent with Robinson (2008), we find that contractual arrangements prevent licensees from terminating projects due to strategic reasons unrelated to the drug, and thus contribute to the higher success rate of in-licensed drugs. However, we find that these two additional mechanisms are distinct and coexist with our proposed mechanism on agency costs.

Overall, we document that while the cost of licensing deals requires managers to hold strict screening standards for drug projects sourced externally, R&D-based managerial compensation gives them a private incentive to relax the screening standard for internal projects. Thus, R&D-based managerial compensation can impose large agency costs on biopharma firms and increase the relative efficacy of licensing as an innovation mode.

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Figure 1. R&D Goals as Component of Executive Variable Compensation

This Figure plots the proportion of biopharma companies that reported to include R&D goals in the calculation of executive variable compensation, between 2000 and 2020. Data are obtained from company annual reports and proxy statements.
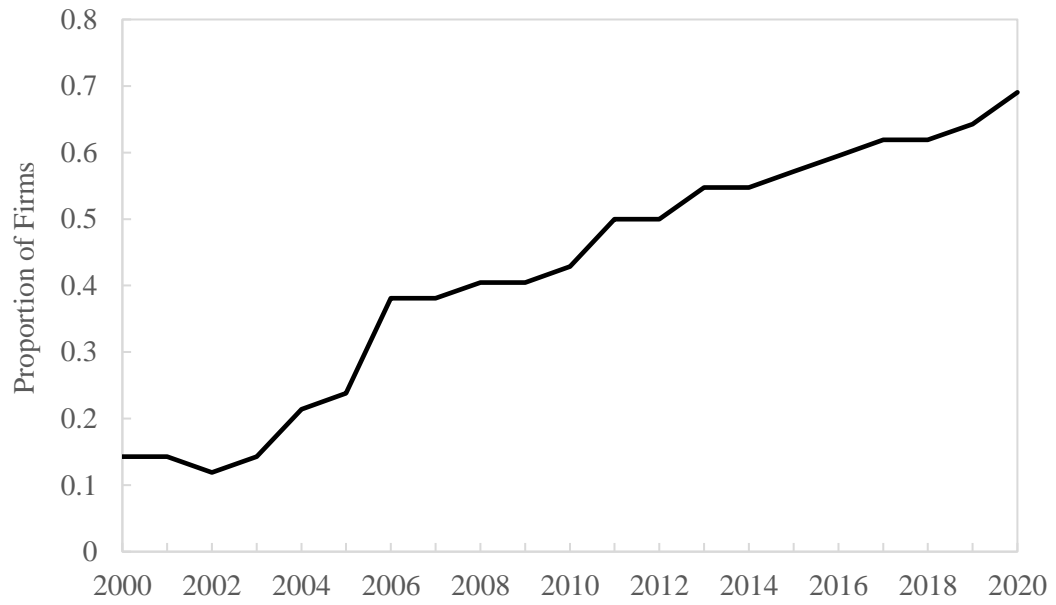
Figure 2. Introduction of R&D-based Managerial Compensation and Phase 2 Success Rate Difference between Internal and In-licensed Drug Projects

The graphs in this Figure show the estimates of the dynamic treatment effects of the introduction of R&D-based managerial compensation on the Phase 2 success rate difference between internal and in-licensed drug projects. The vertical axis reports the IW estimates of β_2^{el} from equation (3) described in Section 3 (Sun, 2021; Sun and Abraham, 2021) with 95% confidence intervals. The horizontal axis measures the leads and lags (in years) since the introduction of the R&D-based compensation; period –1 is the excluded category. The bins for years +/–7 also include more distant leads and lags, respectively. Each graph reports models with the same sets of fixed effects as models (1)-(6) in Tables 6 and 7. Standard errors are clustered by firm.
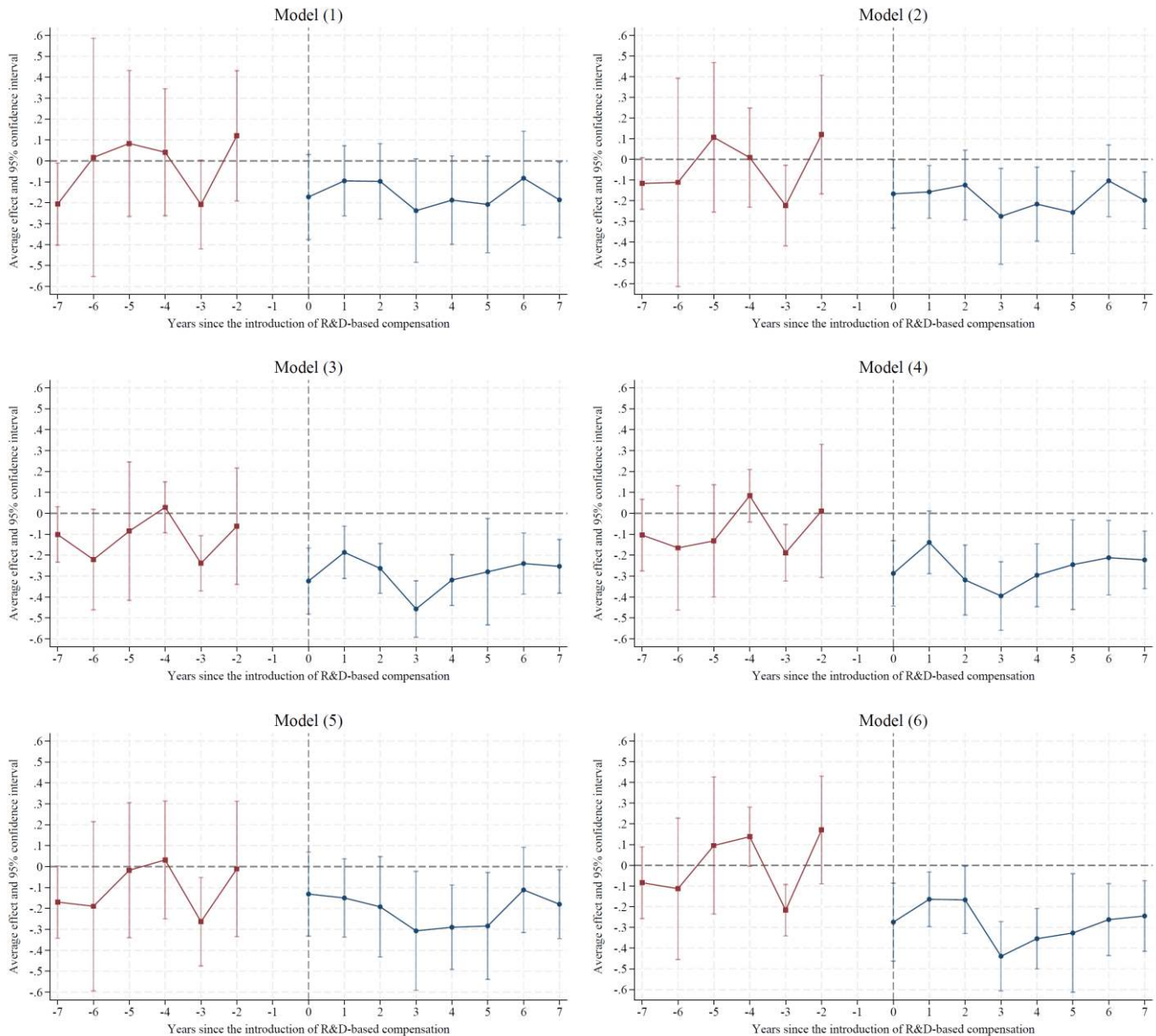
Figure 3. Introduction of R&D-based Managerial Compensation and Number of Internal Drug Projects

The graph shows the estimates of the dynamic treatment effects of the introduction of R&D-based managerial compensation on the number of internal drug projects in a firm's pipeline. The estimates are obtained from a panel of firm-year observations measuring the number of internal projects in the firm's pipeline, aggregate across all phases, for each year between 2001 and 2020. The data source is Evaluate Pharma. Treated cohorts are firms that introduced R&D-based compensation. The control cohort consists of firms that never introduced these compensation schemes ("never treated"). Firms that introduced these compensation schemes before the sample period ("always treated") are excluded from the estimation. The vertical axis reports IW coefficient estimates described in Section 3 (Sun, 2021; Sun and Abraham, 2021) with 95% confidence intervals. The horizontal axis measures the leads and lags (in years) since the introduction of the R&D-based compensation, where period –1 is the excluded category. The bins for years +/–10 also include more distant leads and lags, respectively. The regression specification includes firm and year fixed effects and standard errors are clustered by firm.
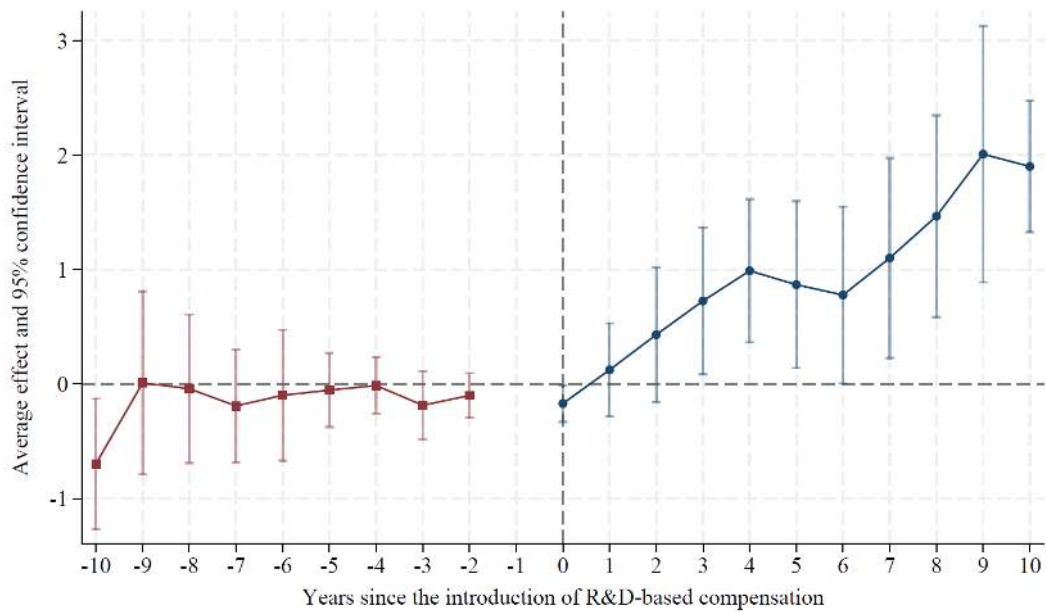
Table 1. Variable Definitions

Panel A. *Phase success dataset*

VARIABLE	DEFINITION	SOURCE
Drug-Project-Level Variables		
Phase Success	A dummy for each phase that equals 1 if the drug project advanced to the next phase and 0 if the project was suspended or did not advance to the next phase within 1.5 times the mean phase duration. Skipped phases are considered successes.	Biomedtracker
Internal	A dummy that equals 1 if the drug project was internally developed and 0 if it was in-licensed.	Biomedtracker, Cortellis, AdisInsight
Phase	Phase of the drug project for the observation. Phases include Phase 1, Phase 2, Phase 3, and the Review by the FDA.	Biomedtracker
Drug Classification	Drugs classification for purposes of FDA review: new molecular entity (NME), biologic, or non-NME. A novel drug that has not been previously approved by the FDA is an NME or biologic. An NME is generally a traditional small molecule drug that is chemically synthesized. A biologic is a drug derived from living organisms. A Non-NME is a drug that has been previously approved by the FDA and has been reformulated or tested in a new indication ('line extension').	Biomedtracker
Molecule Type	The molecule type of the drug. There are 19 types: antisense, carbohydrate/glycoprotein/glycopeptide, cellular, monoclonal antibody, natural protein, non-viral gene therapy, not specified, other nucleic acid, peptide, polyclonal antibody, protein, small molecule, small molecule with liposomal delivery, steroid, viral, viral gene therapy, messenger RNA, microRNA, and siRNA/RNAi.	Biomedtracker
Therapeutic Area	A grouping of diseases with common characteristics, usually aligned with a medical specialty. There are 18 categories: allergy, autoimmune/immunology, cardiovascular, dermatology, endocrine, gastroenterology, hematology, infectious disease, metabolic, neurology, obstetrics/gynecology, oncology, ophthalmology, psychiatry, renal, respiratory, rheumatology, and urology.	Biomedtracker
Sub-therapeutic Area	Sub-category of Therapeutic Area. There are 67 types. For example, solid tumor is a sub-therapeutic area of oncology, and pain is a sub-therapeutic area of neurology.	Biomedtracker
Indication	The disease that the drug is intended to treat. There are 456 indication categories in the dataset.	Biomedtracker
Lead Indication	A dummy that equals 1 if the drug project is the first therapeutic indication tested for the drug and 0 otherwise. A drug can be tested for many indications, the lead indication is the one the firm believes has the highest likelihood of success.	Biomedtracker

FDA Regulatory Designation Variables		
Rare	A dummy that equals 1 if the drug project is a rare disease and 0 otherwise. A rare disease affects fewer than 200,000 people in the US.	Biomedtracker
Orphan	A dummy that equals 1 after the drug project receives Orphan drug FDA designation and 0 otherwise. This designation qualifies a firm for tax credits for clinical trials, fee exemptions, and potentially seven years of market exclusivity after approval for a drug intended to treat a rare disease (Orphan Drug Act,1983).	Biomedtracker
Fast Track	A dummy that equals 1 after the drug project receives Fast Track FDA designation and 0 otherwise. This designation aims to expedite the development and review of drugs to treat serious conditions and fill an unmet medical need. Fast track designation enables more frequent meetings and written communications with the FDA and eligibility for shorter reviews for approval.	Biomedtracker
Breakthrough	A dummy that equals 1 after the drug project receives Breakthrough Therapy FDA designation and 0 otherwise. This designation is granted by the FDA for expedited development and review of a drug intended to treat a serious condition with preliminary clinical evidence that the drug may be a substantial improvement over current therapy.	Biomedtracker
Priority Review	A dummy that equals 1 after the drug project receives Priority Review FDA and 0 otherwise. This designation reduces FDA review time to 6 months for drugs that would be significant improvements compared to standard therapy.	Biomedtracker
Special Protocol Assessment	A dummy that equals 1 after the drug project receives Special Protocol Assessment FDA designation and 0 otherwise. This designation indicates that the FDA agrees that the development plan is adequate to support approval.	Biomedtracker
Managerial Compensation Variables		
R&D-based Managerial Compensation (R&D MC)	A dummy that equals 1 if the firm reported that R&D metrics were used to determine the variable part of executive compensation and 0 otherwise.	Company Financial Statements
R&D-based Short-term Managerial Compensation (R&D STMC)	A dummy that equals 1 if the firm reported that R&D metrics were used to determine short-term executive compensation and 0 otherwise. Short-term incentive compensation is generally an annual cash bonus.	Company Financial Statements
R&D-based Long-term Managerial Compensation (R&D LTMC)	A dummy that equals 1 if the firm reported that R&D metrics were used to determine long-term executive compensation and 0 otherwise. Long-term incentive compensation is generally achieved by granting stock options that vest over several years.	Company Financial Statements
R&D-based Managerial Compensation Intensity (R&D MCI)	The fraction of variable executive compensation determined by R&D-based performance metrics. If a firm reported weights for both short-term and long-term compensation, the higher value was used. If a firm reported using R&D metrics for executive compensation but did not report any weight, the observation is marked as missing. The variable is equal to 0 if a firm does not use R&D metrics to determine the variable part of executive compensation.	Company Financial Statements

Other Firm-Year-Level Attributes		
R&D Intensity	Ratio of annual pharmaceutical R&D spending over annual pharmaceutical sales.	Evaluate Pharma

Panel B. Likelihood of Approval (LOA) dataset

VARIABLE	DEFINITION	SOURCE
LOA	LOA is Biomedtracker's expectation of a drug project's chance of eventual FDA approval at a point in time. LOA estimates are a combination of phase success benchmarks by therapeutic area and analyst opinion based on specific information in the public domain.	Biomedtracker
In-Licensing Deal	A dummy that equals 1 for a licensing deal announcement event and 0 for internally developed projects. Previously licensed drugs are treated as blank.	Biomedtracker
Other variables: same definitions as in Panel A.		

Panel C. Peak sales dataset

VARIABLE	DEFINITION	SOURCE
Peak Sales	Mean peak annual sales by phase from consensus sales forecast for the drug project. The observation is mean peak sales forecast by phase and year, so there can be many observations for each drug project. Analysts forecast sales throughout the year, but most forecasts are in months when quarterly earnings are reported: January, April, July, and October. The regressions consider the natural log of *Peak Sales*.	Evaluate Pharma
Other variables: same definitions as in the previous Panels.		

Panel D. Drug project discontinuation reason dataset

VARIABLE	DEFINITION	SOURCE
Adverse Event	A dummy that equals 1 if the discontinuation reason for a drug project was an adverse event: an undesired occurrence that results from a medication and 0 otherwise.	Cortellis
Lack of Activity or Efficacy	A dummy that equals 1 if the discontinuation reason for a drug project was lack of activity or efficacy–when the drug project had no statistically significant effect, was inferior to a comparator, or when clinical endpoints were not met–and 0 otherwise.	Cortellis
Pipeline Prioritization	A dummy that equals 1 if the discontinuation reason was pipeline prioritization–when a firm discloses reasons such as funding constraints or competition–and 0 otherwise.	Cortellis
Other	A dummy that equals 1 if the discontinuation reason for a drug project does not fall in the other categories and 0 otherwise. Other reasons for termination include problems with clinical trial enrollment, drug formulation, manufacturing, or drug stability.	Cortellis

Phase	Phase of the drug project when discontinuation occurred. Phases include Phase 1, Phase 2, Phase 3, and the Review by the FDA.	Cortellis
Other variables: same definitions as in the previous Panels.		

Table 2. Phase Success Descriptive Statistics
This Table reports the success rates by phase for both internal and in-licensed drug projects between 2006 and 2020. Success means that the project advanced to the next development phase in clinical trials. Success rate for a phase is determined by dividing the number of successful drug project transitions to the next phase by the total number of advanced and suspended drug projects in the pivotal phase. The success rate from Phase 1 to Approval is calculated by compounding the success rates across all phases.

Phase	Obs.	Success rate (%)
Phase 1		
Internal projects	1,162	42.2
In-licensed projects	751	61.4
All projects	1,913	49.7
Phase 2		
Internal projects	960	24.8
In-licensed projects	1,000	34.7
All projects	1,960	29.8
Phase 3		
Internal projects	360	55.0
In-licensed projects	565	67.1
All projects	925	62.4
Review		
Internal projects	220	92.7
In-licensed projects	393	95.4
All projects	613	94.5
Phase 1 to Approval		
Internal projects		5.3
In-licensed projects		13.6
All projects		8.7

Table 3. Licensing Deals by Phase
This Table reports the phase in which the drug projects were in-licensed.

Phase	Obs.	%	Cum. %
Preclinical	920	51.2	51.2
Phase 1	456	25.4	76.6
Phase 2	289	16.1	92.7
Phase 3	119	6.6	99.3
Review	13	0.7	100
Total	1,797	100	

Table 4. Drug Projects' Characteristics, by Phase

This Table reports the distribution of the characteristics of the drug projects in the sample, by phase. See Table 1, Panel A for the definitions. We exclude Sub-therapeutic Area and Indication for brevity due to the large number of categories for these variables (67 and 456, respectively).

	Phase 1		Phase 2		Phase 3		Review	
	Obs.	%	Obs.	%	Obs.	%	Obs.	%
Total	1,913	100.0	1,960	100.0	925	100.0	613	100.0
Drug Classification:								
NME	1,211	63.3	1,259	64.2	468	50.6	262	42.7
Biologic	630	32.9	609	31.1	288	31.1	199	32.5
Non-NME	72	3.8	92	4.7	169	18.3	152	24.8
Therapeutic Area:								
Allergy	25	1.3	30	1.5	15	1.6	8	1.3
Autoimmune/Immunology	171	8.9	219	11.2	133	14.4	80	13.1
Cardiovascular	98	5.1	94	4.8	69	7.5	41	6.7
Dermatology	4	0.2	13	0.7	7	0.8	7	1.1
Endocrine	173	9.0	123	6.3	91	9.8	63	10.3
Gastroenterology	16	0.8	21	1.1	10	1.1	11	1.8
Hematology	48	2.5	55	2.8	39	4.2	29	4.7
Infectious Disease	130	6.8	111	5.7	88	9.5	73	11.9
Metabolic	44	2.3	32	1.6	12	1.3	6	1.0
Neurology	183	9.6	206	10.5	102	11.0	60	9.8
Obstetrics/Gynecology	11	0.6	16	0.8	6	0.6	3	0.5
Oncology	749	39.2	721	36.8	225	24.3	154	25.1
Ophthalmology	26	1.4	56	2.9	35	3.8	20	3.3
Psychiatry	84	4.4	80	4.1	42	4.5	23	3.8
Renal	15	0.8	11	0.6	4	0.4	1	0.2
Respiratory	108	5.6	136	6.9	38	4.1	27	4.4
Rheumatology	18	0.9	18	0.9	0	0.0	0	0.0
Urology	10	0.5	18	0.9	9	1.0	7	1.1
Lead Indication:	1,154	60.3	784	40.0	469	50.7	367	59.9
Molecule Type:								
Antisene	15	0.8	12	0.6	2	0.2	1	0.2
Carbohydrate/Glycoprotein/Glycopeptide	1	0.1	1	0.1	3	0.3	1	0.2
Cellular	17	0.9	13	0.7	2	0.2	3	0.5
Monoclonal Antibody	480	25.1	485	24.7	196	21.2	133	21.7
Natural Protein	2	0.1	1	0.1	2	0.2	2	0.3
Non-Viral Gene Therapy	0	0.0	1	0.1	1	0.1	0	0.0
Not Specified	173	9.0	42	2.1	1	0.1	1	0.2
Other Nucleic Acid	8	0.4	4	0.2	2	0.2	0	0.0
Peptide	77	4.0	50	2.6	45	4.9	32	5.2
Polyclonal Antibody	0	0.0	1	0.1	0	0.0	0	0.0
Protein	85	4.4	84	4.3	72	7.8	48	7.8
Small Molecule	1,037	54.2	1,234	63.0	569	61.5	366	59.7
Small Molecule with Lip. Delivery	3	0.2	5	0.3	1	0.1	1	0.2
Steroid	6	0.3	13	0.7	27	2.9	24	3.9

Viral	1	0.1	1	0.1	0	0.0	0	0.0
Viral Gene Therapy	3	0.2	8	0.4	1	0.1	1	0.2
Messinger RNA	1	0.1	1	0.1	0	0.0	0	0.0
microRNA	2	0.1	1	0.1	0	0.0	0	0.0
siRNA/RNAi	2	0.1	3	0.2	1	0.1	0	0.0
Regulatory Designations (not mutually exclusive):								
Rare	327	17.1	479	24.4	194	21.0	135	22.0
Orphan	63	3.3	138	7.0	182	19.7	161	26.3
Fast Track	27	1.4	59	3.0	106	11.5	89	14.5
Breakthrough	12	0.6	39	2.0	97	10.5	95	15.5
Priority Review	13	0.7	15	0.8	49	5.3	214	34.9
Special Protocol Assessment	4	0.2	6	0.3	20	2.2	14	2.3

Table 5. Managerial Compensation Variables, by Year

This Table reports the number and frequency of firms adopting R&D-based performance metrics as a basis for variable compensation for managers. In the first three columns we report, for each year in our sample, the number of observations and the frequency of a dummy variable measuring the use of R&D-based managerial compensation for company managers. In the fourth column, we report the average weight of incentive pay for the firms that disclosed it. Variables are defined in Panel A of Table 1. Statistics for *R&D-based Managerial Compensation Intensity* are computed using observations greater than 0 and exclude firms with R&D compensation that do not report the weight.

Year	R&D-based Managerial Compensation		R&D-based Short-term Managerial Compensation		R&D-based Long-term Managerial Compensation		R&D-based Managerial Compensation Intensity		
	Obs.	Freq.	Obs.	Prop.	Obs.	Freq.	Obs.	Weight	St. Dev.
2000	6	0.143	5	0.119	2	0.048			
2001	6	0.143	5	0.119	2	0.048			
2002	5	0.119	4	0.095	2	0.048			
2003	6	0.143	4	0.095	3	0.071	1	1.000	
2004	9	0.214	8	0.190	2	0.048	2	0.545	0.643
2005	10	0.238	9	0.214	2	0.048	3	0.414	0.509
2006	16	0.381	15	0.357	2	0.048	9	0.342	0.288
2007	16	0.381	15	0.357	2	0.048	8	0.281	0.142
2008	17	0.405	16	0.381	3	0.071	9	0.272	0.145
2009	17	0.405	16	0.381	3	0.071	9	0.226	0.084
2010	18	0.429	16	0.381	5	0.119	10	0.238	0.112
2011	21	0.500	19	0.452	5	0.119	12	0.246	0.132
2012	21	0.500	19	0.452	5	0.119	11	0.249	0.119
2013	23	0.548	22	0.524	5	0.119	15	0.243	0.114
2014	23	0.548	21	0.500	6	0.143	17	0.218	0.074
2015	24	0.571	21	0.500	7	0.167	17	0.231	0.099
2016	25	0.595	22	0.524	8	0.190	17	0.237	0.084
2017	26	0.619	22	0.524	10	0.238	18	0.247	0.094
2018	26	0.619	23	0.548	13	0.310	18	0.272	0.130
2019	27	0.643	25	0.595	12	0.286	19	0.277	0.126
2020	29	0.690	27	0.643	14	0.333	22	0.280	0.133
Total	**371**	**0.421**	**334**	**0.379**	**113**	**0.128**	**217**	**0.264**	**0.152**

Table 6. Phase Success baseline regressions

This Table reports results from linear probability regressions for Phase 1, Phase 2, Phase 3, and Review success of internal and in-licensed drug projects between 2006 and 2020. The regression model is that of Equation (1), described in Section 3. The dependent variable is *Phase Success*, a dummy that equals 1 if the drug project advanced to the next phase, and 0 if it was suspended or did not advance within 1.5 times the mean phase duration. The main independent variable is *Internal*, a dummy that equals 1 if the drug project was internally developed and 0 if it was in-licensed. Variables are defined in Table 1. Standard errors are clustered by firm and reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% confidence levels, respectively. The number of observations excludes singletons (Correia, 2015).

	(1)	(2)	(3)	(4)	(5)	(6)
Regressions on Phase 1 Success						
Internal	-0.173***	-0.137***	-0.132***	-0.120***	-0.128***	-0.150***
	(0.026)	(0.028)	(0.036)	(0.039)	(0.032)	(0.037)
Observations	1,911	1,905	1,779	1,665	1,724	1,522
R-Squared	0.125	0.219	0.357	0.454	0.329	0.467
Regressions on Phase 2 Success						
Internal	-0.060*	-0.055*	-0.076**	-0.059*	-0.071**	-0.080**
	(0.033)	(0.030)	(0.032)	(0.034)	(0.028)	(0.037)
Observations	1,959	1,957	1,808	1,709	1,754	1,608
R-Squared	0.161	0.282	0.416	0.495	0.394	0.460
Regressions on Phase 3 Success						
Internal	-0.118***	-0.110***	-0.151***	-0.180***	-0.159***	-0.184***
	(0.036)	(0.036)	(0.039)	(0.039)	(0.049)	(0.045)
Observations	923	919	733	620	701	620
R-Squared	0.233	0.362	0.575	0.723	0.528	0.625
Regressions on Review Success						
Internal	-0.055	-0.055	-0.066	-0.178***	0.006	-0.031
	(0.041)	(0.041)	(0.058)	(0.046)	(0.042)	(0.053)
Observations	612	606	445	345	465	355
R-Squared	0.135	0.246	0.488	0.777	0.466	0.637
Fixed Effects						
Drug Classification	Yes	Yes	Yes	Yes	Yes	Yes
Lead Indication	Yes	Yes	Yes	Yes	Yes	Yes
Regulatory Designations	Yes	Yes	Yes	Yes	Yes	Yes
Therapeutic Area	Yes	-	-	-	-	-
Sub-Therapeutic Area	-	Yes	Yes	-	-	Yes
Molecule Type	-	-	Yes	Yes	Yes	-
Indication	-	-	-	Yes	-	-
Firm	Yes	Yes	-	-	Yes	-
Year	-	Yes	-	-	-	-
Firm x Year	-	-	Yes	Yes	-	-
SubTA x Year	-	-	-	-	Yes	-
Mol. x Year x Firm	-	-	-	-	-	Yes

Table 7. Phase Success and R&D Managers' Compensation

This table reports results from linear probability regressions for Phase 1, Phase 2, Phase 3, and Review success of internal and in-licensed drug projects between 2006 and 2020. The regression model is that of Equation (2), described in Section 3, where we interact the main independent variable, *Internal*, with four different measures of R&D managers' compensation. The dependent variable is *Phase Success*, a dummy that equals 1 if the drug project advanced to the next phase, and 0 if it was suspended or did not advance within 1.5 times the mean phase duration. Variables are defined in Table 1. Each panel reports estimates for a different clinical trial phase. Within panels, we report results from four regressions; the regression heading refers to the compensation variable of interest. Standard errors are clustered by firm and reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% confidence levels, respectively. The number of observations excludes singletons (Correia, 2015).

Panel A. Regressions on Phase 1 Success

	(1)	(2)	(3)	(4)	(5)	(6)
R&D-based Managerial Compensation (R&D MC)						
Internal	-0.245***	-0.208***	-0.225***	-0.186***	-0.179***	-0.195***
	(0.038)	(0.036)	(0.029)	(0.056)	(0.039)	(0.051)
Internal x R&D MC	0.112*	0.099*	0.123***	0.087	0.072	0.060
	(0.059)	(0.058)	(0.059)	(0.064)	(0.053)	(0.060)
R&D MC	-0.147***	-0.070			-0.056	
	(0.045)	(0.045)			(0.050)	
Observations	1,911	1,905	1,779	1,665	1,724	1,522
R-Squared	0.129	0.221	0.359	0.455	0.330	0.467
R&D-based Short-Term Managerial Compensation (R&D STMC)						
Internal	-0.208***	-0.178***	-0.190***	-0.151**	-0.158***	-0.174***
	(0.047)	(0.042)	(0.044)	(0.057)	(0.046)	(0.053)
Internal x R&D STMC	0.064	0.063	0.083	0.044	0.048	0.034
	(0.064)	(0.059)	(0.062)	(0.067)	(0.053)	(0.062)
R&D STMC	-0.112**	-0.055			-0.046	
	(0.055)	(0.052)			(0.062)	
Observations	1,911	1,905	1,779	1,665	1,724	1,522
R-Squared	0.127	0.220	0.358	0.455	0.329	0.467
R&D-based Long-Term Managerial Compensation (R&D LTMC)						
Internal	-0.185***	-0.134***	-0.124***	-0.098**	-0.117***	-0.133***
	(0.024)	(0.028)	(0.041)	(0.046)	(0.033)	(0.040)
Internal x R&D LTMC	0.063	-0.012	-0.035	-0.090	-0.050	-0.079
	(0.074)	(0.079)	(0.076)	(0.079)	(0.091)	(0.073)
R&D LTMC	-0.081	-0.002			0.032	
	(0.053)	(0.059)			(0.060)	
Observations	1,911	1,905	1,779	1,665	1,724	1,522
R-Squared	0.126	0.219	0.358	0.455	0.329	0.467
R&D-based Managerial Compensation Intensity (R&D MCI)						
Internal	-0.237***	-0.196***	-0.204***	-0.178***	-0.133***	-0.173***
	(0.049)	(0.044)	(0.053)	(0.060)	(0.040)	(0.061)
Internal x R&D MCI	0.390	0.362	0.390	0.262	-0.079	0.087
	(0.273)	(0.246)	(0.267)	(0.266)	(0.073)	(0.292)
R&D MCI	-0.445*	-0.313				
	(0.262)	(0.204)				
Observations	1,328	1,319	1,207	1,095	1,522	1,018
R-Squared	0.149	0.249	0.396	0.496	0.467	0.493
Fixed Effects						
Drug Classification	Yes	Yes	Yes	Yes	Yes	Yes
Lead Indication	Yes	Yes	Yes	Yes	Yes	Yes
Regulatory Designations	Yes	Yes	Yes	Yes	Yes	Yes
Therapeutic Area	Yes	-	-	-	-	-
Sub-Therapeutic Area	-	Yes	Yes	-	-	Yes
Molecule Type	-	-	Yes	Yes	Yes	-

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Indication	-	-	-	Yes	-	-
Firm	Yes	Yes	-	-	Yes	-
Year	-	Yes	-	-	-	-
Firm x Year	-	-	Yes	Yes	-	-
SubTA x Year	-	-	-	-	Yes	-
Mol. Type x Year x Firm	-	-	-	-	-	Yes

Panel B. Regressions on Phase 2 Success

	(1)	(2)	(3)	(4)	(5)	(6)
R&D-based Managerial Compensation (R&D MC)						
Internal	0.033	0.067*	0.059*	0.067**	0.036	0.114***
	(0.041)	(0.038)	(0.031)	(0.029)	(0.049)	(0.035)
Internal x R&D MC	-0.120**	-0.166***	-0.172***	-0.163***	-0.145**	-0.246***
	(0.050)	(0.044)	(0.043)	(0.044)	(0.054)	(0.055)
R&D MC	-0.039	-0.102*			0.076	
	(0.064)	(0.042)			(0.068)	
Observations	1,959	1,957	1,808	1,709	1,754	1,608
R-Squared	0.167	0.287	0.420	0.498	0.397	0.467
R&D-based Short-Term Managerial Compensation (R&D STMC)						
Internal	0.038	0.063	0.033	0.047	0.045	0.075
	(0.058)	(0.051)	(0.049)	(0.036)	(0.051)	(0.063)
Internal x R&D STMC	-0.139**	-0.173***	-0.148**	-0.144***	-0.166***	-0.208**
	(0.065)	(0.058)	(0.062)	(0.050)	(0.059)	(0.083)
R&D STMC	-0.046	0.078*			0.035	
	(0.055)	(0.031)			(0.047)	
Observations	1,959	1,957	1,808	1,709	1,754	1,608
R-Squared	0.170	0.288	0.419	0.498	0.399	0.466
R&D-based Long-Term Managerial Compensation (R&D LTMC)						
Internal	-0.044*	-0.037	-0.055**	-0.043	-0.065**	-0.044*
	(0.025)	(0.023)	(0.025)	(0.029)	(0.028)	(0.025)
Internal x R&D LTMC	-0.083	-0.093	-0.105	-0.083	-0.044	-0.173**
	(0.080)	(0075)	(0.067)	(0.063)	(0.057)	(0.077)
R&D LTMC	0.058	0.078			0.086	
	(0.076)	(0.077)			(0.077)	
Observations	1,959	1,957	1,808	1,709	1,754	1,608
R-Squared	0.162	0.283	0.417	0.496	0.395	0.464
R&D-based Managerial Compensation Intensity (R&D MCI)						
Internal	0.051	0.077**	0.075**	0.089***	0.043	0.129***
	(0.039)	(0.034)	(0.031)	(0.027)	(0.044)	(0.034)
Internal x R&D MCI	-0.632***	-0.758***	-0.744***	-0.534**	-0.553**	-1.047***
	(0.160)	(0.159)	(0.167)	(0.205)	(0.214)	(0.262)
R&D MCI	0.012	0.479**			0.393	
	(0.298)	(0.202)			(0.276)	
Observations	1,291	1,288	1,164	1,055	1,092	1,003
R-Squared	0.183	0.323	0.469	0.571	0.444	0.518
Fixed Effects						
Drug Classification	Yes	Yes	Yes	Yes	Yes	Yes
Lead Indication	Yes	Yes	Yes	Yes	Yes	Yes
Regulatory Designations	Yes	Yes	Yes	Yes	-	-
Therapeutic Area	Yes	-	-	-	-	-
Sub-Therapeutic Area	-	Yes	Yes	-	-	Yes
Molecule Type	-	-	Yes	Yes	Yes	-
Indication	-	-	-	Yes	-	Yes
Firm	Yes	Yes	-	-	Yes	-
Year	-	Yes	-	-	-	-
Firm x Year	-	-	Yes	Yes	-	-
SubTA x Year	-	-	-	-	Yes	-
Mol. x Year x Firm	-	-	-	-	-	Yes

Panel C. Regressions on Phase 3 Success

	(1)	(2)	(3)	(4)	(5)	(6)
R&D-based Managerial Compensation (R&D MC)						
Internal	-0.129*	-0.136*	-0.296***	-0.314***	-0.175**	-0.305***
	(0.072)	(0.072)	(0.069)	(0.052)	(0.085)	(0.091)
Internal x R&D MC	0.021	0.042	0.202**	0.187***	0.044	0.172
	(0.077)	(0.079)	(0.082)	(0.061)	(0.092)	(0.104)
R&D MC	-0.113*	-0.063			-0.196***	
	(0.059)	(0.059)			(0.063)	
Observations	923	919	733	620	701	620
R-Squared	0.236	0.363	0.579	0.726	0.533	0.627
R&D-based Short-Term Managerial Compensation (R&D STMC)						
Internal	-0.130**	-0.145**	-0.283***	-0.291***	-0.177**	-0.298***
	(0.064)	(0.062)	(0.066)	(0.048)	(0.080)	(0.087)
Internal x R&D STMC	0.025	0.059	0.190**	0.160**	0.054	0.167
	(0.071)	(0.071)	(0.083)	(0.062)	(0.086)	(0.102)
R&D STMC	-0.125*	-0.071			-0.235***	
	(0.069)	(0.046)			(0.047)	
Observations	923	919	733	620	701	620
R-Squared	0.238	0.363	0.579	0.725	0.537	0.627
R&D-based Long-Term Managerial Compensation (R&D LTMC)						
Internal	-0.120***	-0.107**	-0.158***	-0.188***	-0.164***	-0.298***
	(0.041)	(0.039)	(0.043)	(0.047)	(0.051)	(0.087)
Internal x R&D LTMC	0.018	-0.028	0.051	0.046	0.073	0.167
	(0.046)	(0.061)	(0.049)	(0.080)	(0.082)	(0.102)
R&D LTMC	0.003	-0.007			0.026	
	(0.076)	(0.085)			(0.096)	
Observations	923	919	733	620	701	620
R-Squared	0.233	0.362	0.575	0.723	0.528	0.627
R&D-based Managerial Compensation Intensity (R&D MCI)						
Internal	-0.150**	-0.125	-0.219**	-0.286***	-0.247***	-0.269**
	(0.060)	(0.074)	(0.085)	(0.056)	(0.082)	(0.111)
Internal x R&D MCI	0.244	0.107	0.314	0.515	0.483	0.112
	(0.258)	(0.349)	(0.519)	(0.439)	(0.483)	(0.613)
R&D MCI	-0.370	0.145			-0.247	
	(0.245)	(0.261)			(0.462)	
Observations	651	645	484	385	462	406
R-Squared	0.228	0.389	0.588	0.769	0.568	0.638
Fixed Effects						
Drug Classification	Yes	Yes	Yes	Yes	Yes	Yes
Lead Indication	Yes	Yes	Yes	Yes	Yes	Yes
Regulatory Designations	Yes	Yes	Yes	Yes	Yes	Yes
Therapeutic Area	Yes	-	-	-	-	-
Sub-Therapeutic Area	-	Yes	Yes	-	-	Yes
Molecule Type	-	-	Yes	Yes	Yes	-
Indication	-	-	-	Yes	-	-
Firm	Yes	Yes	-	-	Yes	-
Year	-	Yes	-	-	-	-
Firm x Year	-	-	Yes	Yes	-	-
SubTA x Year	-	-	-	-	Yes	-
Mol. x Year x Firm	-	-	-	-	-	Yes

Panel D. Regressions on Review Phase Success

	(1)	(2)	(3)	(4)	(5)	(6)
R&D-based Managerial Compensation (R&D MC)						
Internal	-0.035	-0.027	-0.021	-0.120	0.036	0.091
	(0.049)	(0.045)	(0.084)	(0.076)	(0.049)	(0.060)
Internal x R&D MC	-0.029	-0.039	-0.056	-0.072	-0.041	-0.234**
	(0.064)	(0.060)	(0.104)	(0.101)	(0.070)	(0.097)
R&D MC	0.069	0.050			0.011	
	(0.049)	(0.052)			(0.062)	
Observations	612	606	445	345	465	373
R-Squared	0.140	0.248	0.489	0.778	0.467	0.539
R&D-based Short-Term Managerial Compensation (R&D STMC)						
Internal	-0.066	-0.058	-0.041	-0.134**	0.003	-0.016
	(0.058)	(0.049)	(0.081)	(0.058)	(0.049)	(0.129)
Internal x R&D STMC	0.014	0.003	-0.033	-0.058	0.004	-0.097
	(0.061)	(0.056)	(0.103)	(0.093)	(0.070)	(0.118)
R&D STMC	0.049	0.031			0.003	
	(0.040)	(0.040)			(0.053)	
Observations	612	606	445	345	465	373
R-Squared	0.140	0.247	0.489	0.778	0.466	0.529
R&D-based Long-Term Managerial Compensation (R&D LTMC)						
Internal	-0.052	-0.047	-0.060	-0.151**	0.008	-0.056
	(0.039)	(0.039)	(0.065)	(0.062)	(0.043)	(0.070)
Internal x R&D LTMC	-0.002	-0.035	-0.024	-0.109	-0.017	-0.139
	(0.045)	(0.046)	(0.075)	(0.112)	(0.066)	(0.119)
R&D LTMC	0.063*	0.040			-0.023	
	(0.037)	(0.044)			(0.061)	
Observations	612	606	445	345	465	373
R-Squared	0.139	0.248	0.488	0.779	0.466	0.530
R&D-based Managerial Compensation Intensity (R&D MCI)						
Internal	-0.051	-0.046	-0.074	-0.168	0.011	0.079
	(0.035)	(0.039)	(0.071)	(0.108)	(0.032)	(0.067)
Internal x R&D MCI	-0.113	-0.110	-0.028	-0.041	-0.139	-0.696*
	(0.174)	(0.157)	(0.378)	(0.503)	(0.234)	(0.394)
R&D MCI	0.303**	0.325**			0.557**	
	(0.126)	(0.136)			(0.222)	
Observations	461	453	317	230	333	278
R-Squared	0.167	0.264	0.552	0.767	0.574	0.595
Fixed Effects						
Drug Classification	Yes	Yes	Yes	Yes	Yes	Yes
Lead Indication	Yes	Yes	Yes	Yes	Yes	Yes
Regulatory Designations	Yes	Yes	Yes	Yes	Yes	Yes
Therapeutic Area	Yes	-	-	-	-	-
Sub-Therapeutic Area	-	Yes	Yes	-	-	Yes
Molecule Type	-	-	Yes	Yes	Yes	-
Indication	-	-	-	Yes	-	-
Firm	Yes	Yes	-	-	Yes	-
Year	-	Yes	-	-	-	-
Firm x Year	-	-	Yes	Yes	-	-
SubTA x Year	-	-	-	-	Yes	-
Mol. x Year x Firm	-	-	-	-	-	Yes

Table 8. Likelihood of Approval (LOA): Descriptive Statistics

This Table shows summary statistics for LOA by clinical trial phase for internal and in-licensed projects between 2006 and 2020. LOA is defined in Panel B of Table 1, and measured at the date of the deal announcement for in-licensed drug projects, and at a phase initiation event for internally developed drug projects.

Phase	Obs.	Mean %	St. Dev. %
Phase 1			
Internal projects	1,804	78.3	4.5
In-licensed projects	288	78.9	4.5
All projects	2,092	78.4	4.5
Phase 2			
Internal projects	2,157	15.9	5.9
In-licensed projects	391	15.0	6.3
All projects	2,548	15.7	6.0
Phase 3			
Internal projects	1,325	55.3	8.7
In-licensed projects	202	53.5	11.3
All projects	1,527	55.1	9.1
Review			
Internal projects	423	92.5	6.6
In-licensed projects	57	93.3	6.8
All projects	480	92.6	6.6

Table 9. Likelihood of Approval (LOA) at In-Licensing Deal Announcement

This Table reports results from linear regressions. The regression model is that of Equation (1), described in Section 3, where the dependent variable is the LOA for each drug development project. For in-licensed projects, the LOA is measured at the time of the in-licensing deal. For internally developed projects, LOA is measured at the phase initiation event. The main independent variable is *In-Licensing Deal*, a dummy that equals 1 if an in-licensing deal announcement event occurred, and 0 otherwise. Variables are defined in Table 1. Standard errors are clustered by firm and reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% confidence levels, respectively. The number of observations excludes singletons (Correia, 2015).

	(1)	(2)	(3)	(4)
In-licensing Deal	0.006**	0.008***	0.008***	0.006**
	(0.002)	(0.002)	(0.002)	(0.002)
Fixed Effects				
Phase	Yes	Yes	Yes	Yes
Drug Classification	Yes	Yes	Yes	Yes
Lead Indication	Yes	Yes	Yes	Yes
Reg. Designations	Yes	Yes	Yes	Yes
Therapeutic Area	Yes	Yes	Yes	Yes
Molecule Type	-	-	Yes	Yes
Firm	Yes	Yes	Yes	-
Year	-	Yes	Yes	-
Firm x Year	-	-	-	Yes
Observations	6,645	6,645	6,645	6,582
R-Squared	0.979	0.979	0.979	0.982

Table 10. Peak Sales Forecast: Descriptive Statistics
This Table shows descriptive statistics for peak sales forecasts, by phase, for large biopharma firms' internal and in-licensed projects for each phase between 2006 and 2020, in dollar millions. There are 12,573 sales forecast observations of 1,032 drug projects: 544 Internal and 488 In-licensed.

Phase	Obs.	Mean	St. Dev.
Phase 1			
Internal projects	396	28.9	68.0
In-licensed projects	160	41.2	95.9
All projects	556	32.4	77.2
Phase 2			
Internal projects	2,040	69.6	264.0
In-licensed projects	1,912	77.7	139.0
All projects	3,952	73.5	212.9
Phase 3			
Internal projects	2,585	395.4	609.1
In-licensed projects	3,608	365.0	462.5
All projects	6,193	377.7	528.8
Review			
Internal projects	677	804.5	1,043.3
In-licensed projects	1,195	693.9	801.0
All projects	1,872	733.9	887.5

Table 11. Peak Sales Forecasts

This Table reports results from linear regressions. The regression model is that of Equation (1), described in Section 3, where the dependent variable is now the log of *Peak Sales Forecast* for internal and in-licensed drug development projects developed by large biopharma firms between 2006 and 2020. The main independent variable is *Internal*, a dummy that equals 1 if the drug project was internally developed, and 0 if it was in-licensed. Variables are defined in Table 1. Standard errors are clustered by firm and reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% confidence levels, respectively. The number of observations excludes singletons (Correia, 2015).

	(1)	(2)	(3)	(4)	(5)	(6)
Internal	-0.177**	-0.150*	-0.200**	-0.163*	-0.151*	-0.164*
	(0.081)	(0.082)	(0.080)	(0.084)	(0.086)	(0.088)
Fixed Effects						
Phase	Yes	Yes	Yes	Yes	Yes	Yes
Drug Classification	Yes	Yes	Yes	Yes	Yes	Yes
Therapeutic Area	Yes	-	-	-	-	-
Sub-Therapeutic Area	Yes	Yes	-	-	-	Yes
Indication	Yes	-	Yes	Yes	-	-
Molecule Type	-	Yes	Yes	Yes	Yes	-
Firm	Yes	Yes	Yes	-	Yes	-
Year	-	Yes	Yes	-	-	-
Firm x Year	-	-	-	Yes	-	-
SubTA x Year	-	-	-	-	Yes	-
Mol. x Year x Firm	-	-	-	-	-	Yes
Observations	12,572	12,571	12,568	12,543	12,484	12,452
R-Squared	0.487	0.539	0.577	0.651	0.606	0.675

Table 12. Phase 2 Likelihood of Approval (LOA) and R&D-based Managerial Compensation Interactions

This Table reports results from linear regressions. The regression model is a variation of Equation (2), described in Section 3, where the dependent variable is the Likelihood of Approval (LOA) for internal and in-licensed drug development projects developed by large biopharma firms between 2006 and 2020. For in-licensed projects, the LOA is measured at the time of the in-licensing deal. For internally developed projects, the LOA is measured at the phase initiation event. The main independent variable is *In-Licensing Deal*, a dummy that equals 1 if an in-licensing deal announcement event occurred, and 0 if not. The sample focuses on projects in Phase 2. All variables are defined in Table 1. Standard errors are clustered by firm and reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% confidence levels, respectively. The number of observations excludes singletons (Correia, 2015).

	(1)	(2)	(3)	(4)
In-Licensing Deal	0.006	0.007	0.007	0.009
	(0.005)	(0.005)	(0.004)	(0.006)
R&D MC	0.002	0.001	0.000	-0.005
	(0.001)	(0.001)	(0.001)	(0.009)
In-Licensing Deal x R&D MC	-0.001	-0.002	-0.001	-0.009
	(0.005)	(0.005)	(0.005)	(0.006)
<u>Fixed Effects</u>				
Drug Classification	Yes	Yes	Yes	Yes
Lead Indication	Yes	Yes	Yes	Yes
Regulatory Designations	Yes	Yes	Yes	Yes
Therapeutic Area	Yes	Yes	Yes	Yes
Molecule Type	-	-	Yes	Yes
Firm	Yes	Yes	Yes	-
Year	-	Yes	Yes	-
Firm x Year	-	-	-	Yes
Observations	2,547	2,547	2546	2,429
R-Squared	0.903	0.904	0.905	0.940

Table 13. Drug Project Discontinuation Reasons: Descriptive Statistics

This Table shows the reason for drug project discontinuation observations, by phase, for both internal and in-licensed projects between 2006 and 2020. Adverse Events, Lack of Activity or Efficacy, and Other are considered drug project-related discontinuation reasons. Pipeline Prioritization is a discontinuation reason that is not related to the drug project, such as a strategic or budgeting decision. Variables are defined in Table 1.

	Project Related			Not Project Related	
	Adverse Event	Lack of Activity or Efficacy	Other	Pipeline Prioritization	Total
Phase 1					
Internal projects	2	6	4	3	15
In-licensed projects	0	4	2	3	9
All Projects	2	10	6	6	24
Phase 2					
Internal projects	5	36	11	28	80
In-licensed projects	5	73	21	10	109
All Projects	10	109	32	38	189
Phase 3					
Internal projects	4	45	8	7	64
In-licensed projects	4	56	10	6	76
All Projects	8	101	18	13	140
Review					
Internal projects	0	2	2	2	6
In-licensed projects	0	4	13	1	18
All Projects	0	6	15	3	24
All Phases					
Internal projects	11	89	25	40	165
In-licensed projects	9	137	46	20	212
All Projects	20	226	71	60	377

Table 14. Pipeline Prioritization Discontinuation Reason

This table reports results from linear probability regressions. The regression model is that of Equation (1), described in Section 3, where the dependent variable is the Pipeline Prioritization discontinuation reason dummy. The sample includes internal and in-licensed projects terminated between 2006 and 2020. The main independent variable, *Internal*, is a dummy that equals 1 if the drug project was internally developed and 0 if it was in-licensed. Variables are defined in Table 1. Standard errors are clustered by firm and reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% confidence levels, respectively. The number of observations excludes singletons (Correia, 2015).

	(1)	(2)	(3)	(4)
Internal	0.148**	0.151**	0.162**	0.186***
	(0.069)	(0.064)	(0.067)	(0.061)
Fixed Effects				
Phase	Yes	Yes	Yes	Yes
Drug Classification	-	Yes	Yes	Yes
Therapeutic Area	-	-	Yes	Yes
Year	-	-	-	Yes
Observations	377	376	372	372
R-Squared	0.063	0.081	0.160	0.210

Online Appendix

A. SAMPLE COMPOSITION

Table A1. Large Public Biopharma Firm Cohort.

Firm	Pharma Exec Top 50 Rank	2020 Pharma Sales ($B)	2020 R&D Expenditure ($B)
1. AbbVie Inc.	3	44.34	5.83
2. Alexion Pharmaceuticals Inc.	27	6.07	1.00
3. Allergan plc	33	4.77	0.61
4. Amgen Inc.	12	24.10	4.09
5. Astellas Pharma Inc.	18	11.52	2.12
6. AstraZeneca plc	11	25.52	5.87
7. Aurobindo Pharma Limited	46	3.00	0.11
8. Bausch Health Companies Inc.	32	4.88	0.45
9. Bayer AG	16	19.00	3.13
10. Biogen Inc.	21	10.69	3.99
11. Boehringer Ingelheim GmbH	17	16.46	3.75
12. Bristol Myers Squibb Company	5	41.90	9.24
13. Chugai Pharmaceutical Co. Ltd.	41	3.88	1.06
14. CSL Limited	22	9.66	0.96
15. CSPC Pharmaceutical Group Limited	44	3.24	0.39
16. Daiichi Sankyo Co. Ltd.	23	8.03	2.15
17. Eisai Co. Ltd.	31	5.11	1.45
18. Eli Lilly and Company	14	22.65	6.09
19. Endo International plc	49	2.90	0.16
20. Fresenius SE & Co. KGaA	37	4.22	0.63
21. Gilead Sciences Inc.	13	23.81	4.86
22. GlaxoSmithKline plc	9	30.59	5.91
23. Ipsen SA	47	2.96	0.46
24. Jiangsu Hengrui Medicine Co. Ltd.	38	4.20	0.71
25. Johnson & Johnson	4	43.15	9.56
26. Merck & Co. Inc.	6	41.44	9.23
27. Merck KGaA	24	7.58	1.87
28. Novartis AG	2	47.20	8.48
29. Novo Nordisk A/S	15	19.44	2.37
30. Ono Pharmaceutical Company Ltd.	48	2.91	0.62
31. Otsuka Holdings Co. Ltd.	25	7.22	1.93
32. Pfizer Inc.	8	35.61	8.88
33. Regeneron Pharmaceuticals Inc.	28	5.57	2.65
34. Roche Holding AG	1	47.49	11.30
35. Sanofi	7	35.80	5.89
36. Sumitomo Dainippon Pharma Co. Ltd.	39	4.03	0.99
37. Sun Pharmaceutical Industries Ltd.	35	4.63	0.27
38. Takeda Pharmaceutical Co. Ltd.	10	27.90	4.39
39. Teva Pharmaceutical Industries Ltd.	20	11.01	1.00

40. UCB S.A.	29	5.46	1.79
41. Vertex Pharmaceuticals Incorporated	26	6.20	1.64
42. Viatris Inc.	19	11.50	0.51
Total		**697.60**	**138.37**

Estimated 2020 Total Pharmaceutical Sales: $1,228.5B
Of which:
42 Firm Pharmaceutical Sales: $697.6B
42 Firm % of Pharmaceutical Sales: 57%

Estimated 2020 Total Pharmaceutical R&D Spend: $198B
Of which:
42 Firm Pharmaceutical R&D Spend: $138.4B
42 Firm % of Pharmaceutical R&D Spend: 70%

Sources:

1) 2020 Firm-level Pharmaceutical Sales and R&D Spending: Christel, M. (2021)
2) 2020 Pharmaceutical Sales: Research and Markets (2021)
3) 2020 Pharmaceutical R&D Spending: International Federation of Pharmaceutical Manufacturers & Associations (2022)

B. DETAILS ON PHASE DURATION

**Table B1. Clinical Phase Durations for Phase Success Calculations**
This table shows the phase durations used to calculate phase success based on 1.5 times the median phase durations reported in Martin et al. (2017).

Clinical Trial Phase	Duration Benchmark (months)	Phase Failure Duration (months)
Phase 1	30	45
Phase 2	35	53
Phase 3	41	62

C. SUPPLEMENTARY ANALYSES

Figure C1. Introduction of R&D-based Managerial Compensation and Phase 2 Success Rate of In-licensed Drug Projects

The graph shows the estimates of the dynamic treatment effect of the introduction of R&D-based managerial compensation on the success rate in Phase 2 of in-licensed drug projects. The vertical axis reports the IW estimates described in Section 3 (Sun, 2021; Sun and Abraham, 2021) with 95% confidence intervals. The horizontal axis measures the leads and lags (in years) since the introduction of the R&D-based compensation, where period –1 is the excluded category. The bins for years +/–7 also include more distant leads and lags, respectively. The estimates are obtained from the subsample of in-licensed drug projects. Treated cohorts are in-licensed drug projects of firms that introduced R&D-based compensation. The control cohort consists of in-licensed drug projects of firms that never introduced these compensation schemes ("never treated"). In-licensed drug projects of firms that introduced these compensation schemes before the sample period ("always treated") are excluded from the estimation. The estimates are obtained using the same set of fixed effects as model (2) in Tables 6 and 7. More restrictive specifications with firm × year fixed effects cannot be used here because they would absorb the relative time periods (since the sample includes in-licensed drug projects only). Standard errors are clustered by firm.
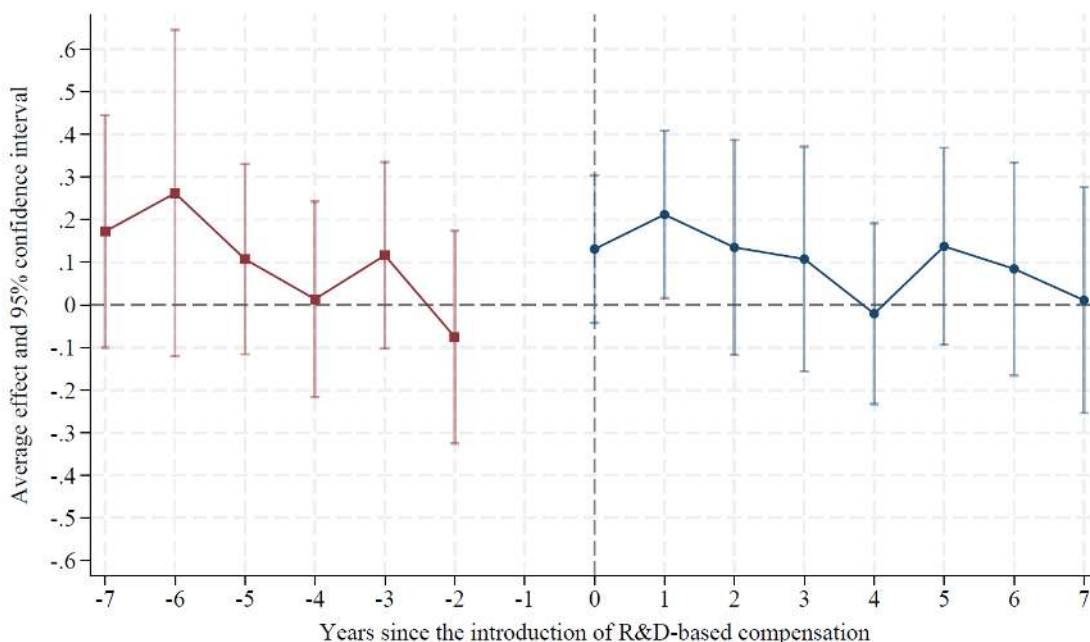
Table C1. Phase Success and Absorptive Capacity

This Table reports results from linear probability regressions for Phase success of internal and in-licensed projects between 2006 and 2020. The regression model is that of Equation (2), described in Section 3, where we interact the main independent variable, *Internal*, with *R&D intensity*. The dependent variable is *Phase Success*, a dummy that equals 1 if the drug project advanced to the next phase, and 0 if it was suspended, or did not advance within 1.5 times the mean phase duration. The sample includes projects in all phases and the regressions include phase fixed effects. Variables are defined in Table 1. Standard errors are clustered by firm and reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% confidence levels, respectively. The number of observations excludes singletons (Correia, 2015).

	(1)	(2)	(3)	(4)	(5)	(6)
Internal	-0.118***	-0.105***	-0.095***	-0.088***	-0.103***	-0.103**
	(0.025)	(0.025)	(0.026)	(0.028)	(0.029)	(0.028)
Internal x R&D Intensity	-0.010	-0.025*	-0.092***	-0.097***	-0.015	-0.103***
	(0.015)	(0.014)	(0.025)	(0.023)	(0.020)	(0.030)
R&D Intensity	0.010	0.023*			0.017	
	(0.014)	(0.013)			(0.024)	
Observations	5,410	5,408	5,277	5,212	5,185	4,884
R-Squared	0.234	0.297	0.378	0.438	0.369	0.436
Fixed Effects						
Phase	Yes	Yes	Yes	Yes	Yes	Yes
Drug Classification	Yes	Yes	Yes	Yes	Yes	Yes
Lead Indication	Yes	Yes	Yes	Yes	Yes	Yes
Regulatory Designations	Yes	Yes	Yes	Yes	Yes	Yes
Therapeutic Area	Yes	-	-	-	-	-
Sub-Therapeutic Area	-	Yes	Yes	-	-	Yes
Molecule Type	-	-	Yes	Yes	Yes	-
Indication	-	-	-	Yes	-	-
Firm	Yes	Yes	-	-	Yes	-
Year	-	Yes	-	-	-	-
Firm x Year	-	-	Yes	Yes	-	-
SubTA x Year	-	-	-	-	Yes	-
Mol. x Year x Firm	-	-	-	-	-	Yes

Table C2. Phase 2 R&D Compensation Variables Interactions Robustness.
This Table reports linear probability regressions of Phase 2 success of internal and in-licensed projects between 2006 and 2020, including the interactions between the *Internal* and R&D-compensation variables. The table replicates the regressions reported in Table 7 in the main text but excludes projects discontinued due to pipeline prioritization reasons (14 observations). Variables are defined in Table 1. Standard errors are clustered by firm and reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. The number of observations excludes singletons (Correia, 2015).

	(1)	(2)	(3)	(4)	(5)	(6)
R&D-based Managerial Compensation (R&D MC)						
Internal	0.034	0.070*	0.048	0.052	0.038	0.105***
	(0.044)	(0.040)	(0.034)	(0.031)	(0.053)	(0.035)
Internal x R&D MC	-0.122**	-0.171***	-0.164***	-0.150***	-0.147**	-0.240***
	(0.052)	(0.046)	(0.046)	(0.048)	(0.058)	(0.056)
R&D MC	-0.037	-0.106**			0.082	
	(0.064)	(0.043)			(0.068)	
Observations	1,945	1,943	1,794	1,693	1,737	1,592
R-Squared	0.168	0.288	0.423	0.503	0.398	0.470
R&D-based Short-Term Managerial Compensation (R&D STMC)						
Internal	0.038	0.066	0.024	0.034	0.046	0.067
	(0.059)	(0.053)	(0.051)	(0.036)	(0.055)	(0.064)
Internal x R&D STMC	-0.141**	-0.177***	-0.141**	-0.133**	-0.168**	-0.203**
	(0.067)	(0.060)	(0.064)	(0.052)	(0.062)	(0.084)
R&D STMC	-0.043	0.081**			0.038	
	(0.054)	(0.032)			(0.048)	
Observations	1,945	1,943	1,794	1,693	1,737	1,592
R-Squared	0.171	0.289	0.423	0.503	0.400	0.469
R&D-based Long-Term Managerial Compensation (R&D LTMC)						
Internal	-0.045*	-0.038	-0.061**	-0.048	-0.065**	-0.049*
	(0.025)	(0.023)	(0.025)	(0.030)	(0.029)	(0.025)
Internal x R&D LTMC	-0.085	-0.095	-0.104	-0.088	-0.044	-0.174**
	(0.081)	(0.075)	(0.069)	(0.066)	(0.057)	(0.081)
R&D LTMC	0.058	0.080			0.090	
	(0.077)	(0.077)			(0.076)	
Observations	1,945	1,943	1,794	1,693	1,737	1,592
R-Squared	0.163	0.285	0.421	0.501	0.395	0.468
R&D-based Managerial Compensation Intensity (R&D MCI)						
Internal	0.053	0.081**	0.068**	0.073**	0.047	0.121***
	(0.041)	(0.035)	(0.032)	(0.027)	(0.047)	(0.034)
Internal x R&D MCI	-0.634***	-0.765***	-0.720***	-0.485**	-0.554**	-1.019***
	(0.165)	(0.161)	(0.170)	(0.207)	(0.220)	(0.264)
R&D MCI	0.015	0.484**			0.408	
	(0.299)	(0.202)			(0.276)	
Observations	1,281	1,278	1,154	1,047	1,081	990
R-Squared	0.183	0.323	0.471	0.572	0.444	0.519
Fixed Effects						
Drug Classification	Yes	Yes	Yes	Yes	Yes	Yes
Lead Indication	Yes	Yes	Yes	Yes	Yes	Yes
Regulatory Designations	Yes	Yes	Yes	Yes	Yes	Yes
Therapeutic Area	Yes	-	-	-	-	-
Sub-Therapeutic Area	-	Yes	Yes	-	-	Yes

Molecule Type	-	-	Yes	Yes	Yes	-
Indication	-	-	-	Yes	-	-
Firm	Yes	Yes	-	-	Yes	-
Year	-	Yes	-	-	-	-
Firm x Year	-	-	Yes	Yes	-	-
SubTA x Year	-	-	-	-	Yes	-
Mol. x Year x Firm	-	-	-	-	-	Yes