Investing in AI: Clinical Trial Efficiency and Market Reaction

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Abstract

While artificial intelligence (AI) is heralded as a panacea, we still grapple with the optimal ways to harness its potential. Using project-level clinical trial data, we find that pharmaceutical firms' AI investment, on average, does not improve trial efficiency or financial prospects. We identify the contexts where AI adds value and when it does not. Overall, complementary human expertise, balanced regulation, and optimization objective clarity are critical for realizing AI's potential. When these factors come together, AI can improve efficiency and financial prospects of clinical trials, which in turn enhances social welfare. Our analysis addresses an emerging question: not whether firms should adopt AI, but how they can do so effectively.

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I. Introduction

Recent advances in artificial intelligence (AI) and the spread of large language models such as ChatGPT are fueling the belief that AI will reshape every aspect of human life, from autonomous vehicles and diagnostic support in healthcare to personalized financial services. Research has shown that investing in AI leads to increased productivity, sales growth, enhanced market recognition, and greater demand for AI talent (Alekseeva et al. 2021; Acemoglu et al. 2022). In the finance domain, AI, and more broadly machine learning, are used to predict stock returns (Gu, Kelly, and Xiu 2020; Cao et al. 2024; Li et al. 2025), analyze product markets (Hoberg and Maksimovic 2022) and innovation trends (Kelly et al. 2021), decipher corporate disclosures (Hanley and Hoberg 2019; Bochkay et al. 2020; Huang et al. 2023), assist personal financial advising (D'Acunto, Prabhala, and Rossi 2019; Rossi and Utkus 2024), and improve underwriting quality (Jansen et al. 2025). Despite this enthusiasm, AI may not be a panacea; it may actually destroy productivity. For example, a recent report finds that 95 percent of organizations are seeing zero return on in-house AI investments (Challapally et al. 2025). Another recent study reports that AI increases the amount of work that appears valuable but lacks substance—colloquially referred to as "workslop" (Niederhoffer et al. 2025).

Researchers, practitioners, and regulators are increasingly acknowledging that the use of AI alone does not guarantee success. Successful application requires industry knowledge and understanding of AI and other information technologies. Meanwhile, the opacity of AI models has drawn regulatory scrutiny (Goodman and Flaxman 2017). In 2024 alone, nearly 700 AI related bills were introduced in state legislatures (Sonnenfeld and Henriques 2025) on top of 59 AI regulations initiated by federal agencies (AI Index Steering Committee 2025), which highlights a rapidly evolving regulatory environment and greater investment risk. Furthermore, effective use

of AI depends on a well-specified optimization objective; yet many tasks are multi-faceted in practice. By "optimization objective," we mean how clearly defined and measurable the goals or success criteria of a task are defined for an AI system. For example, corporate governance involves balancing the interests of shareholders, accommodating the preferences of other stakeholders, and adhering to legal requirements as well as established policies and customs. When AI is applied to such complex tasks with competing objectives, AI's decisions may not achieve the intended optimization (Foucault et al. 2025).[1] Against this backdrop, this study investigates how AI investment affects clinical trials efficiency, and more importantly, what conditions help avoid futile AI spending and release the full potential of AI. Answers to these questions will help separate hope from hype and result in informed decision-making on optimal AI investment.

We make the empirical choice to study the pharmaceutical industry for three reasons. First, conventional drug development is lengthy, expensive, and fraught with a high failure rate (Chen et al. 2021), which thwarts investment in novel medical solutions (Krieger, Li, and Papanikolaou 2022). Such a challenge creates a natural demand for AI technologies which could streamline development and improve trial success rates. Reflecting this potential, AI investment within the pharmaceutical industry has surged. For example, Pfizer has used supercomputing and AI since 2020 to develop new drugs like PAXLOVID; Novartis has more than 150 ongoing projects applying AI; and Lilly aims to expand its digital workforce through over 100 AI projects (Buntz 2023). Second, AI applications are multifaceted, which makes it hard to pinpoint what business activities benefit from AI investment and how those benefits translate into firm-level outcomes. Public clinical trial data provide granular, project-level timelines and outcomes, allowing us to

[1] For example, AI-driven algorithms could leverage vast amounts of market data to determine the optimal strategy for stock buybacks that aligns better with market conditions than traditional human-led approaches. However, such an AI program could result in unintended consequences such as signal insider-like behavior, create liquidity imbalances, or distort market prices (Foucault et al. 2025).

focus on outcomes directly tied to the drug development process rather than broad firm-level aggregated metrics. Third, clinical trials are complex processes that deploy AI at multiple stages for diverse objectives. For instance, some trials examine safety and effectiveness of drugs while others test accuracy of medical devices; some trials deploy AI upstream for research design while other trials use AI downstream for result measurement and analyses (Chen et al. 2021). This heterogeneity offers an ideal setting to identify AI's effectiveness in complex tasks and where AI adds the most value.

Following prior studies (Babina et al. 2024), we measure AI investment using both AI employment from Revelio Labs and AI job posting data from Burning Glass.[2] At the trial level, we focus on three outcomes, two of which measure trial efficiency and the other measures financial impact. Trial efficiency is evaluated by trial duration (i.e., days to trial completion) and the likelihood of trial completion (Operational Efficiency Working Group 2010). In addition, within 12 months of the primary completion date, the sponsoring firm must file an information package with the FDA. Investors closely follow these updates to evaluate the drug's safety, efficacy, and approval prospects. Therefore, we measure trial financial prospects using trial completion announcement returns.

AI investment is correlated with an array of firm and industry characteristics (Babina et al. 2024), raising concerns about correlated omitted variables and reverse causality. We therefore employ an instrumental variable strategy that uses the supply of AI talent as an instrument for firm-level AI adoption (Cao et al. 2023). Using this approach, we find little evidence that AI affects the days required to complete clinical trials, the likelihood of trial completion, or market reactions to

[2] The Revelio Lab data tracks the actual employment of AI-skilled professionals and reflects the stock of AI workers. The Burning Glass job posting data measures each firm's demand for AI-related human capital through job postings. Together, these measures capture complementary aspects of a firm's overall AI investment.

trial completion announcements. The negative or null effect of AI investment is in sharp contrast to the rosy prospects of AI portrayed in mass media.

Motivated by this perception–performance gap, we next explore the conditions when AI improves trial efficiency and delivers values. Prior studies suggest that effective deployment of AI relies on complementary human, regulation, and technical factors (Cao et al. 2025). Therefore, we study three factors relating to human expertise, regulatory oversight, and technical design that might moderate the effect of AI investment. First, effective application of AI requires "human-AI collaboration" (Levina 2005; Foucault et al. 2025). Modern AI solutions often function as "black boxes" to users, creating obstacles for effective collaboration between humans and AI (Wang et al. 2023). Expertise and knowledge are key elements that help a decision-maker to integrate diverse knowledge and information (Lawrence and Lorsch 1967). Therefore, we first explore whether executives with stronger technology domain expertise are better able to unlock the benefits of AI.

Second, regulatory approval is a pivotal milestone for any pharmaceutical company (Enache, Li, and Riedl 2022). Regulatory oversight is critical determinants of efficiency and quality of the drug development process (Cohen, Gurun, and Li 2021). U.S. regulators have shown great interest in AI's potential of improving efficiency and quality but also its issue of accountability and interpretability. We next investigate how regulatory oversight influences AI effectiveness.

Third, technical factors include algorithms, computational power, training datasets and clarity of optimization objectives. Even with better algorithms, greater computational power, more training datasets, AI's objectives are task-specific and understudied, which complicates its application in more specialized domains. Researchers find that AI could not achieve the intended optimization when applied to complex tasks with multiple objectives (Foucault et al. 2025).

Therefore, we examine whether objective function clarity moderates AI effectiveness in clinical trials.

We find that AI shortens clinical trial duration when firms employ executives with technology backgrounds. The benefits are economically meaningful: for these firms, a one standard deviation increase in the employment-based AI measure reduces time to completion by nearly one year. Consistent with improved efficiency, investors react more positively to trial completion by AI-intensive firms whose executives have technology backgrounds.

The effect of regulation is nuanced. Holding the regulatory environment constant, AI accelerates clinical trial processes and increases completion rates. However, under intense regulatory scrutiny, AI lengthens clinical trial processes and decreases trial completion rates. Despite its negative effect on efficiency, announcement returns are more favorable for firms with stronger regulatory scrutiny, suggesting investors view rigorous regulatory oversight as a gatekeeper that ensures completed AI-involved trials are more likely to obtain regulatory approval and achieve drug commercialization.

Exploiting cross-trial heterogeneity, we find that the positive effect of AI increases with the clarity of the optimization objective. Specifically, when the goal of a trial is simpler and easier to define, we find AI not only accelerates the trials but also raises its completion rates. A one-standard-deviation increase in AI investment could reduce trial duration by one to two years and increase the completion rates by over five percentage points.

Our study contributes to the growing research on AI's effect on individual productivity (Noy and Zhang 2023; Cao et al. 2024), firm performance (Acemoglu et al. 2022; Babina et al. 2024), and social welfare (Rossi and Utkus 2024). We add to this literature by providing direct evidence on AI's impact using project-level (trial) analyses of firms' core business activities. More

importantly, we show that AI's effect is context specific and identify the factors that help or hurt AI's effectiveness. Prior studies document that pharmaceutical companies are cautious about investing in novel drugs because of risk and reward concerns (Krieger et al. 2022). The new evidence of our study provides practical solutions to improve trial efficiency and financial prospects which, in turn, could tilt the risk-reward tradeoff towards valuable radical innovation.

Second, discussions of AI typically center on algorithm validity, computational resources, and training data. Yet a few prescient researchers have argued that the objective function is task- and domain-specific, and that mis-specified optimization objectives can derail performance (Foucault et al. 2025). Recent research in clinical trials argues for a backward approach where objectives inform the design, the data, and the planning (Joshi et al. 2025). Consistent with this view, we find that AI improves clinical-trial efficiency when the objective can be clearly stated and operationalized. Our evidence lends empirical support to the emerging emphasis on precise and context-appropriate objective definitions when deploying AI across heterogenous tasks.

Third, our study is related to health finance literature. Recent studies document that financial health (Adelino et al. 2022), private equity investment (Gao et al. 2025), and credit shocks (Aghamolla et al. 2024) all impact hospital's operational efficiency and healthcare quality. Meanwhile, disruptive technologies like AI have the potential to reform the healthcare industry (Bavafa et al. 2018; Cornaggia et a. 2024). Our study contributes to the literature by identifying conditions under which pharmaceutical companies can leverage AI investment to achieve trial efficiency gains and thus enhance healthcare welfare.

Finally, the pharmaceutical industry operates under stringent regulation which ensures the quality and safety of clinical trials (Cohen et al. 2021). The integration of AI in clinical trials has drawn increased attention from regulators. The FDA, for example, has issued a series of guidance

and discussion papers addressing this issue and soliciting public feedback.[3] Prior studies document that regulatory environment can shape innovation investment and outcomes (Amable et al. 2016; Aghion et al. 2023) and the debates surrounding regulation over AI have been particularly contentious. Our study finds that under intense regulatory scrutiny, AI reduces the efficiency of clinical trials but induces more favorable market reactions. This suggests that investors view regulation as a gatekeeper that enhances credibility of AI-involved clinical trials and their potential for FDA approval and commercialization. These findings have practical implications for regulators who are tasked to provide guidance on the appropriate use of AI in clinical trials.

II. Institutional Background

2.1 The pharmaceutical industry and drug development

The pharmaceutical industry is among the most research-intensive industries. Research and development of new drugs and devices sits at the core of firm activities (Scherer 2000). In 2023, the top 25 pharmaceutical companies invested an estimated 187 billion in R&D, representing about 24 percent of their sales (Buntz 2024).

Clinical trials are research studies conducted with human participants to evaluate safety, efficacy, and overall effectiveness of new medical drugs or devices (Kandi and Vadakedath 2023). Drug and device trials differ in evidence standards and practical execution. Drug trials usually follow randomized or blinded studies to deliver substantial evidence of safety and efficacy. These clinical trials are divided into four phases (Chow and Liu 2013). Phase I studies, also known as human-safety trials, assess the safety of a new drug and often involve fewer than 100 participants. Phase II studies focus on evaluating the effectiveness of the drug and identifying side effects. They

[3] https://www.fda.gov/media/165743/download; https://www.fda.gov/medical-devices/software-medical-device-samd/transparency-machine-learning-enabled-medical-devices-guiding-principles

usually involve several hundred patients. Once the preliminary effectiveness of the drug is demonstrated, phase III studies are conducted to gather additional information about effectiveness, safety, and the overall benefit-risk relationship. Phase III studies could involve several hundred to several thousand patients. Phase IV trials are performed after the drug is approved for marketing. The purpose of Phase IV trials is to gather further safety and efficacy information such as adverse reactions.

Device evaluations are risk-based and aim at reasonable assurance of safety and effectiveness. The pre-market approval process typically includes a pilot study and a pivotal trial. The pilot study, equivalent to phase I of a drug trial, determines preliminary safety and performance. The pivotal trial, similar to phase III of a drug trial, requires a large population to determine effectiveness and adverse effects. After approval, a post-approval study is required to collect long-term data and adverse effects. This requirement resembles phase IV of drug trials. Overall, drug trials tend to be larger and longer with stricter blinding, while device trials adopt a more targeted approach.

2.2 Artificial intelligence in clinical trials

Clinical trials are costly and uncertain processes. They account for more than half of pharmaceutical companies' total R&D investment (Congressional Budget Office 2021). It is estimated that the average R&D costs per drug range from $1 billion to $2 billion. Approximately one-fifth of proposed drugs reach phase III (Capkun et al. 2023), and only 12 percent obtain final approval for marketing (Congressional Budget Office 2021).

AI solutions are appealing to pharmaceutical companies due to their automated nature and predictive capabilities, which could increase the efficiency of the drug development process by

shortening the development time and increasing the probability of success (Harrer 2022; Rajpurkar et al. 2022; Hutson 2024). In the clinical design phase, AI can improve trial design and effectiveness by predicting outcomes and identifying measures with strong statistical power. For patient recruitment, which can account for up to one-third of the overall trial duration, AI can analyze medical records and social media content to identify suitable participants. During trials, AI enables continuous, real-time, and personalized monitoring and coaching of patients, leading to more precise interventions and reducing patient dropout rates. For outcome measurement and assessment, AI can interpret scans and wearable signals, process lab results, and summarize patient surveys. AI can also help ensure consistent and comparable result assessments using uniform algorithms.

III. Data and Research Design

3.1 Sample selection

Clinical trial data is obtained from the U.S. National Institutes of Health (NIH)[4] and the Clinical Trials Transformation Initiative (CTTI) database.[5] NIH provides a searchable registry and results database of federally and privately sponsored trials conducted in the United States and around the world. CTTI is a public-private partnership between Duke University and the U.S. FDA, aimed at increasing the efficiency of clinical trials by organizing and tabulating textual information from the original data (Grignolo 2011). For each clinical trial, the databases report a unique trial identifier, sponsor, investigator, start and completion dates, phase, study type, medical conditions, Medical Subject Headings (MeSH) for the conditions, facilities, recruitment status, and enrollment. We begin with trials starting between January 1, 2010, and December 31, 2022. For

[4] https://clinicaltrials.gov/
[5] https://aact.ctti-clinicaltrials.org

this period, the two databases contain more than 343,000 unique trials. We remove trials where the recruitment status is active, recruiting, or unknown, leaving us with more than 213,000 trials with known outcomes in our initial sample.

We link trial data to financial data using the names of sponsoring companies. First, we exclude trials sponsored by individuals and identify the ultimate parent company of each sponsor.[6] We then standardize the sponsor names in the trial data and historic company names in Compustat. Using an automated fuzzy matching routine, we match trial sponsors with firms in Compustat. For unmatched sponsoring companies, we manually review those with 10 or more trials and link them to Compustat. Each trial is matched to financial information for the period ending immediately before the trial start date. Our final estimation sample contains 18,289 trials with corresponding financial data from Compustat and other necessary variables.

3.2 Measuring AI investment

The intuition of measuring AI investment is that the application of AI technologies requires professionals with AI expertise. We leverage the comprehensive online professional profile dataset from Revelio Lab to measure firm-level AI human capital. The dataset covers over 24 million holding companies and their subsidiaries worldwide. For the pharmaceutical companies in our sample, the profiles represent 67.8 percent of the total Compustat-reported employee count. Each professional profile contains a time series of work history, including dates of employment, employer companies, job titles, job descriptions, education, self-reported skills, etc. Revelio Labs

[6] We use the OpenAI API to distinguish individuals from entities and to identify the sponsor's ultimate parent. We used the following prompt: "*You are a helpful assistant. I am going to provide you with a firm name and a year and I would like you to provide me with one (and only one) of the following response options (no extra words should be returned): (1) ONLY the standardized name of the firm's ultimate parent, (2) if the firm name is a person, return only 'person', or (3) if no information is available, return only 'no information'. The firm and year is:* "

classifys all positions into 1,500 job roles mapped to 383 Occupational Information Network (O*NET) codes. For example, "computer programmer" and "analyst programmer" are both mapped to O*NET code 15-1251.00 while a "teacher" is mapped to O*NET code 25-2032.00.

We classify positions as AI-related using a two-step procedure. In the first step, we sample 100,000 positions and use GPT (model 4o mini) to determine whether each position involves AI technologies, including machine learning, neural networks, deep learning, and data science, based on time-variant job titles and descriptions, standardized job categories and roles, and the year when a position is held. From this, we calculate the proportion of AI-related positions in each of the 1,500 job roles. A job role is labeled AI-related if at least one percent of its positions require AI expertise; all remaining roles (e.g., waitress, substitute teacher) are labeled non–AI-related. In the second step, for positions falling within AI-related roles, we again use GPT (model 4o mini) to evaluate whether the position requires AI expertise. This two-step approach reduces cost while limiting Type II error. Detailed information about the process, the prompt, and several examples are provided in Online Appendix Exhibit OA1.

We then create two firm-level measures of AI investment. The first measure, *Share AI Invest (Emp),* accounts for the size effect and is calculated as the percentage change in the share of positions requiring AI expertise at a given firm from year t-3 to year t. The second measure, *N AI Invest (Emp*), is the percentage change in the number of positions requiring AI expertise at a given firm from year t-3 to year t. The change in these two employment-based measures comes from both new hiring, layoffs, or changes in job responsibilities of existing employees.

While the professional profile dataset shows who is actually working at each company, it may not fully reflect firms' total AI investments. For example, AI investment may include expenditure on the technology infrastructure or the usage of AI service firms. Unfortunately, we

are not able to obtain data for either of these. Instead, following Babina et al. (2024), we use AI-related job postings to proxy for a firm's demand for AI human capital. Such demand is likely to correlate with AI capital investment or usage of external AI service providers. Job posting data is obtained from the Burning Glass Institute. Each posting includes the job title, the employer company, and a detailed description of the required skills and responsibilities. To quantify a posting's AI-relatedness, we first calculate AI-relatedness at the skill level and then aggregate the skill-level measures to the job posting level. The AI-relatedness of a skill is defined as the number of times the skill co-occurs with AI and its three subfields—machine learning, natural language processing, and computer vision—in job postings, scaled by the total number of job postings requiring that skill. The AI-relatedness of a job posting is the mean skill-level AI-relatedness of all the required skills for that job. A job posting is considered AI-related if its AI-relatedness is above 0.1.

Using the classification, we construct two posting-based AI investment measures. The first measure, *Share AI Invest (Posts)*, is the number of AI-related job postings by a sponsoring firm in a given year, scaled by the total number of job postings by the firm that year, averaged across the most recent three years.[7] The second measure, *N AI Invest (Posts)*, is the total number of AI-related job postings by a sponsoring firm in the most recent three years. *N AI Invest (Posts)* captures the absolute importance of AI and *Share AI Invest (Posts)* reflects the relative importance of AI for sponsoring firms.

Figure 1a plots the annual average number of AI-related positions (*N AI Invest (Emp)*) and the share of AI-related positions (*Share AI Invest (Emp)*) for the sample pharmaceutical companies from 2010 to 2022. Both metrics trend upward, with a noticeable acceleration around 2017. The

[7] *Share AI Jobs (Posts)* is set to missing for firm-years without any job postings.

average number of AI-related positions increases from roughly 0 in 2010 to about 100 by 2017 and then exceeds 300 by 2022. Similarly, the average share of AI-related positions grows from 0.2 percent in 2010 to 0.4 percent in 2016 and then rises to more than one percent by the end of 2022. Figure 1b plots the annual average number of AI-related job postings (*N AI Invest (Posts)*) and the share of AI-related job postings (*Share AI Invest (Posts)*). The trend in figure 1b mirrors that in figure 1a. The number of AI-related job postings quadrupled between 2016 and 2022, while the share of AI-related job postings increased more than fivefold from 0.2 percent to one percent during the six years. The explosive growth after 2016 coincides with various breakthroughs in AI such as the launch of TensorFlow by Google and PyTorch by Meta around that time.

[Insert Figure 1 about here]

Conceptually, *Share AI Invest* measures the relative scale of a firm's AI investment, whereas *N AI Invest* measures the absolute level of AI investment. Because a single AI hire could carry very different economic weight in a 50-person biotech startup than in a Fortune 500 pharmaceutical company, unscaled counts are mechanically correlated with firm size and are not directly comparable across firms. We therefore use the share-based measures, *Share AI Invest (Emp)* and *Share AI Invest (Posts)*, as our primary AI measures. Estimates based on the level measures, *N AI Invest (Emp)* and *N AI Invest (Posts)*, are reported in the Online Appendix. To facilitate the comparison of coefficients and calculation of marginal effects, all subsequent regressions use standardized AI measures (mean of zero with a standard deviation of one). As a result, the coefficients for these AI investment variables represent the change in the dependent variable for a one standard deviation change in AI investment.

3.3 Measuring trial efficiency

Operational efficiency in clinical trials primarily relates to trial duration and trial completion (Group OEW 2010). The NIH and CTTI datasets include each trial's start and tend date and its final status. Using this granular data, we construct two trial efficiency measures. The first measure, *Time to Completion,* is computed as the number of days between the start and completion date of a clinical trial. The second measure, *Trial Completion*, is an indicator variable that equals one if a trial's final status is "completed," and zero when the final status is "terminated", "withdrawn", or "suspended."

Clinical trials vary widely in design, scope, and purpose. Broadly, they are either observational or interventional. Interventional studies are more common (86.2% of our sample) and involve treatment such as a new drug or medical device and proceed in four phases. Observational studies, on the other hand, are less invasive as researchers observe participants without assigning a specific treatment. Figure 2a plots *Time to Completion* and *Trial Completion* by trial type and phase. It shows that completing a trial typically requires several years. Phase I interventional trials are the fastest, averaging about 400 days, whereas Phase III trials take more than two years. Despite long timelines, most initiated trials are ultimately completed. For example, nearly 90 percent of Phase I interventional trials reach completion, while Phase II trials exhibit the lowest completion rate, at around 75 percent.

Each clinical trial is assigned one or more MeSH codes that identifies the disease area under study. We rely on the MeSH codes to classify trials into disease categories.[8] Figure 2b shows that trials related to neoplasms (tumors) and blood and lymphatic diseases are the most time-consuming, requiring more than three years on average to complete. By contrast, trials in metabolic diseases typically conclude in about 500 days. Completion rates also vary systematically across

[8] For simplicity, MeSH categories with less than 500 trials are grouped together.

disease categories: trials in metabolic diseases have the highest rates of completion, whereas more than one-quarter of those involving neoplasms are withdrawn before completion.

[Insert Figure 2 about here]

3.4 Measuring market reaction to trial completion

Although completing a trial quickly is important, completing a successful trial leading to a commercialized drug creates more value for investors and society. However, at the time of trial completion, and potentially not for an extended period afterwards, it is not yet observable whether a given trial contributes to a marketed product. Instead, the mandatory result information package provides outcomes that enable investors to evaluate and update their expectations about the drug's safety, efficacy, and prospects for commercialization. Therefore, we lean on prior research that measures the future value of various business projects (e.g., clinical trials) using market reactions (Ecker et al. 2006; Bao and Edmans 2011; Froot et al. 2017), and measure a trial's prospective financial value with cumulative abnormal announcement returns surrounding the date when trial completion is publicly disclosed (hereafter the *Public Completion Date*).[9]

[9] This date should not be confused with the completion date available on www.clinicaltrials.gov. For many of the trials in our sample, the posted completion date is not revealed to the public until the sponsor updates the trial record. Because of this, we focus on the date when investors are made aware that the trial was completed. This is best illustrated by trial NCT01054729 sponsored by Gilead Sciences. The trial's record tracks the dates when there are updates (https://clinicaltrials.gov/study/NCT01054729?tab=history) and on January 21, 2010, the earliest record was posted, stating that the expected study completion date was "2011-11 [Estimated]." In subsequent updates the study status changed from "Recruiting" to "Active, not recruiting" and then on May 24, 2012, it changed to "Completed"; in this same record, the study completion date changed to "2011-08 [Actual]." While the information on the actual completion date did not become known until May 24, 2012, the study completion date in the original data is "2011-08" (nearly 10 months prior). Based on this example, for each trial, we use a Python script to determine the first date when the completion date is recorded as "[Actual]"—in this case, May 24, 2012. We call this date the *Public Completion Date.*

There is limited evidence on when and how the stock market reacts to announcements of trial completion. To verify that equity investors react to these announcements and to explore timing, we plot abnormal share turnover during the 21 trading days surrounding trial public completion dates (Chae 2005). As shown in Figure 3, abnormal turnover nearly doubles from day *t-3* to day *t,* the public completion date, and then quickly returns to pre-announcement levels. Accordingly, we calculate *CAR*s during [*t-2, t+2*] (*Trial CAR[–2,+2]*) and [*t-3, t+3*] (*Trial CAR[–3,+3]*) windows, where *t* is the public completion date.

[Insert Figure 3 about here]

Exhibit OA2 compares abnormal turnover around trial completion announcements across trial types. Phase I–III interventional trials exhibit a pronounced spike around day 0, whereas observational studies and Phase IV interventional trials show much smaller effects. This is consistent with Phase I to III interventional trials providing more valuable information about the prospects of drug commercialization. Exhibit OA3 examines disease categories. Investors react to completion announcements across all trials in the 13 disease categories. The strongest reactions are observed among trials relating to blood and lymphatic diseases, cardiovascular diseases, nervous system, respiratory diseases, and urogenital diseases. These diseases feature large patient populations and chronic, long-duration treatment, which suggests potential for strong recurring financial returns if a trial leads to successful drugs.

3.5 Empirical strategy

To examine the effect of AI on operational efficiency of and market reaction to clinical trials, we estimate model (1) below

$$Efficiency_{ijt}/CAR_{ijt} = \alpha_0 + \alpha_1 AIInvest_{jt} + \mathbf{X}_{ijt} + \mathbf{Y}_{jt} + \text{Year} + \text{Phase} + \text{MeSH} + \varepsilon_{ijt} \quad (1)$$

where *Efficiency* is one of the two measures of trial efficiency (i.e., *Time to Completion*, *Trial Completion*) for trial *i* conducted by sponsoring firm *j* in year *t*; *CAR* is one of the two measures of market reaction (i.e., *Trial CAR[–2,+2]* and *Trial CAR[–3,+3]*). *AIInvest* is one of the AI investment measures of firm *j* in year *t* (i.e., *Share AI (emp)* and *Share AI (posts)*).

X is an array of the following trial-level characteristics: *ln total outcomes* is the natural logarithm of one plus the count of outcomes observed in the study; *ln facilities* is the natural logarithm of one plus the count of the number of facilities used for the clinical trials; *ln conditions* is the natural logarithm of one plus the count of the number of conditions studied in the trial; and *ln enrollment* is the natural logarithm of one plus the count of participants in the study. These variables control for the scale and complexity of clinical trials.

Y is a series of firm characteristics that could impact firm performance. For instance, larger and more profitable firms are more likely to adopt new technologies because of greater appropriability and resource availability (Scherer 1965). We thus control for the following: the natural logarithm of assets (*ln assets*), return on assets (*ROA*),[10] an indicator for losses (*Net loss*), and the ratio of cash to total assets (*Cash to assets*). Given that growth and research-intensive firms tend to have a higher demand for new technologies (Acemoglu et al. 2018), we also include the market-to-book ratio (*Market to book*), year-on-year sales growth (*Sales growth*), and research intensity (*R&D intensity*). Additionally, we control for one-year stock returns to account for the capital market impact (*Stock return*). Each clinical trial is matched with firm-level characteristics from the fiscal year ending immediately before the trial's start date. We include year fixed effects to account for time trends. As discussed in 3.3, trial duration and completion rates vary across trial

[10] ROA for *firm-years* with negative earnings are set to 0 (Harris and O'Brien 2018).

types, phases, and disease categories; thus, we also include phase and MeSH fixed effects. We report robust standard errors adjusted for heteroskedasticity.

Prior studies argue that firm-level AI investment is endogenous and correlated with an array of firm characteristics that could simultaneously influence a firm's demand for AI investment and firm performance (e.g., Cao et al. 2023; Babina et al. 2024). To isolate the effect of AI, we employ an instrumental variable approach. A valid instrument is correlated with firm-level AI investment but uncorrelated with trial-level dependent variables except through other independent variables. As Babina et al. (2024) argue, firm-level AI investment is strongly influenced by the local supply of AI talent. Meanwhile, there is no strong rationale for a mechanical link between local AI talent supply and the efficiency or the market reaction of individual clinical trials. Therefore, we instrument firm-level AI investment using the supply of local AI talent supply (*AI Talent Supply*) in the labor market where the sponsoring firm's corporate or U.S. headquarters are located.[11] *AI Talent Supply* is defined as the number of individuals aged 18 to 64 with degrees in information technology, normalized by the state-year population, as reported by the Integrated Public Use Microdata Series (IPUMS) surveys.[12] The first-stage regression (model [1a]) links AI talent supply in state *k*, year *t*, to AI investment by firm *j* in year *t*, where firm *j*'s U.S. headquarter is in state *k*. We also include all control variables from model (1) in model (1a).

$$AIInvest_{jt} = \lambda_0 + \lambda_1 AITalentSupply_{kt} + \mathbf{X}_{ijt} + \mathbf{Y}_{jt} + \text{Year} + \text{Phase} + \text{MeSH} + \varepsilon_{ijt} \quad (1a)$$

IV. Empirical Results

[11] U.S. firms' headquarters are determined based on the address reported in their SEC filings. Non-U.S. firms' U.S. headquarters are determined based on the location of the U.S. subsidiary that is either (1) the announced U.S. headquarters based on a manual Google search, (2) most frequent state mentioned in the WRDS subsidiaries data based on SEC Form 21, or (3) conducts the most clinical trials.

[12] We use an updated version with data through 2021; for 2022 we assume that the level remains unchanged from 2021.

4.1 Descriptives

Table 1 presents the descriptives for trial and firm characteristics. It takes on average 649 days to complete a trial, and 85 percent of the trials are completed. Announcement returns to trial completion are slightly negative on average at –0.1 percent. On average, trials report eight outcomes, are conducted across nine facilities, involve about two conditions, and have a mean enrollment of 84 participants, using unlogged values. At the firm-year level, the average change in the share of employees with AI expertise over a three-year window exceeds 50 percent, or 78 employees. The sample pharmaceutical firms post a mean of 52 AI-related job openings per year, representing 0.25% of total postings. Firms' financial characteristics indicate that the firms are mostly growth and R&D intensive firms with a mean ROA of 8.7 percent; 14 percent of them report losses.

[Insert Table 1 about here]

Table 2, Panel A presents the top AI-intensive sponsoring firms in the sample. Column (1) ranks firms by the number of clinical trials. GSK plc is the most active, followed by Johnson & Johnson and Pfizer Inc. Columns (2) and (3) rank firms by growth in the proportion and the number of AI-related positions. Karyopharm Therapeuticals Inc. and Nektar Therapeutics are the fastest growing pharmaceutical companies in terms of AI workforce. Columns (4) and (5) rank firms based on the proportion and the number of AI-related job postings. The largest pharmaceutical companies in column (1) are also heavy AI recruiters in column (4). In contrast, column (5) reveals a greater presence of smaller pharmaceutical companies when ranked by size-scaled AI recruitment. Overall, these patterns suggest that emerging pharmaceutical firms are leveraging AI to build comparative advantage, while incumbent leaders are simultaneously investing to deepen AI capabilities.

[Insert Table 2 about here]

4.2 The impact of AI on trial efficiency

Table 3 presents the results from estimating model (1a). The instrumental variable, *AI Talent Supply*, is significantly positively correlated with both AI investment measures at the one percent level, suggesting that local AI talent supply is associated with higher AI investment by local firms. The first-stage R-squares are 0.203 and 0.594, respectively, indicating good model fit. Stock-Yogo F-statistics are 95.982 and 639.810, respectively, far exceed the conventional rule-of-thumb threshold of 10. This confirms that local AI talent supply is strongly correlated with firm-level AI investment and establishes the strength of our instrument.

[Insert Table 3 about here]

Table 4 reports the results from estimating model (1) to examine the effect of AI investment on trial efficiency. Columns (1) and (3) use *Share AI Investment (Emp)* as the AI investment measure and show no statistically significant association with trial duration or completion likelihood. By contrast, Columns (2) and (4), which measure AI investment using job postings, show that *Share AI Investment (Posts)* are positively associated with both trial duration and completion probability, with the coefficients significant at the ten percent level or higher. This result suggests that AI investment may lengthen the time required to complete trials, while increasing completion rates. Taken together, these results depict a mixed effect of AI on trial efficiency. Regarding the control variables, more complex trials with more outcomes, conducted across more facilities, and involving more conditions tend to take longer to finish. Trial complexity also lowers the likelihood of completion, as multi-facility or multi-condition trials are less likely to be completed.

[Insert Table 4 about here]

Next, we investigate the effect of AI investment on trial efficiency across different types and phases with model (2). In model (2), $Phasek_{ijt}$ is an indicator variable that equals one if trial i by firm j in year t is in phase k, and zero otherwise.[13] The interaction between $AIInvest$ and $Phase_k$ (β_2) represents the effect of AI investment on trial efficiency for clinical trials in a given phase or type relative to all the other clinical trials.

$$Efficiency_{ijt}=\beta_0+\beta_1 AIInvest_{jt}+\beta_2 AIInvest_{jt}\times Phasek_{ijt}+\mathbf{X}_{ijt}+\mathbf{Y}_{jt}+\text{Year}+\text{Phase}+\text{MeSH}++\varepsilon_{ijt} \quad (2)$$

We estimate model (2) separately for observational trials and for interventional trials by phase. Figures 4a and 4b plot the coefficients on $AIInvest\times Phase_k$ from estimating model (2) with *Time to Completion* as the dependent variable. The results indicate that AI investment significantly shortens trial durations for observational trials, whereas its effects on interventional trials are less consistent and generally insignificant. Figures 4c and 4d examine the effect of AI on completion likelihoods. Both AI investment measures are associated with a higher probability of trial completion for observational trials, but the effects for interventional trials are mixed and statistically insignificant across phases.

To explore whether the effect of AI varies across disease areas, we re-estimate model (2) by MeSH-defined disease category. Figures 5a and 5b plot the coefficients on the interaction terms (β_2) with time to completion as the dependent variable. Using employment-based AI intensity measure, we find some evidence that AI investment is associated with longer trial durations for digestive system diseases, metabolic diseases, and pathological conditions; however, these results do not hold when AI investment is measured using AI job postings. Figures 5c and 5d report AI's

[13] For trials that where multiple phases are combined (e.g., Phase 1 and Phase 2), the indicator $Phasek_{ijt}$ denotes that more advanced of the two stages (e.g., Phase 2).

effects on completion likelihood. Across all twelve disease categories, neither AI measure exhibits a statistically significant association with the probability of trial completion.

[Insert Table 5 about here]

4.3 Market reaction to clinical trials

Table 5 presents the market reactions to clinical trial completions. Columns (1) and (3) use *Share AI Invest (Emp),* and columns (2) and (4) use *Share AI Invest (Posts)* as the AI investment proxy. In column (2), *Share AI Invest (Posts)* is negatively associated with seven-day announcement returns at the ten percent level. A one-standard-deviation increase in *Share AI Invest (Posts)* corresponds to a reduction of approximately 104 basis points in the seven-day announcement returns. The remaining specifications show no statistically significant relation between AI investment and either seven-day or five-day announcement returns.

[Insert Table 5 about here]

We also compare market reactions to clinical trials completed by AI-intensive firms across phases and disease areas by replacing the dependent variable in models (2) with *Trial CAR[-2,+2]* and *Trial CAR [-3,+3]*. Figures 4e to 4h plot market reactions by trial phases. We find some evidence that AI investment is associated with a more positive five-day completion announcement returns for observational trials, but more negative five-day returns for Phase III interventional trials (Figure 4g and Figure 4h). Figures 5e and 5h report market reactions by disease area. We find little evidence that AI investment impact market reactions to trial completion across all twelve disease categories. Overall, market responses to completions by AI-intensive firms are at best muted, and even negative, which again stands in sharp contrast to the prevailing optimism towards AI.

[Insert Figure 4 about here]

4.4 When does AI help?

The previous analyses demonstrate that AI, in its current state, has mixed effects on trial efficiency and market reactions. These findings highlight the need to understand how the adverse effects of AI can be mitigated while its benefits amplified. In this section, we investigate the conditions under which AI investment is most likely to generate positive outcomes.

We estimate model (3) via 2SLS to examine the moderating effect.[14] In model (3), *Condition* represents a factor that could moderate the effect of AI investment on trial outcomes. We interact *Condition* with *AIInvest*, and the coefficient, δ_3, reflects the incremental effect of AI investment on trial efficiency or the market reactions when the examined condition is present.

$$Efficiency_{ijt}/CAR_{ijt}=\delta_0+\delta_1 AIInvest_{jt}+\delta_2 Condition_{jt} \quad (3)$$
$$+\delta_3 AIInvest_{jt} \times Condition_{jt}+\mathbf{X}_{ijt}+\mathbf{Y}_{jt}+\text{Year}+\text{Phase}+\text{MeSH}+\varepsilon_{ijt}$$

The impact of complementary human expertise

Recent studies in AI and healthcare highlight limited trust in AI among senior management and a shortage of AI-skilled professionals (Wang et al. 2023). We first explore whether a technology background serves as complementary human expertise that facilitates integrating domain knowledge with AI technologies, thereby maximizing AI's potential to improve trial efficiency and financial prospects.

Prior studies document that Chief Executive Officers (CEOs) steer strategic directions, while Chief Financial Officers (CFOs) influence firms' financial decisions (Geiger and North 2006; Lafley 2009). In practice, CEOs and CFOs collaborate on financial-related decisions to

[14] In this 2SLS regression and those that follow, we instrument for AI investment using *AI Talent Supply*. To account for the interaction between AI investment and a cross-sectional variable (e.g., *Tech Executive*), we also include the interaction with the cross-sectional variable and *AI Talent Supply* and the cross-sectional variable as instruments.

deliver desirable business results (Jiang et al. 2010). CFOs are also increasingly involved in strategic management (Egon Zehnder 2008). Given that AI investment involves both strategic and financial planning, we focus on both CEOs and CFOs.

We identify CEOs' and CFOs' professional backgrounds using their education and career experience from Boardex. An executive is classified as having a technology background if either the education or employment history includes at least one tech-related keyword (e.g., "AI", "software", and "programming)."[15] We then construct *Tech Executive*, an indicator variable that equals one when either the CEO or the CFO has a tech background.

Table 6 reports the results of estimating model (3) replacing *Condition* with *Tech Executive*. The sample size is smaller due to Boardex coverage of executives. Approximately 45 percent of these trials are conducted by sponsoring firms with a CEO or a CFO with a technology background. As reported in column (1) of panel A, the coefficient on *Share AI Invest (Emp)*×*Tech Executive* is –209.75 and significant at the one percent level, suggesting that AI investment shortens trial duration when senior leadership has technology training. For firms with tech-background executives, a one-standard-deviation increase in *Share AI Invest (Emp)* is associated with a reduction in trial duration of 97 days (the sum of the coefficients on the interaction term and *Share AI Jobs*, –209.75+112.70), approximately 15 percent of the average trial duration. Column (2), which uses *Share AI Invest (Posts)* as the AI investment proxy, similarly shows that AI investment reduces the time required to complete trials. A one-standard-deviation increase in *Share AI Invest (Posts)* corresponds to a 175-day reduction in trial duration (the sum of the coefficients on the interaction term and *Share AI Invest*, –151.39–24.01), or 27 percent of the average trial duration.

[15] The tech keywords include: IT, Information Technology, digital, AI, Artificial Intelligence, systems, data, cybersecurity, software, cloud, computing, analytics, machine learning, ML, Internet, virtual, CIO, CTO, CDO, Chief Technology, information, business intelligence, security, programmer, and programming.

Columns (3) and (4) examine the probability of trial completion. Neither *Share AI Invest (Emp)×Tech Executive* nor *Share AI Invest (Posts) ×Tech Executive* is significantly associated with higher completion probabilities.

Panel B of Table 6 reports how announcement returns vary with senior management's technology backgrounds. In columns (1) and (3), we find that *Share AI Invest (Emp) ×Tech Executive* is positively associated with announcement returns across both event windows, with coefficients significant at the 10 percent level or higher. Although the main effect of *Share AI Invest (Emp)* is negative, the positive moderating effect of executives' IT expertise more than offsets this negative main effect. For example, in column (1), a one-standard-deviation increase in employment-based AI intensity lowers completion-announcement returns by 95 basis points for firms without tech-background executives but raises returns by seven basis points for firms with such executives. In columns (2) and (4), which use postings-based S*hare AI Invest (Posts),* the interaction terms (*Share AI Invest (Posts)×Tech Executive*) remain positive but are no longer statistically significant.

The results in Table 6 indicate that tech-background executives help unlock AI's potential by accelerating trial completion and improving market reactions. These findings highlight the value of having complementary human expertise for realizing AI's benefits in clinical trials.

[Insert Table 6 about here]

The impact of regulation

The pharmaceutical industry is subject to intensive regulation by federal and state agencies. The rise of AI has drawn heightened regulatory attention. For instance, the FDA's Center for Drug Evaluation and Research has issued a discussion paper on AI in drug manufacturing; and the FDA,

collaborating with Health Canada and the United Kingdom's Medicines and Healthcare products Regulatory Agency (MHRA), has released 10 guiding principles for good machine learning practice (GMLP) (Health Canada 2021). Regulation is designed to address market failures and promote welfare (Pigou 1938), but it can also introduce rent-seeking opportunities (Stigler 1971) and increase the compliance burden (Dambra and Gustafson 2021; Kalmenovitz 2023). In this section, we explore the impact of regulations on the relation between AI and both trial efficiency and market reactions.

To perform the analyses, we employ two measures for regulation intensity from prior studies. The first measure, regulation fragmentation, reflects a firm's exposure to regulatory topics overseen by multiple regulatory agencies. The measure was developed by Kalmenovitz et al. (2024) based on notices, proposed rules, passed rules, and regulations published by federal agencies. Greater regulation fragmentation indicates a heavier compliance burden but also potentially more guidance. We define *High Reg Frag* as an indicator variable that equals to one for firm-years at or above the annual median, and zero otherwise. The second measure, regulation intensity, reflects the extent of regulatory scrutiny based on the number of responses, hours of compliance, and dollar costs of compliance (Kalmenovitz 2023). Higher regulation intensity suggests greater compliance costs and closer scrutiny. We define *High Reg In* as an indicator variable that equals one for firm-years at or above the annual median of regulation intensity, and zero otherwise. The interaction terms between *AIInvest* and *High Reg Frag* or *High Reg In* reflect the moderating effect of regulation on AI effectiveness in clinical trials.

Table 7, Panel A reports the results of examining the moderating role of regulation on trial efficiency. Columns (1) and (2) examine the moderating effect of regulation fragmentation on trial duration. The interaction terms *Share AI Invest (Emp)×High Reg Frag* and *Share AI Invest*

(Posts)×High Reg Frag are positive and significant at the one percent level or higher, while the main effect of *Share AI Invest (Emp)* and *Share AI Invest (Posts*) are significantly negative. These results suggest that, holding regulation fragmentation low, AI investment shortens trial duration, but higher regulation fragmentation attenuates and fully offsets the positive effect of AI. Columns (5) and (6) investigate the role of regulation intensity on trial duration. The inferences are very similar in that both AI investment measures are negatively associated with *Time to Completion* at the one percent level, whereas the interaction terms with *High Reg Int* are positive and significant. They confirm that that intense regulation dampens AI's time-saving benefits.

Regarding the moderating effect of regulation on completion probability, the coefficients on *Share AI Invest (Emp)×High Reg Frag* and *Share AI Invest (Posts)×High Reg Frag* are negative in columns (3), (4), (7), and (8), and significant at the ten percent level or higher in three out of the four specifications. They suggest that, when regulation fragmentation or intensity is higher, AI investment is associated with a lower likelihood of completion. The results are consistent with stringent regulation exacerbating AI's impact on trial efficiency.

Panel B of Table 7 examines market reactions to trial completion announcements as a function of regulatory environment. Columns (1) to (4) use regulation fragmentation as the proxy for regulatory scrutiny. The interaction terms between AI Investment and *High Reg Frag* are positive in all specifications, three of which are statistically significant at the 10% level or higher. Columns (5) to (8) measure regulatory environment with regulation intensity. The interaction terms between AI investment and *High Reg Int* are again predominantly positive, with three significant at the five percent level or higher. These results suggest that stronger regulatory environments induce more favorable market reactions to trial completions by AI-intensive firms.

The findings in Table 7 are intriguing in that it shows regulation's double-edged role in determining AI's net effect on clinical trials. On one hand, a higher burden of regulatory compliance slows AI-involved trials; on the other hand, investors react more favorably to completions of these trials in a stronger regulatory environment. The latter is consistent with regulatory guidance improving the conduct of clinical trials and the perceived likelihood of regulatory approval (Cohen et al. 2021), thereby generating more favorable investor responses.

[Insert Table 7 about here]

The impact of optimization objective clarity

AI tools optimize based on programmed objective functions. AI performance therefore hinges on how clearly the optimization objective is defined. However, the objective is not always clear when applying AI to various tasks and domains. In general, AI has difficulties in understanding the objective of a task when it is used upstream and the task requires common sense (Foucault et al. 2025). For example, in drug trials, AI is often deployed upstream for such tasks as target selection, trial design, and patient recruitment and monitoring. The distance to the ultimate trial outcome creates objective ambiguity and forces trade-offs among efficacy, safety, speed, cost, and feasibility across multiple stakeholders based on laws, customs, and policies. By contrast, medical device trials typically apply AI downstream, closer to the endpoint, to analyze device-generated images or signals that directly inform effectiveness and safety. The proximity to outcome measurement makes it easier to define the ultimate trial objective. Accordingly, we expect AI to boost trial outcome more for device trials than for drug trials.

Optimization objective clarity also varies with outcome multiplicity. Some clinical trials focus on one primary outcome as the main success metrics, others are designed to evaluate a

portfolio of outcomes (e.g., survival rates, quality of life, biomarkers, etc.). Each additional outcome imposes constraints for design, planning, and implementation of the trials, which inevitably complicates the definition and alignment of stage-specific objectives with the trial's ultimate goal. Therefore, we also expect AI to be more effective in trials with less outcomes.

We create *High Clarity Device* indicating medical device trials, and *High Clarity Outcome* which equals one if the number of total outcomes is below the median value for each year. We then estimate model (3) replacing *Condition* with *High Clarity Device* or *High Clarity Outcome*. The interaction term between *AIInvest* and *High Clarity Device* or *High Clarity Outcome* reflects the incremental effect of AI when optimization objectives are clearer.

In Table 8, as reported in columns (1) and (2) of panel A, the coefficients on *Share AI Invest (Emp)×High Clarity Device* and *Share AI Invest (Posts)× High Clarity Device* are both significantly negative at the one percent level (–650.2243 and –393.9001), suggesting AI accelerates the completion for device trials. Economically, a one-standard-deviation increase in AI investment shortens device-trial duration by more than one year in both specifications. Columns (3) and (4) show that the interaction terms between AI investment and *High Clarity Device* are significantly positive at the five percent level or higher when trial completion is the dependent variable. A one-standard-deviation increase in AI investment increases the propensity of device trial completion by 5.70 to 13.46 percentage points. Columns (5) to (8) compare trials with fewer and more outcomes. We find that neither *Share AI Invest (Emp)×High_Clarity Outcome* nor *Share AI Invest (Posts)× High_Clarity Outcome* is significant for trial duration (columns [5] and [6]), but are positive and significant at the five percent level or higher in columns (7) and (8) for trial completion. A one-standard-deviation increase in AI investment is associated with approximately five to six percentage point increase in completion likelihood for lower-outcome trials.

However, the efficiency gains documented in panel A do not translate into favorable market reaction in Panel B of Table 8. It is plausible that it is easier to anticipate the results and AI's benefits for these trials with clearer objectives and so investors already incorporate the expectation in stock valuation prior to trial completions. Nevertheless, the results in this set of analyses demonstrate that AI is most effective for trials where optimization objectives are clear. This finding highlights the importance of carefully defining objective functions when applying AI across specialized domains.

[Insert Table 8 about here]

4.5 Additional analyses

Market reaction reversal

To verify that the market reaction results represent a real change in expected future value for the sponsoring firm and are not subject to short-term reversals, we re-estimate the market reaction regressions over two alternative windows, days [+4,+8] (*Trial CAR[+4, +8]*), and the subsequent week, days [+9,+13] (*Trial CAR[+9, +13]*). As shown in panel A and panel B of Table 9, in 18 out of 20 regressions, the coefficient on the interaction between AI investment and each of the variables used in the cross-sectional tests (column [7]) is not significantly different from zero.[16] The lack of significance implies that the change in value for the sponsoring firm is isolated to the period when the completion status is made public and does not reverse or drift in the two weeks following the announcement.

[Insert Table 9 about here]

[16] In the two cases where the coefficients are statistically significant, they are positive, suggesting the change in value does not reverse.

Alternative measures of AI investment

We use size-scaled AI investment measures in the primary analyses because they reflect intensity of AI investment that is comparable across firms. It is plausible that the level of AI investment matters as well. Therefore, we show in Online Appendix Table 3 to Table 8 that the inferences remain similar when measuring AI investment using the level measures (i.e., *N AI Invest (Emp) or N AI Invest (Posts)*). We continue to find weak to null effect of AI investment on trial efficiency and market reactions to trial completion on average. Senior management's IT skills enhance the positive potential of AI on trial efficiency and induces more positive market reactions to trial completion. Meanwhile, regulation environment continues to show a mixed effect in that stronger regulatory scrutiny hurts trial efficiency of AI-intensive firms, but trials completed by these firms are assessed more favorably by the market in a stronger regulatory environment. Having clear optimization objectives also amplify the positive effect of AI on clinical trials. However, the effect of long managerial horizon is largely insignificant using the level measures.

Conclusions

This study provides early evidence on AI's complex role within the pharmaceutical industry. We find mixed average effects of AI investment on trial efficiency measured by duration and completion, and on financial prospects measured by market reactions to completion announcements. Delving deeper into the heterogeneity of the effect, we find AI investment improves efficiency and elicits more favorable market reactions with complementary human expertise. Regulatory oversight is a double-edged sword which increases market confidence of trial financial prospect but hampers trial efficiency simultaneously. Consistent with the importance

of objective-function clarity, AI's positive impact on efficiency is stronger when trial goals are clearer; however, markets appear to anticipate these efficiency gains, yielding muted announcement returns for such trials.

Prior studies on AI in the finance domain explore the adoption of AI in various finance-related tasks (D'Acunto et al. 2019; Gu et al. 2020; Kelly et al. 2021; Hoberg and Maksimovic 2022; Huang et al. 2023; Rossi and Utkus 2024; Jansen et al. 2025; Li et al. 2025) and its influence on productivity (Noy and Zhang 2023; Acemoglu et al. 2022; Babina et al. 2024). Our study contributes to the literature by identifying key moderators that shape the effectiveness of AI investment, including management technology background, balanced regulation, and objective clarity for AI tools. Our study also relates to the health finance literature (Adelino et al. 2022; Aghamolla 2024; Gao et al. 2025;) by documenting when AI investment together with the right complements can enhance efficiency and financial prospects of clinical trials, thereby influencing pharmaceutical firms' reward-and-risk tradeoff and improving social welfare (Krieger et al. 2022). Finally, our study contributes to the literature on regulation and investments (Amable et al. 2016; Cohen et al. 2021; Aghion et al. 2023) by showing the nuanced effect that the markets favor stringent regulation over AI usage in clinical trials even though such regulation diminishes the positive effect of AI on trial efficiency. These findings offer valuable implications for researchers, practitioners, and policymakers as they seek to harness the transformative power of AI while mitigating its potential downside.

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Appendix A: Variable Names and Definitions

VARIABLE	Definition
Trial-level outcome variables	
Time to Completion	Number of days between the trial's start date and its completion date.
Trial Completed	Indicator variable that equals one if the trial is completed, and zero otherwise.
Trial CAR[-3,+3]	Standard market model (CAPM) cumulative abnormal returns (CAR) for the event window spanning from three days before to three days after the trial's completion status is made public. The calculation uses equally weighted returns and a 100-day estimation period (50-day gap).
Trial CAR[-2,+2]	Standard market model (CAPM) cumulative abnormal returns (CAR) for the event window spanning from two days before to two days after the trial's completion status is made public. The calculation uses equally weighted returns and a 100-day estimation period (50-day gap).
AI investment measures	
Share AI Invest (Emp)	The percentage change in the share of positions (from Revelio Labs) requiring AI expertise at the sponsor firm in the past three years.
*Share AI I*nvest (*Posts)*	Ratio of AI-related job postings (from Burning Glass) to total job postings by the sponsor firm in that year, averaged over the past three years.
N AI Invest (Emp)	The percentage change in the number of positions (from Revelio Labs) requiring AI expertise at the sponsor firm in the past three years.
*N AI I*nvest (*Posts)*	Total number of AI-related job postings (from Burning Glass) by the sponsor firm in the past three years.
Firm-level cross-sectional variables	
Tech Executive	Indicator variable that equals one if either the CEO or CFO has a technology-related background, and zero otherwise.
High Reg Frag	Indicator variable that equals one for years when the firm's exposure to regulation fragmentation (Kalmenovitz et al. 2024) is greater than or equal to the median sample firm for that year, and zero otherwise.
High Reg In	Indicator variable that equals one for years when the firm's exposure to regulation intensity (Kalmenovitz 2023) is greater than or equal to the median sample firm for that year, and zero otherwise.
High Clarity Device	Indicator variable that equals one if a trial is a device trial, and zero otherwise.
High Clarity Outcome	Indicator variable that equals one if the number of total trial outcomes is less than or equal to the median for that year, and zero otherwise.
Trial-level control variables	
ln total outcomes	Natural logarithm of one plus the number of outcomes observed in the trial.
ln facilities	Natural logarithm of one plus the number of facilities used for the clinical trial.
ln conditions	Natural logarithm of one plus the number of conditions studied in the trial.
ln enrollment	Natural logarithm of one plus the number of participants enrolled in the trial.
Firm-level control variables	
ln assets	Natural logarithm of total assets.
Cash to assets	Ratio of cash and cash equivalents to total assets.
Market to book	Market-to-book ratio.
Sales growth	Percentage growth in sales during the previous fiscal year.
ROA	Return on assets (ROA). If ROA is negative, it is set to zero, and the Net loss indicator equals one.
Net loss	Indicator variable that equals one if the firm reports a negative ROA for the fiscal year, and zero otherwise.
R&D intensity	Ratio of R&D expenses to total assets.
Stock return	Past year's stock return.
Instrumental variable	
AI Talent Supply	Number of individuals aged 18 to 64 with degrees in information technology, normalized by the state-year population.

Figure 1 Annual AI Investment

Figure 1a: Revelio Labs Employment Data

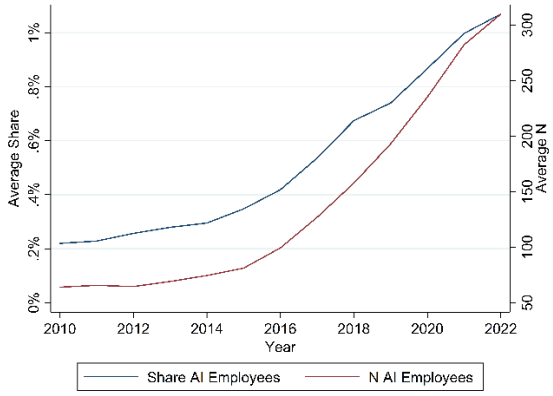


Figure 1b: Burning Glass Job Posting Data

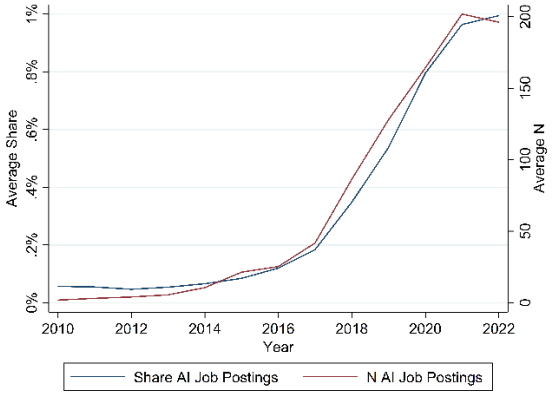


Figure 1a plots the number of AI employment (*N AI Invest(Emp)*, red line) and the number of AI employment scaled by the total number of employees (*Share AI Invest (Emp),* blue line) averaged across sponsoring firms by year for the sample period of year 2010 to year 2022. Figure 1b plots the number of AI-related job postings (*N AI Invest (Posts)*, red line) and the number of AI-related job postings scaled by the total number of job postings (*Share AI Invest (Posts)*, blue line) averaged across sponsoring firms by year for the sample period of year 2010 to year 2022. All variables are winsorized by year at the top and the bottom one percentile.

Figure 2 Trial Efficiency by Phase and MeSH Category

Figure 2a: Phase Type

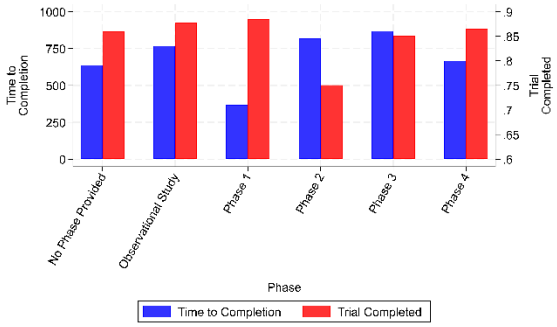


Figure 2b: MeSH Category

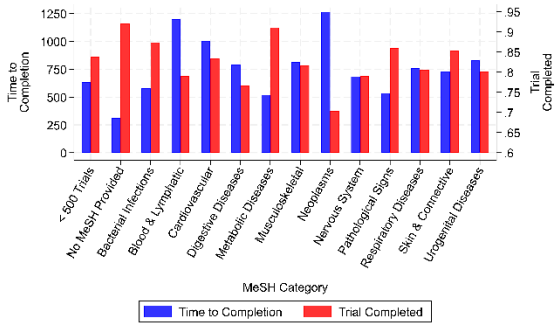
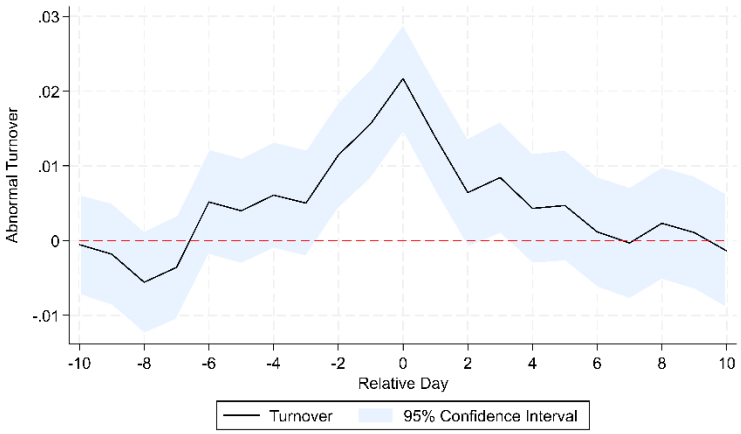


Figure 2a plots *Time to Completion* (blue bar) and *Trial Completed* (red bar) averaged across clinical trials by trial type/phase. Figure 2b plots *Time to Completion* (blue bar) and *Trial Completed* (red bar) averaged across clinical trials by MeSH.

Figure 3 Abnormal turnover surrounding trial completion



This figure plots the abnormal stock turnover of sponsoring firms during [*t*-10, *t*+10] where day t is filing dates of trial completion (*Public Completion Date*). The shaded area corresponds to the 95% confidence interval bands. The abnormal turnover is calculated according to Chae (2005).

Figure 4 AI Investment and Trial Efficiency by Trial Type and Phase

Figure 4a: *Time to Completion* and *Share AI Invest (Emp)*

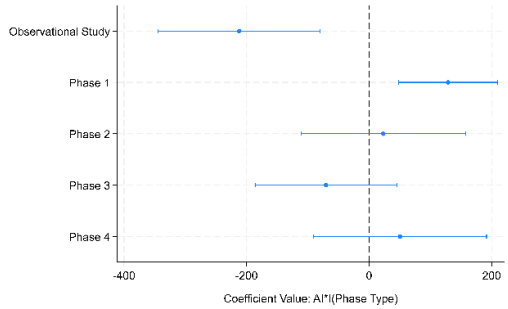


Figure 4b: *Time to Completion* and *Share AI Invest (Posts)*

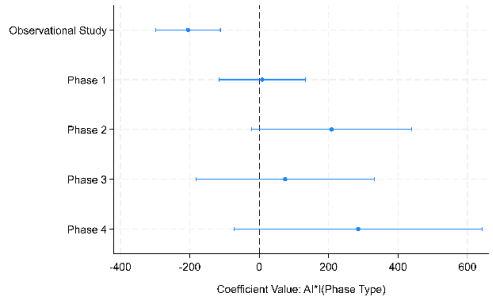


Figure 4c: *Trial Completion* and *Share AI Invest (Emp)*

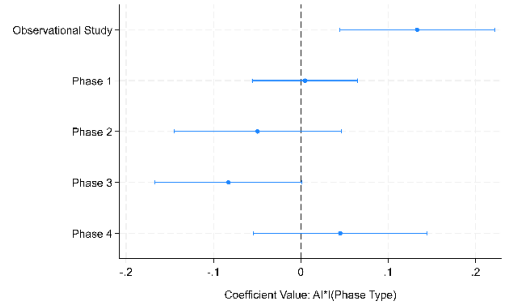


Figure 4d: *Trial Completion* and *Share AI Invest (Posts)*

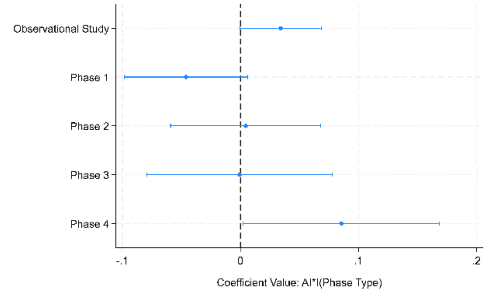


Figure 4e: *Trial CAR[-3,+3]* and *Share AI Invest (Emp)*

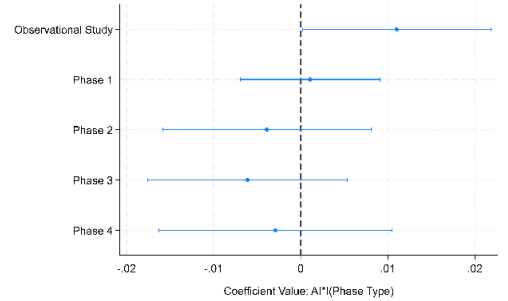


Figure 4f: *Trial CAR[-3,+3]* and *Share AI Invest (Posts)*

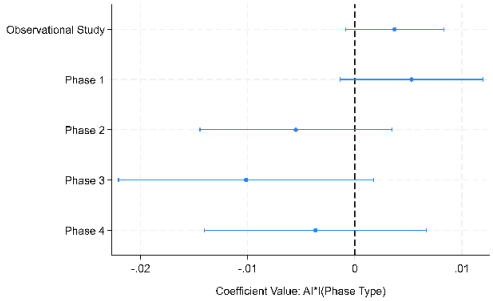


Figure 4g: *Trial CAR[-2,+2]* and *Share AI Invest (Emp)*

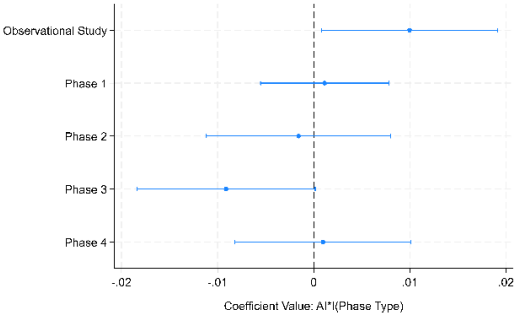


Figure 4h: *Trial CAR[-2,+2]* and *Share AI Invest (Posts)*

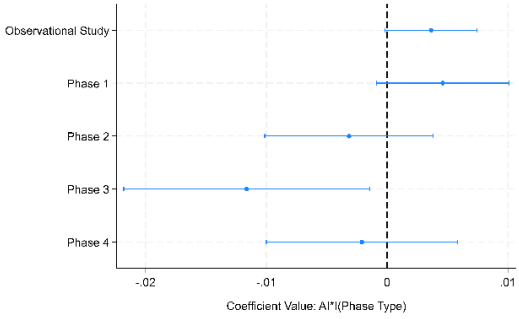


Figure 4 plots the interaction coefficients from five separate 2SLS regressions of model (1) with the addition of an interaction between the *Share AI Invest* and an indicator for the trial belonging to one of the groups shown below. The interaction variable captures the differential effect of AI investment on trial efficiency and market reaction by trial types and phases. Trials with missing phase/type information are dropped from this analysis. The figure reports the coefficient (the dot) and the 95% confidence interval (using robust standard errors).

Figure 5: AI Investment and Trial Efficiency by MeSH Category

Figure 5a: *Time to Completion* and *Share AI Invest (Emp)*

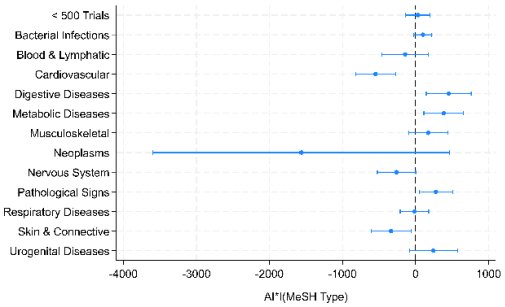


Figure 5b: *Time to Completion* and *Share AI Invest (Posts)*

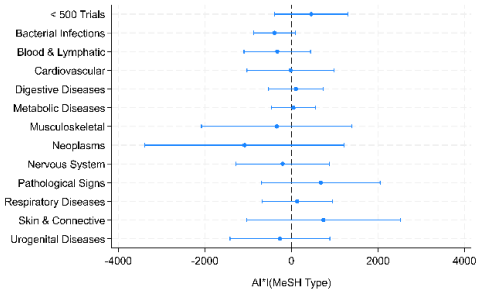


Figure 5c: *Trial Completion* and *Share AI Invest (Emp)*

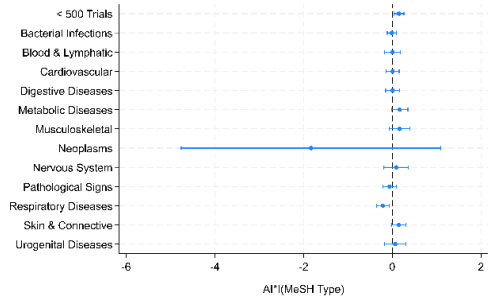


Figure 5d: *Trial Completion* and *Share AI Invest (Posts)*

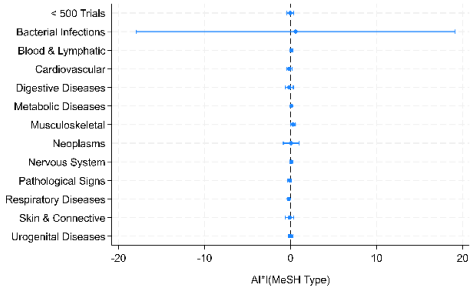


Figure 5e: *Trial CAR[-3,+3]* and *Share AI Invest (Emp)*

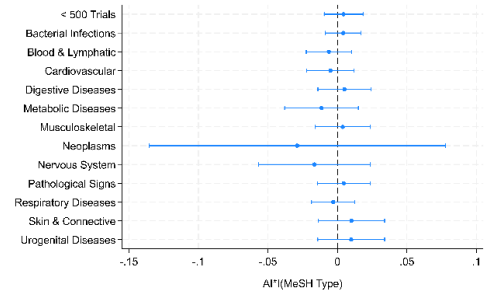


Figure 4f: *Trial CAR[-3,+3]* and *Share AI Invest (Posts)*

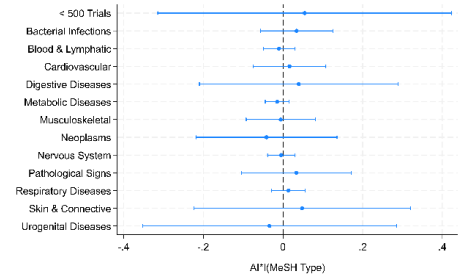


Figure 5g: Trial CAR[-2,+2] and Share AI Invest (Emp)

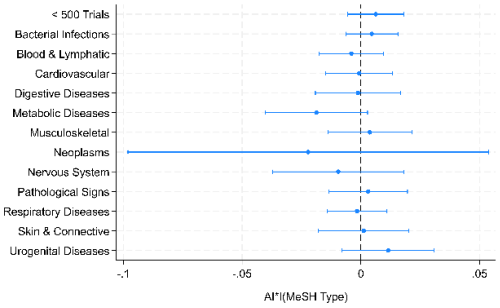


Figure 5h: Trial CAR[-2,+2] and Share AI Invest (Posts)

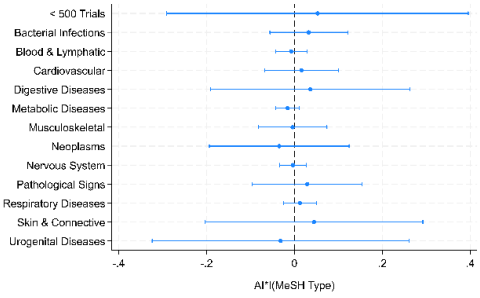


Figure 5 plots the interaction coefficients from 13 separate 2SLS regressions of model (1) with the addition of an interaction between the *Share AI Invest* and an indicator for the trial belonging to one of the groups shown below. The interaction variable captures the differential effect of AI investment on trial efficiency by disease area. Trials with missing MeSH codes are dropped from this analysis. The figure reports the coefficient (the dot) and the 95% confidence interval (using robust standard errors).

Table 1 Summary Statistics

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(6)
VARIABLES	N	Mean	Std. Dev.	Min	P25	P50	P75	Max
Trial characteristics								
Time to Completion	14,517	648.9580	639.0786	0.0000	166.0000	453.0000	912.0000	3370.0000
Trial Completed	18,289	0.8471	0.3599	0.0000	1.0000	1.0000	1.0000	1.0000
Trial CAR[-3,+3]	14,988	-0.0005	0.0452	-0.2100	-0.0227	-0.0004	0.0221	0.2021
Trial CAR[-2,+2]	14,988	-0.0006	0.0371	-0.1633	-0.0180	-0.0004	0.0176	0.1564
ln total outcomes	18,289	2.0930	0.7641	0.0000	1.6094	2.0794	2.6391	3.7377
ln facilities	18,289	2.1758	1.3782	0.6931	0.6931	1.9459	3.3322	5.0239
ln conditions	18,289	0.8033	0.2621	0.6931	0.6931	0.6931	0.6931	2.1972
ln enrollment	18,289	4.4384	1.6573	0.0000	3.3673	4.2905	5.5452	9.5544
Firm characteristics								
Share AI Invest (Emp)	12,245	51.3337	61.7903	-100.0000	23.8097	43.0192	69.0293	648.2260
N AI Invest (Emp)	12,245	77.6942	99.4559	-100.0000	31.3726	57.3529	90.9091	1100.0000
Share AI Invest (Posts)	16,165	0.2496	0.4210	0.0000	0.0000	0.0616	0.3151	2.8177
N AI Invest (Posts)	18,289	51.7065	154.8634	0.0000	0.0000	4.0000	27.0000	1138.0000
Tech Executive	8,784	0.4513	0.4976	0.0000	0.0000	0.0000	1.0000	1.0000
High Reg Frag	9,022	0.4447	0.4970	0.0000	0.0000	0.0000	1.0000	1.0000
High Reg In	11,873	0.4655	0.4988	0.0000	0.0000	0.0000	1.0000	1.0000
High Clarity Device	18,289	0.1159	0.3201	0.0000	0.0000	0.0000	0.0000	1.0000
High Clarity Outcome	18,289	0.5276	0.4993	0.0000	0.0000	1.0000	1.0000	1.0000
ln assets	18,289	10.0552	2.1944	3.1632	9.4724	10.9313	11.6503	12.2688
Cash to assets	18,289	0.2366	0.2171	0.0037	0.1028	0.1590	0.2688	0.9671
Market to book	18,289	5.8048	7.3414	-42.7322	2.5581	3.8515	6.7935	63.2424
Sales growth	18,289	0.4697	6.9823	-1.0000	-0.0210	0.0425	0.1432	221.7916
ROA	18,289	0.0872	0.0754	0.0000	0.0387	0.0776	0.1234	0.4946
Net loss	18,289	0.1434	0.3505	0.0000	0.0000	0.0000	0.0000	1.0000
R&D intensity	18,289	0.1154	0.1098	0.0097	0.0573	0.0803	0.1327	0.8790
Stock return	18,289	0.1635	0.4833	-0.7497	-0.0492	0.0902	0.2287	6.9124
AI talent supply	18,289	0.0087	0.0029	0.0026	0.0064	0.0087	0.0109	0.0165

Table 1 reports trial and firm characteristics for trials completed between year 2010 and 2022. All variables are defined in Appendix A. All continuous variables are winsorized by year at the 1st and 99th percentiles.

Table 2 AI Intensity of Sponsoring Firms

Rank	Top firms with most clinical trials (1)	Top AI-intensive sponsoring firms: *N AI Invest (Emp)* (2)	Top AI-intensive sponsoring firms: *Share AI Invest (Emp)* (3)	Top AI-intensive sponsoring firms: *N AI* Invest (*Posts*) (4)	Top AI-intensive sponsoring firms: *Share AI* Invest (*Posts)* (5)
1	GSK PLC	KARYOPHARM THERAPEUTICS INC	KARYOPHARM THERAPEUTICS INC	JOHNSON & JOHNSON	PROTAGONIST THERAPEUTICS INC
2	JOHNSON & JOHNSON	NEKTAR THERAPEUTICS	NEKTAR THERAPEUTICS	PFIZER INC	TANDEM DIABETES CARE INC
3	PFIZER INC	TANDEM DIABETES CARE INC	THERAVANCE BIOPHARMA INC	MERCK & CO	VANDA PHARMACEUTICALS INC
4	NOVARTIS AG	ACADIA PHARMACEUTICALS INC	GILEAD SCIENCES INC	KONINKLIJKE PHILIPS NV	ALCON INC
5	ASTRAZENECA PLC	INSULET CORP	TANDEM DIABETES CARE INC	ASTRAZENECA PLC	IONIS PHARMACEUTICALS INC
6	LILLY (ELI) & CO	GILEAD SCIENCES INC	INSULET CORP	AMGEN INC	INTUITIVE SURGICAL INC
7	SANOFI	ALECTOR INC	ACADIA PHARMACEUTICALS INC	ABBVIE INC	CAREDX INC
8	BRISTOL-MYERS SQUIBB CO	VIR BIOTECHNOLOGY INC	BAUSCH HEALTH COMPANIES INC	NOVARTIS AG	KONINKLIJKE PHILIPS NV
9	NOVO NORDISK A/S	CUREVAC N.V.	GLOBUS MEDICAL INC	INTUITIVE SURGICAL INC	IRHYTHM TECHNOLOGIES INC
10	ABBOTT LABORATORIES	FATE THERAPEUTICS INC	JAZZ PHARMACEUTICALS PLC	SANOFI	KARYOPHARM THERAPEUTICS INC

This table lists top 10 firms with most clinical trials in column (1) and top 10 AI-intensive sponsoring firms in columns (2) to (5) based on average *N AI Invest (Emp)* (column [2]), *Share AI Invest (Emp)* (column [3]), *N AI Invest (Posts)* (column [4]), and *Share AI Invest (Posts)* (column [5]). *Share AI Invest (Emp)* is the percentage change in the share of positions requiring AI expertise at the sponsor firm in the past three years. *Share AI Invest (Posts)* is the ratio of AI-related job postings to total job postings by the sponsor firm in that year, averaged over the past three years. *N AI Invest (Emp)* is the percentage change in the number of positions requiring AI expertise at the sponsor firm in the past three years. *N AI I*nvest (*Posts)* is total number of AI-related job postings by the sponsor firm in the past three years.

Table 3 Local AI Talent Supply and AI Investment

Dependent variable	*Share AI Invest (Emp)* (1)	*Share AI Invest (Posts)* (2)
AI talent supply	**5,718.4482*****	**10.9362*****
	(0.000)	**(0.000)**
ln assets	7.0302***	0.0602***
	(0.000)	(0.000)
Cash to assets	–24.9437***	0.2011***
	(0.000)	(0.000)
Market to book	0.7077***	0.0037***
	(0.000)	(0.000)
Sales growth	–4.5756***	–0.0010***
	(0.000)	(0.000)
ROA	51.5835***	–0.3033***
	(0.000)	(0.000)
Net Loss	–25.5794***	–0.1135***
	(0.000)	(0.000)
R&D intensity	41.8814***	–0.1307***
	(0.000)	(0.007)
Stock return	12.8585***	0.0074
	(0.000)	(0.465)
ln total outcomes	–2.0214***	0.0239***
	(0.004)	(0.000)
ln facilities	0.6241	–0.0091***
	(0.308)	(0.000)
ln conditions	5.4453*	–0.0575***
	(0.061)	(0.000)
ln enrollment	0.1553	0.0103***
	(0.693)	(0.000)
Constant	–78.0636***	–0.5225***
	(0.000)	(0.000)
Observations	12,245	16,165
Year, Phase, and MeSH FEs	Included	Included
R–Squared	0.203	0.594
F–test of excluded instruments	690.339	95.982

This table presents the first stage Ordinary Least Square (OLS) regression for the 2010-2022 sample period. The dependent variables are the AI investment measures, *Share AI Invest (Emp)* (column 1) and *Share AI Invest (Posts)* (column 2). *Share AI Invest (Emp)* is the percentage change in the share of positions requiring AI expertise at the sponsor firm in the past three years. *Share AI I*nvest (*Posts)* is the ratio of AI-related job postings to total job postings by the sponsor firm in that year, averaged over the past three years. *AI talent supply* is the state-level number of individuals with degrees in information technology, normalized by the state-year population. All specifications include year, phase, and MeSH fixed effects. F-tests for excluded instruments and R-Squared values are shown at the bottom of the table. Variable definitions are provided in Appendix A. Robust *p*-values are presented in parentheses below the estimated coefficients. ***, **, and * indicate significance of the coefficients at the 1%, 5%, and 10% levels, respectively.

Table 4 AI Investment and Trial Efficiency

Dependent variable	*Time to Completion*		*Trial Completion*	
	(1)	(2)	(3)	(4)
Share AI Invest (Emp)	**15.6135**		**–0.0060**	
	(0.476)		**(0.700)**	
Share AI Invest (Posts)		**147.4097****		**0.0745***
		(0.031)		**(0.087)**
ln total outcomes	91.8571***	83.8591***	–0.0064	–0.0046
	(0.000)	(0.000)	(0.140)	(0.285)
ln facilities	186.1181***	190.3080***	–0.0544***	–0.0507***
	(0.000)	(0.000)	(0.000)	(0.000)
ln conditions	166.7628***	155.2823***	–0.0528***	–0.0401***
	(0.000)	(0.000)	(0.000)	(0.002)
ln enrollment	15.6472***	3.0131	0.1010***	0.0975***
	(0.004)	(0.550)	(0.000)	(0.000)
ln assets	–44.3992***	–39.8076***	0.0091**	–0.0127*
	(0.000)	(0.001)	(0.035)	(0.065)
Cash to assets	–88.2568*	–30.7494	–0.0057	–0.0945***
	(0.060)	(0.613)	(0.842)	(0.005)
Market to book	–0.0289	–1.6398*	0.0012***	0.0007
	(0.965)	(0.053)	(0.007)	(0.199)
Sales growth	–11.9559***	–0.3363	0.0021	0.0014***
	(0.009)	(0.473)	(0.497)	(0.000)
ROA	–19.1384	–204.1207***	–0.0211	0.1008**
	(0.847)	(0.009)	(0.719)	(0.021)
Net Loss	29.0365	22.3645	–0.0186	–0.0192
	(0.383)	(0.446)	(0.292)	(0.285)
R&D intensity	–204.1691**	145.0128	0.1966***	0.0589
	(0.034)	(0.111)	(0.001)	(0.293)
Stock return	13.5651	14.8562	–0.0135	0.0025
	(0.446)	(0.355)	(0.219)	(0.795)
Observations	9,759	12,902	12,245	16,165
Year, Phase, and MeSH FEs	Included	Included	Included	Included

This table presents the second stage results examining the effect of AI investment on trial efficiency from two-stage least-squares (2SLS) regressions using *AI talent supply* as the instrumental variable for the 2010-2022 sample period (first-stage results in Table 3). The dependent variables are *Time to Completion* in columns (1) and (2) and *Trial Completion* in columns (3) and (4). *Time to Completion* is the number of days between the trial's start date and its completion date. *Trial Completion* is an indicator variable that equals one if the trial is completed, and zero otherwise. *Share AI Invest (Emp)* is the percentage change in the share of positions requiring AI expertise at the sponsor firm in the past three years. *Share AI I*nvest (*Posts)* is the ratio of AI-related job postings to total job postings by the sponsor firm in that year, averaged over the past three years. All specifications include year, phase, and MeSH fixed effects. Variable definitions are provided in Appendix A. Robust *p*-values are in parentheses below coefficients. ***, **, and * denote significance at the 1%, 5%, and 10% levels.

Table 5 AI Investment and Market Reactions

Dependent variable	*Trial CAR[–3,+3]*		*Trial CAR[–2,+2]*	
	(1)	(2)	(3)	(4)
Share AI Invest (Emp)	**–0.0025**		**–0.0011**	
	(0.187)		**(0.511)**	
Share AI Invest (Posts)		**–0.0104***		**–0.0073**
		(0.065)		**(0.116)**
ln total outcomes	–0.0009	0.0002	–0.0005	0.0002
	(0.135)	(0.730)	(0.274)	(0.634)
ln facilities	–0.0002	–0.0001	–0.0004	–0.0003
	(0.583)	(0.843)	(0.262)	(0.435)
ln conditions	0.0031	0.0021	0.0020	0.0001
	(0.105)	(0.219)	(0.178)	(0.951)
ln enrollment	0.0004	0.0005	0.0005*	0.0004
	(0.262)	(0.206)	(0.100)	(0.140)
ln assets	0.0006	0.0011	0.0001	0.0011
	(0.351)	(0.269)	(0.856)	(0.149)
Cash to assets	0.0030	0.0044	0.0032	0.0057
	(0.526)	(0.425)	(0.398)	(0.217)
Market to book	0.0001	0.0001*	0.0000	0.0001
	(0.453)	(0.088)	(0.668)	(0.100)
Sales growth	0.0002	0.0001	0.0004	0.0001
	(0.822)	(0.387)	(0.479)	(0.474)
ROA	–0.0045	–0.0099	0.0019	–0.0034
	(0.622)	(0.151)	(0.788)	(0.546)
Net Loss	–0.0003	–0.0030	–0.0004	–0.0011
	(0.907)	(0.338)	(0.863)	(0.665)
R&D intensity	–0.0024	–0.0123	–0.0045	–0.0137
	(0.832)	(0.304)	(0.633)	(0.155)
Stock return	–0.0044**	–0.0057**	–0.0045**	–0.0025
	(0.038)	(0.010)	(0.012)	(0.140)
Observations	10,344	13,389	10,344	13,389
Year, Phase, and MeSH FEs	Included	Included	Included	Included

This table presents the second stage results examining the effect of AI investment on completion returns from two-stage least-squares (2SLS) regressions using *AI talent supply* as the instrumental variable for the 2010-2022 sample period (first-stage results in Table 3). *Trial CAR[-3,+3]* (*Trial CAR[-2,+2]*) is CAPM cumulative abnormal return over seven (five) days around the announcement of trial completion. *Share AI Invest (Emp)* is the percentage change in the share of positions requiring AI expertise at the sponsor firm in the past three years. *Share AI I*nvest (*Posts)* is the ratio of AI-related job postings to total job postings by the sponsor firm in that year, averaged over the past three years. All specifications include year, phase, and MeSH fixed effects. Variable definitions are provided in Appendix A. Robust *p*-values are in parentheses below coefficients. ***, **, and * denote significance at the 1%, 5%, and 10% levels.

Table 6 AI Investment, Senior Management's IT Skill, and Trial Outcomes

Panel A: Trial Efficiency

Dependent variable	*Time to Completion*		*Trial Completion*	
	(1)	(2)	(3)	(4)
Tech Executive	35.6432**	–11.2730	0.0093	0.0204*
	(0.046)	(0.540)	(0.395)	(0.063)
Share AI Invest (Emp)	112.7032***		–0.0433	
	(0.008)		(0.132)	
Share AI Invest (Emp) × Tech Executive	**–209.7451*** **		**0.0570**	
	(0.000)		**(0.112)**	
Share AI Invest (Posts)		–24.0173		0.0089
		(0.158)		(0.433)
Share AI Invest (Posts) × Tech Executive		**–151.3871*** **		**0.0669*** **
		(0.000)		**(0.007)**
Observations	5,439	5,577	6,891	7,051
Year, Phase, and MeSH FEs	Included	Included	Included	Included
Controls	Included	Included	Included	Included

Panel B: Market Reaction

Dependent variable	CAR[–3,+3]		CAR[–2,+2]	
	(1)	(2)	(3)	(4)
Tech Executive	–0.0010	–0.0013	–0.0019	–0.0011
	(0.544)	(0.418)	(0.140)	(0.395)
Share AI Invest (Emp)	–0.0095**		–0.0055	
	(0.022)		(0.106)	
Share AI Invest (Emp) × Tech Executive	**0.0102** **		**0.0074***	
	(0.026)		**(0.052)**	
Share AI Invest (Posts)		–0.0049***		–0.0032**
		(0.007)		(0.031)
Share AI Invest (Posts) × Tech Executive		**0.0027**		**0.0026**
		(0.397)		**(0.320)**
Observations	5,740	5,795	5,740	5,795
Year, Phase, and MeSH FEs	Included	Included	Included	Included
Controls	Included	Included	Included	Included

This table presents the second stage results examining the moderating effect of tech-executives on the relation between AI investment and trial outcomes for the 2010-2022 sample period. *Tech Executive* is an indicator variable that equals one if either the CEO or CFO has a technology-related background. Panel A dependent variables are *Time to Completion* and *Trial Completion*. *Time to Completion* is the number of days between the trial's start date and its completion date. *Trial Completion* is an indicator variable that equals one if the trial is completed, and zero otherwise. Panel B dependent variables are CAPM cumulative abnormal return over seven/five days around the announcement of trial completion (*Trial CAR[-3,+3]*/ *Trial CAR[-2,+2]*). *Share AI Invest (Emp)* is the percentage change in the share of positions requiring AI expertise at the sponsor firm in the past three years. *Share AI I*nvest (*Posts)* is the ratio of AI-related job postings to total job postings by the sponsor firm in that year, averaged over the past three years. The following control variables are included but omitted for brevity: *Intervention, ln total outcomes, ln facilities, ln conditions, ln enrollment, ln assets, Cash to assets, Market to book, Sales growth, ROA, Net loss, R&D intensity,* and *Stock return*. All specifications include year, phase, and MeSH fixed effects. Variable definitions are provided in Appendix A. Robust *p*-values are in parentheses below coefficients. ***, **, and * denote significance at the 1%, 5%, and 10% levels.

Table 7 AI Investment, Regulatory Environment, and Trial Outcomes

Panel A: Trial Efficiency

Dependent variable	Regulation Fragmentation				Regulation Intensity			
	Time to Completion		*Trial Completion*		*Time to Completion*		*Trial Completion*	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
High Reg	182.6319***	44.9934**	–0.0687	–0.0367***	39.9831**	22.3176	0.0136	0.0168
	(0.007)	(0.043)	(0.195)	(0.002)	(0.032)	(0.275)	(0.126)	(0.105)
Share AI Invest (Emp)	–951.0866***		0.2873		–502.0310***		0.0744	
	(0.004)		(0.257)		(0.000)		(0.190)	
Share AI Invest (Emp)	**943.6171*** **		**–0.2782**		**385.0095*** **		**–0.0891***	
× *High Reg Frag/ High Reg In*	**(0.002)**		**(0.242)**		**(0.000)**		**(0.081)**	
Share AI Invest (Posts)		–309.3668***		0.1289***		–1,154.4120***		0.3995**
		(0.002)		(0.009)		(0.005)		(0.036)
Share AI Invest (Posts)		**259.4314*** **		**–0.0966*** **		**836.6063*** **		**–0.3160****
× *High Reg Frag/ High Reg In*		**(0.001)**		**(0.010)**		**(0.007)**		**(0.030)**
Observations	7,041	7,788	9,027	9,993	5,906	7,196	6,485	7,923
Year, Phase, and MeSH FEs	Included	Included	Included	Included	Included	Included	Included	Included
Controls	Included	Included	Included	Included	Included	Included	Included	Included

Panel B: Market Reaction

Dependent variable	Regulation Fragmentation				Regulation Intensity			
	CAR[–3,+3]		CAR[–2,+2]		CAR[–3,+3]		CAR[–2,+2]	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
High Reg	0.0091	0.0018	0.0090	0.0016	–0.0010	–0.0002	0.0000	0.0005
	(0.162)	(0.301)	(0.103)	(0.250)	(0.398)	(0.863)	(0.985)	(0.631)
Share AI Invest (Emp)	–0.0494		–0.0477*		–0.0144*		–0.0167**	
	(0.103)		(0.066)		(0.071)		(0.013)	
Share AI Invest (Emp)	**0.0460**		**0.0463***		**0.0112**		**0.0149****	
× *High Reg Frag/ High Reg In*	**(0.111)**		**(0.060)**		**(0.122)**		**(0.015)**	
Share AI Invest (Posts)		–0.0149**		–0.0131**		–0.0366**		–0.0319**
		(0.030)		(0.020)		(0.017)		(0.011)
Share AI Invest (Posts)		**0.0114****		**0.0111*** **		**0.0273****		**0.0239****
× *High Reg Frag/ High Reg In*		**(0.030)**		**(0.009)**		**(0.018)**		**(0.012)**
Observations	7,491	8,021	7,491	8,021	6,041	6,489	6,041	6,489
Year, Phase, and MeSH FEs	Included	Included	Included	Included	Included	Included	Included	Included
Controls	Included	Included	Included	Included	Included	Included	Included	Included

Table 7 (continued)

This table presents the second stage results from two-stage least-squares (2SLS) regressions examining the moderating effect of regulatory environment on the relation between AI investment and trial outcomes for the 2010-2022 sample period. *High Reg Frag* in columns (1)-(4) is an indicator variable that equals one for firm-years when the firm's exposure to regulation fragmentation (Kalmenovitz et al. 2024) is greater than or equal to the median sample firm for that year, and zero otherwise. *High Reg In* in columns (5)-(8) is an indicator variable that equals one for firm-years when the firm's exposure to regulation intensity (Kalmenovitz 2023) is greater than or equal to the median sample firm for that year, and zero otherwise. Panel A dependent variables are *Time to Completion* and *Trial Completion*. *Time to Completion* is the number of days between the trial's start date and its completion date. *Trial Completion* is an indicator variable that equals one if the trial is completed, and zero otherwise. Panel B dependent variables are CAPM cumulative abnormal return over seven/five days around the announcement of trial completion. (*Trial CAR[-3,+3]*/ *Trial CAR[-2,+2]*). *Share AI Invest (Emp)* is the percentage change in the share of positions requiring AI expertise at the sponsor firm in the past three years. *Share AI I*nvest (*Posts)* is the ratio of AI-related job postings to total job postings by the sponsor firm in that year, averaged over the past three years. The following control variables are included but omitted for brevity: *Intervention, ln total outcomes, ln facilities, ln conditions, ln enrollment, ln assets, Cash to assets, Market to book, Sales growth, ROA, Net loss, R&D intensity,* and *Stock return*. All specifications include year, phase, and MeSH fixed effects. Variable definitions are provided in Appendix A. Robust *p*-values are in parentheses below coefficients. ***, **, and * denote significance at the 1%, 5%, and 10% levels.

Table 8 AI Investment, Objective Clarity, and Trial Efficiency

Panel A: Trial Efficiency

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Medical Device Trials				Low Outcome Trials			
VARIABLES	*Time to Completion*		*Trial Completion*		*Time to Completion*		*Trial Completion*	
High Clarity	164.4620***	139.2368***	0.0165	0.0118	–23.0110	–31.0602*	0.0033	0.0070
	(0.000)	(0.000)	(0.214)	(0.366)	(0.192)	(0.061)	(0.747)	(0.452)
Share AI Invest (Emp)	111.6493***		–0.0258		27.7184		–0.0362*	
	(0.000)		(0.109)		(0.326)		(0.066)	
Share AI Invest (Emp)	**–650.2243*** **		**0.1346*** **		**–23.9701**		**0.0585** **	
× *High Clarity Device/High Clarity Outcome*	**(0.000)**		**(0.000)**		**(0.519)**		**(0.034)**	
Share AI Invest (Posts)		409.4644***		0.0410		179.5836**		0.0348
		(0.000)		(0.431)		(0.050)		(0.471)
Share AI Invest (Posts)		**–393.9001*** **		**0.0570** **		**–39.2437**		**0.0522*** **
× *High Clarity Device/High Clarity Outcome*		**(0.000)**		**(0.015)**		**(0.253)**		**(0.001)**
Observations	9,759	12,902	12,245	16,165	9,759	12,902	12,245	16,165
Year, Phase, and MeSH FEs	Included	Included	Included	Included	Included	Included	Included	Included
Controls	Included	Included	Included	Included	Included	Included	Included	Included

Panel B: Market Reaction

	Medical Device Trials				Low Outcome Trials			
Dependent variable	CAR[–3,+3]		CAR[–2,+2]		CAR[–3,+3]		CAR[–2,+2]	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
High Clarity	0.0018	0.0010	0.0017	0.0014	0.0019	0.0020	0.0004	0.0005
	(0.261)	(0.536)	(0.191)	(0.317)	(0.163)	(0.126)	(0.729)	(0.667)
Share AI Invest (Emp)	–0.0034		–0.0020		–0.0007		0.0011	
	(0.100)		(0.250)		(0.789)		(0.620)	
Share AI Invest (Emp)	**0.0046**		**0.0050**		**–0.0033**		**–0.0039**	
× *High Clarity Device/High Clarity Outcome*	**(0.267)**		**(0.151)**		**(0.350)**		**(0.184)**	
Share AI Invest (Posts)		–0.0129*		–0.0098*		–0.0101		–0.0077
		(0.062)		(0.087)		(0.128)		(0.158)
Share AI Invest (Posts)		**0.0041**		**0.0041** *		**0.0000**		**0.0006**
× *High Clarity Device/High Clarity Outcome*		**(0.169)**		**(0.092)**		**(0.999)**		**(0.747)**
Observations	16,165	10,344	13,389	10,344	10,344	13,389	10,344	13,389
Year, Phase, and MeSH FEs	Included	Included	Included	Included	Included	Included	Included	Included
Controls	Included	Included	Included	Included	Included	Included	Included	Included

Table 8 (continued)

This table presents the second stage results from two-stage least-squares (2SLS) regressions examining the moderating effect of objective clarity on the relation between AI investment and trial outcomes for the 2010-2022 sample period. *High Clarity Device* in columns (1)-(4) is an indicator variable that equals one if a trial is a device trial, and zero otherwise. *High Clarity Outcome* in columns (5)-(8) is an indicator variable that equals one the number of total trial outcomes is less than or equal to the median for that year, and zero otherwise. Panel A dependent variables are *Time to Completion* and *Trial Completion*. *Time to Completion* is the number of days between the trial's start date and its completion date. *Trial Completion* is an indicator variable that equals one if the trial is completed, and zero otherwise. Panel B dependent variables are CAPM cumulative abnormal return over seven/five days around the announcement of trial completion. (*Trial CAR[-3,+3]/ Trial CAR[-2,+2]*). *Share AI Invest (Emp)* is the percentage change in the share of positions requiring AI expertise at the sponsor firm in the past three years. *Share AI I*nvest (*Posts)* is the ratio of AI-related job postings to total job postings by the sponsor firm in that year, averaged over the past three years. The following control variables are included but omitted for brevity: *Intervention, ln total outcomes, ln facilities, ln conditions, ln enrollment, ln assets, Cash to assets, Market to book, Sales growth, ROA, Net loss, R&D intensity,* and *Stock return*. All specifications include year, phase, and MeSH fixed effects. Variable definitions are provided in Appendix A. Robust *p*-values are in parentheses below coefficients. ***, **, and * denote significance at the 1%, 5%, and 10% level.

Table 9 Robustness Tests of Short-Term Stock Price Reversals

Panel A: First Week, *Trial CAR[+4, +8]*

(1) AI	(2) Variable	(3) AI	(4) p-value	(5) Variable	(6) p-value	(7) AI×Variable	(8) p-value	(9) Observations	(10) Year, Phase, MeSH FEs
Share AI Invest (Emp)		0.0026	(0.103)					10,332	Included
	Tech Executive	0.0032	(0.349)	–0.0018	(0.146)	–0.0015	(0.695)	5,735	Included
	High Reg Frag	0.0068	(0.749)	–0.0002	(0.961)	–0.0066	(0.746)	7,484	Included
	High Reg In	0.0034	(0.598)	–0.0025***	(0.007)	0.0017	(0.775)	6,038	Included
	High Clarity Device	0.0022	(0.210)	0.0006	(0.637)	0.0025	(0.451)	10,332	Included
	High Clarity Outcomes	0.0002	(0.906)	0.0002	(0.870)	0.0044	(0.118)	10,332	Included
Share AI Invest (Posts)		0.0058	(0.180)					13,366	Included
	Tech Executive	0.0012	(0.374)	0.0013	(0.331)	0.0020	(0.442)	5,788	Included
	High Reg Frag	0.0001	(0.981)	0.0011	(0.422)	0.0001	(0.988)	8,006	Included
	High Reg In	0.0052	(0.648)	–0.0025***	(0.010)	–0.0018	(0.832)	6,484	Included
	High Clarity Device	0.0066	(0.203)	0.0010	(0.469)	–0.0015	(0.510)	13,366	Included
	High Clarity Outcomes	0.0055	(0.274)	0.0002	(0.820)	0.0004	(0.820)	13,366	Included

Panel B: Second Week, *Trial CAR[+9, +13]*

(1) AI	(2) Variable	(3) AI	(4) p–value	(5) Variable	(6) p–value	(7) AI×Variable	(8) p–value	(9) Observations	(10) Year, Phase, MeSH FEs
Share AI Invest (Emp)		–0.0015	(0.363)					10,303	Included
	Tech Executive	0.0016	(0.624)	–0.0005	(0.697)	–0.0034	(0.365)	5,719	Included
	High Reg Frag	0.0006	(0.979)	–0.0020	(0.664)	–0.0007	(0.971)	7,462	Included
	High Reg In	–0.0131*	(0.056)	0.0002	(0.804)	0.0099	(0.111)	6,030	Included
	High Clarity Device	–0.0020	(0.250)	0.0011	(0.399)	0.0028	(0.442)	10,303	Included
	High Clarity Outcomes	–0.0010	(0.625)	–0.0003	(0.804)	–0.0008	(0.769)	10,303	Included
Share AI Invest (Posts)		0.0016	(0.711)					13,332	Included
	Tech Executive	–0.0017	(0.221)	–0.0023*	(0.080)	–0.0018	(0.476)	5,772	Included
	High Reg Frag	–0.0114**	(0.034)	0.0016	(0.257)	0.0094**	(0.022)	7,984	Included
	High Reg In	–0.0212*	(0.086)	–0.0004	(0.719)	0.0154*	(0.096)	6,475	Included
	High Clarity Device	0.0009	(0.870)	0.0022	(0.106)	0.0013	(0.582)	13,332	Included
	High Clarity Outcomes	0.0025	(0.623)	–0.0015	(0.159)	–0.0014	(0.438)	13,332	Included

This table presents the second stage results from two-stage least-squares (2SLS) regressions examining the relation between AI investment and market reactions over a longer window for the 2010-2022 sample period. In panel A (panel B), the dependent variable is *Trial CAR [+4, +8] (Trial CAR [+9,+13])*—the cumulative abnormal return (*CAR*) for the first (second) week following the original event window, [-3,+3]). All CARs are estimated using market-model (CAPM). The following variables from the previous tables and their interaction terms with each AI investment measure are included: *Tech Executive*, *High Reg Frag*, *High Reg In, High Clarity Device,* and *High Clarity Outcome*. The table is arranged such that each row represents one regression, with the AI measure indicated in column (1), the interaction term in column (2), and the corresponding coefficients and *p*-values in the next six columns. All specifications include year, phase, and MeSH fixed effects. The following control variables are included but their coefficients are suppressed for brevity: *Intervention, ln total outcomes, ln facilities, ln conditions, ln enrollment, ln assets, Cash to assets, Market to book, Sales growth, ROA, Net loss, R&D intensity,* and *Stock return*. Detailed variable definitions are provided in Appendix A. Robust *p*-values are presented in parentheses next to the estimated coefficients. ***, **, and * indicate significance of the coefficients at the 1%, 5%, and 10% levels, respectively