Artificial Intelligence, clinical trial efficiency, and market reaction

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Abstract

While AI is often heralded as a panacea, we still grapple with understanding the optimal ways to harness its potential. This study examines the factors that enhance AI's application in clinical trials. We find that, on average, AI decreases the efficiency of trial development and leads to lower market reactions to trial completion. However, when management has a technical background that enables them to integrate the medical domain knowledge with AI, trial efficiency and market reactions improve. A long-term perspective on corporate investment also enhances AI's effectiveness; a short-term perspective may compromise the timeline necessary to achieve the long-term benefits of AI. Although intensive regulation is associated with more positive market reactions to trial completion when AI is used, it often reduces efficiency, revealing regulatory oversight's double-edged nature. Our findings highlight that AI is not universally beneficial as media sentiment suggests. Effective adoption of AI in medical trials requires proper calibration of things such as incorporating tech domain knowledge and a long-term vision.

I. Introduction

We have entered an era of artificial intelligence (AI) where ChatGPT, a conversational AI bot, attracted over 100 million users in just two months after launching in November 2022; for comparison, it took TikTok about nine months and Instagram 2.5 years to reach this same benchmark (Reuters 2023). Recent advancements in artificial intelligence (AI) are fueling the belief that AI has the potential to impact every aspect of human life, from autonomous vehicles and AI-driven diagnostics enhancing healthcare to personalized financial services and intelligent assistants. Research has shown that firms who invest in AI enjoy increased productivity, sales growth, and enhanced market recognition (Rock 2021; Babina et al. 2024), while AI applications demand more workers with AI-related skills who receive wage premiums (Alekseeva et al. 2021; Acemoglu et al. 2022; Babina et al. 2023).

Despite this enthusiasm, AI may not be a panacea. A survey of executives in 2019 found that 70 percent of all digital transformation initiatives do not reach their goals, wasting $900 billion of $1.3 trillion in annual spending (Tabrizi et al. 2019). Effective application of AI requires not only industry domain knowledge but also an understanding of AI and related information technologies (Felten et al. 2019; Rock 2021; Jiang et al. 2021). Managers must carefully evaluate which AI solutions are worth implementing (Lebovitz, Lifshitz-Assaf, and Levina 2022) and consider a series of key questions: What problems can AI solve? What data is required? How can the data be acquired? How should AI output inform decisions? (Alekseeva et al. 2020). After initial investment, it may take years to fully realize the returns from AI investment (Manso 2011), yet capital market and career pressure might incentivize managers to invest in AI projects requiring lower upfront costs and promising quicker payoffs regardless of real long-term value (Dechow and Sloan 1991; Xue 2007; Cohen and Zarowin 2010). Furthermore, AI's reliance on massive amounts

of data (Brynjolfsson and McAfee 2014) raises concerns about data privacy (Beraja et al. 2023). The opaque nature of AI models prompts scrutiny of AI-driven decisions (Goodman and Flaxman 2017). Thus, this study explores when AI is effective and when it is not; more importantly, how to address the challenges and release the full potential of AI. Answers to these questions will help separate hope from hype and result in informed decision-making on the optimal use of AI.

The pharmaceutical industry offers a unique setting to empirically explore these important questions. It plays a crucial role in saving lives through advancements like life-saving antibiotics, antiviral drugs, and treatments for chronic conditions like diabetes and heart disease. These advancements have significantly extended life expectancy and improved the quality of life. Nevertheless, the conventional drug development process is lengthy, expensive, and fraught with a high failure rate. Developing a new drug typically requires billions of U.S. dollars and over 10 years of effort (Chen et al. 2021). AI technologies could potentially streamline this process and improve trial success rates. For example, AstraZeneca's partnership with BenevolentAI in 2019 used the knowledge graph technology to find connections among various data and visualize the patterns, thereby offering insights more efficiently than any single set of experiments (Nature 2021). As such, 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 more than 100 AI projects (Buntz 2023).

Furthermore, AI is applied across diverse functions within firms, such as research and development (R&D), production, supply chains, human resources, and customer services. While documenting the correlation between AI adoption and firm-level outcomes is useful, it does not reveal which specific functions within a firm benefit from AI, nor does it suggest how to address

potential limitations of AI. To address this challenge, we employ a comprehensive dataset on clinical trials by pharmaceutical companies to investigate how AI influences trial-level outcomes. Clinical trials represent a primary area for AI application in the pharmaceutical industry. By establishing a link between AI adoption and trial-level outcomes, we can provide direct evidence on whether and how AI improves firm-level outcomes.

Specifically, we focus on two trial-level operational outcomes: the number of days to completion and the probability of completion, which reflects trial operational efficiency (OEW 2010). As clinical trials become increasingly lengthy and prone to failure, improving operational efficiency is crucial for saving lives. We also examine the announcement returns upon trial completion. Clinical trials are key steps for developing commercialized drugs that will generate future sales and profits. As investors update their expectations of future cash flows based on new information (Verrecchia 1980), the stock market's reaction to trial completion news is an indicator of the expected likelihood of drug commercialization and, if successful, its potential sales and profits. Together, the three trial-level measures depict the operational and financial success of a clinical trial.

Investment in AI is correlated with an array of firm and industry characteristics (Babina et al. 2024; Zolas et al. 2020), leading to concerns about correlated omitted variables and reverse causality. Accordingly, we employ an instrumental variable strategy, using the supply of AI talent as an instrument for firm-level AI adoption (Jiang et al. 2021; Cao et al. 2023), to isolate the effect of exogenous AI adoption. Using this approach, we document that AI increases the days required to complete clinical trials, suggesting that AI decreases the efficiency of clinical trials for pharmaceutical companies. Furthermore, the relationship between AI usage and announcement returns for these clinical trials is significantly negative, suggesting that AI is not necessarily

associated with trials that elicit a positive response from investors. These results indicate that pharmaceutical companies face hurdles to reap the real benefits of AI. Hence, we next explore the conditions that mitigate the negative impact of AI and facilitate the successful application of AI in clinical trials.

First, effective application of AI requires "human-AI collaboration" (Carlile 2004; Levina 2005). However, modern AI solutions often function as "black boxes" to users, creating obstacles for effective collaboration between humans and AI (Wang et al. 2023). The management literature documents that expertise and knowledge are key elements that allow a decision-maker to integrate diverse knowledge domains (Lawrence and Lorsch 1967). We posit that tech domain knowledge allows executives to better understand various AI solutions and unlock the benefits of AI. Second, AI investment represents innovations that could fundamentally improve firms' competitive positions (Crawford 1994). Such investment is often characterized by significant upfront investment and a long payback period. However, investments are often distorted away from long-term projects when under pressure to meet a short-term target (Graham et al. 2005; Budish et al. 2015). We thus investigate whether executives' long-term visions are associated with the effective application of AI.

Nevertheless, executives with tech-heavy backgrounds may prioritize AI at the expense of other critical business aspects such as financial feasibility, customer experience, and employee morale. Research also suggests that the ideal executive background is contingent on firm and industry characteristics (Lawrence 1967; Koyuncu et al. 2010). In the pharmaceutical industry, for instance, medical expertise may be more valuable than a tech-focused background. Moreover, long-term vision could sometimes lead to a loss of focus on the ultimate goals of creating firm value and promoting social welfare (Li and Peng 2020). Hence, it remains an open question

whether executive tech background and long-term horizons are the keys for effective AI applications.

We find that AI reduces the days required to complete clinical trials, increases the probability of trial completion, and generates more positive market reactions when firm executives possess tech domain knowledge. The benefits are economically meaningful: for firms employing executives with tech domain knowledge, a one standard deviation increase in our AI measure decreases the days to completion by nearly one year, increases the probability of completion by 6 percentage points, and raises announcement returns by almost 31 basis points with no subsequent reversal. The analyses also suggest that firms less constrained by the pressure to meet short-term targets benefit more from AI adoption. Specifically, they complete clinical trials faster, and their clinical trials elicit more positive market reactions that are not subsequently reversed. The findings highlight the importance of long-term horizons in improving the effectiveness of AI adoption.

Regulatory approval is one of the most important milestones for any pharmaceutical company (Enache, Li, and Riedl 2022). In the United States, various government agencies such as the Department of Health and Human Services (DHHS) and the Food and Drug Administration (FDA) impose stringent regulations for clinical trials. Given the importance of regulatory approval for the commercialization of new drugs, we next investigate the impact of regulatory intensity on the application of AI in clinical trials. Using two measures of firm-level regulation intensity, we document that clinical trials by AI firms under stronger regulatory scrutiny receive more positive market reactions that do not subsequently reverse. Specifically, a one standard deviation increase in AI investment is associated with a one to two percent higher announcement returns upon trial completion. However, in the presence of intense regulation, AI lengthens the clinical trial process and decreases trial completion rates. The results together suggest that while regulatory scrutiny

acts as a gatekeeper to ensure the approval and commercialization of drugs from AI-driven clinical trials, it comes at the cost of decreased efficiency.

Our study contributes to the growing literature on the impact of AI on individual and firm productivity (Noy and Zhang 2023; Cao et al. 2024) where recent studies have documented a positive impact of AI on firm growth and market value (Babina et al. 2024). In today's business environment, AI tools are increasingly used by professionals across various functions within firms. More granular data is needed to shed light on whether and how AI creates value. We focus on clinical trials, a critical yet costly component of pharmaceutical companies' operations. By examining the effect of AI adoption on trial-level outcomes, our study provides direct evidence of AI's impact on firms' core business activities. We find that AI could impair efficiency and decrease the announcement returns of clinical trials, which exposes the potential dark side of AI. More importantly, by providing new evidence from this unique setting, our study suggests practical solutions to mitigate the potential negative impact of AI adoption.

Our research also relates to the studies on the influence of managerial ability on firm performance (e.g., Baik et al. 2011; Demerjian et al. 2012; Demerjian et al. 2013). Recent research on AI shows that the rise of AI increases the demand for labor with relevant skills (Alekseeva et al. 2021; Acemoglu et al. 2022). We document that top executives with IT skills significantly improve the benefits of AI adoption. The findings extend the literature on firm management and highlight the importance of IT skills for top executives in the AI era.

Third, our study contributes to the literature on the dynamic relationship between innovation and capital markets (He and Tian 2013; Guo et al. 2019). Pharmaceutical companies, which heavily rely on external capital to fund their R&D activities (Enache et al., 2022), are particularly sensitive to capital market pressures to meet financial targets. Our findings indicate

that pharmaceutical companies less vulnerable to short-term pressures gain more from AI in clinical trials, suggesting that a long-term perspective can facilitate more effective AI applications.

Finally, the pharmaceutical industry has long been subject to stringent regulation. The recent 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.[1] Our study finds that under intense regulatory scrutiny, AI may reduce the efficiency of clinical trials, but increases the market reaction. 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

The pharmaceutical industry and drug development

The pharmaceutical industry is one of the most research-intensive industries. Research and development of new drugs play a central role in the activities of pharmaceutical companies (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 account for more than half of pharmaceutical companies' total R&D investment (Congressional Budget Office 2021). Clinical trials are research studies conducted with human participants to evaluate the safety, efficacy, and overall effectiveness of new medical treatments, drugs, devices, or interventions. Clinical trials are divided into four phases (Chow and Liu 2008). 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

[1] 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

the drug and identifying side effects. They usually involve several hundred patients. In some clinical trials, phase I and phase II are combined. 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.

Drug development is a costly and uncertain process. 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). Other than a few established pharmaceutical companies with brand-name drugs, most pharmaceutical companies need to seek external financing to fund their R&D activities. It is difficult for these firms to obtain bank loans because they have limited collateral and face uncertain drug development outcomes (Danzon and Nicholson 2012). As a result, external equity capital becomes a vital source of capital to sustain pharmaceutical companies' R&D investment.

Artificial intelligence in clinical trials

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 (Kolluri et al. 2022; 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.

However, the application of AI in clinical trials also presents several challenges. One major issue is the shortage of professionals with AI-related tech expertise. AI does not instantly improve every aspect of clinical trials; managers must identify and prioritize where AI is most likely to create value. Nevertheless, the rapid development of AI has exacerbated the shortage of professionals with AI-related tech domain knowledge (Deloitte 2024; Financial Times 2024). Second, implementing AI in clinical trials requires significant upfront investment in technology and infrastructure (Chopra et al. 2023). However, pharmaceutical companies seeking external capital often face immense pressure to deliver satisfying quarterly earnings (Cohen and Zarowin 2010; Kothari et al. 2016), which can lead to underinvestment in AI or investment in AI projects promising quicker returns at the expense of long-term value. Regulatory oversight also plays a significant role in the application of AI in clinical trials. The FDA mandates stringent requirements for clinical validation, quality control, and good machine learning practices (Askin et al. 2023). Non-compliance with these requirements could negate the advantages of AI. Additionally, data privacy regulations restrict access to individual patient data which could further complicate the integration of AI into clinical trials.

III. Data and Research Design

Sample selection

Clinical trial data is obtained from the U.S. National Institutes of Health (NIH)[2] and the Clinical Trials Transformation Initiative (CTTI) database.[3] NIH provides a searchable registry and results database of federally and privately supported clinical 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). We begin with the individual clinical trials started between January 1, 2010, and December 31, 2022. For this time period, www.clinicaltrials.gov contains information on more than 343,000 unique trials. We remove trials where the status is active, recruiting, or unknown, leaving us with more than 213,000 trials with known outcomes in our initial sample.

We link the clinical 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.[4] We then standardize the sponsor names in the clinical trial data and the historical company names in Compustat. Using an automated fuzzy matching routine, we match trial sponsors with firms in Compustat. For unmatched sponsoring companies, we review those with 10 or more trials and manually 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.

[2] https://clinicaltrials.gov/
[3] https://aact.ctti-clinicaltrials.org
[4] 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:* "

Measuring AI investment

Following Babina et al. (2024), we use AI-related job postings to proxy for a trial-sponsoring firm's investment in AI. Job posting data from the Burning Glass Institute provides detailed descriptions of each job's required skills and responsibilities. To assess the AI-relatedness of each job, we first calculate the AI-relatedness of individual skills and then aggregate these measures to the job level. Specifically, 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.

We then create two firm-level measures of AI investment. The first measure, *N AI Jobs*, is the number of AI-related job postings by a sponsoring firm in a given year. While *N AI Jobs* reflects a firm's demand for AI skills, it does not account for the size effect. The second measure, *Share AI Jobs*, 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.[5] Hence *N AI Jobs* captures the absolute importance of AI and *Share AI Jobs* reflects the relative importance of AI for sponsoring firms.

Figure 1 plots the average number of AI-related job postings (*N AI Jobs*) and the share of AI-related job postings (*Share AI Jobs*) for the sample pharmaceutical companies by year from 2010 to 2022. Both metrics increase steadily during the sample period, with a noticeable spike in the year 2017. The average number of AI-related job postings increased from 0 to 50 between the years 2010 and 2017 and then quadrupled to around 200 by the end of our sample period. Similarly,

[5] *Share AI Jobs* is set to missing for firm-years without any job postings.

the average proportion of AI-related job postings grows from zero percent to 0.2 percent in the first seven years of our sample period and rises to nearly 1 percent by the end of 2022. The trends are consistent with the surge in demand for AI talents observed in recent years.

To facilitate the comparison of coefficients and calculation of marginal effects, all subsequent regressions use standardized *Share AI Jobs* and *N AI Jobs* (mean of zero and 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.

Measuring trial efficiency and market reaction

Operational efficiency in clinical trials primarily relates to trial duration and trial completion (Group OEW 2010). Clinical trial information from NIH and CTTI includes start and end dates and the final status of a trial. Using the granular data, we construct two measures to proxy for the operational efficiency of clinical trials. The first measure is computed as the number of days between the start and completion dates of a clinical trial (*Time to Completion*). 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" (*Trial Completion*).

In addition to operational efficiency, successful trials should lead to commercialized drugs. However, at the time of trial completion (and potentially not for an extended period afterwards), we do not observe whether a clinical trial ultimately contributes to a commercialized drug. Instead, we lean on prior research that measures the future value of various business projects (e.g., clinical trials) using stock returns (Ecker et al. 2006; Bao and Edmans 2011; Froot et al. 2017) and measure the trial's future financial value with cumulative abnormal announcement returns surrounding the

date when trial completion is revealed to the public (hereafter the *Public Completion Date*).[6] Any news about a trial's completion provides investors with valuable information that might help them update their expectations about future drug commercialization. Compared to other business activities, 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 explore the timing, we plot abnormal share turnover during the 21 days surrounding trial public completion dates (Chae 2005). As shown in Figure 2, the level of abnormal turnover nearly doubles from day *t-3* to the public completion date and then quickly returns to the pre-announcement level. Accordingly, we calculate *CAR*s during [t-2, t+2] and [t-3, t+3] day periods where *t* is the public completion date (*Trial CAR[-2,+2]* and *Trial CAR[-3,+3]).*

Empirical strategy

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

$$Outcome_{ijt}=\alpha_0+\alpha_1 AIInvest_{jt}+\mathbf{X}_{ijt}+\mathbf{Y}_{jt}+\varepsilon_{ijt} \quad (1)$$

[6] 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 when the completion date is recorded as "[Actual]"—in this case, May 24, 2012. We call this date the *Public Completion Date.*

where *Outcome* is one of the two measures of trial efficiency (i.e., *Time to Completion*, *Trial Completion*) or one of the two market reaction measures (i.e., *Trial CAR[-2,+2]* or *Trial CAR[-3,+3]*) for trial *i* conducted by sponsoring firm *j* in year *t*. *AIInvest* is one of the two firm-level AI investment proxies (i.e., *N AI Jobs* and *Share AI Jobs*) for firm *j* in year *t*.

X is an array of the following trial-level characteristics: *Intervention* is an indicator that equals one if the trial is an intervention, and zero if the trial is an observation study; *ln total outcomes* is the natural log of one plus the count of outcomes observed in the study; *ln facilities* is the natural log of one plus the count of the number of facilities used for the clinical trials; *ln conditions* is the natural log of one plus the count of the number of conditions studied in the trial; and *ln enrollment* is the natural log 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 (Hall and Khan 2003). We thus control for firm size using the natural log of assets (*ln assets*), return on assets (*ROA*),[7] 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 (*MTB*), year-on-year sales growth (*sale growth*), and research intensity (*R&D intensity*, ratio of R&D to assets). 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

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

year fixed effects to account for time trends. Standard errors are 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., Babina et al. 2024, Cao et al. 2023, Jiang et al. 2021). 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 the 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.[8] *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.[9] 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).

$$AIInvest_{jt} = \alpha_0 + \alpha_1 AITalentSupply_{kt} + \mathbf{X}_{ijt} + \mathbf{Y}_{jt} + \varepsilon_{ijt} \quad (1a)$$

[8] 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.

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

IV. Empirical Results

Descriptives

Table 1 presents the descriptives of the trial and the 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. The trials have two outcomes on average, are conducted mostly in one facility, involve about four conditions, and have a mean enrollment of 84 participants. At the firm-year level, approximately 52 job postings are AI-related job postings, accounting for 0.2 percent of total job postings of a firm in a given year. In the states where the sample pharmaceutical companies operate, 0.9 percent of individuals aged 18 to 64 possess a degree in information technology. 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.

Table 2, Panel A presents the top AI-intensive sponsoring firms in the sample. Column (1) ranks firms based on the number of AI-related job postings (*N AI Jobs*) and column (2) ranks them based on the proportion of AI-related job postings (*Share AI Jobs*). Column (3) lists the firms with the highest number of clinical trials for comparison. There is a significant overlap between the top AI-intensive firms in column (1) and the leading trial sponsors in column (3), indicating that firms conducting more clinical trials tend to be heavier investors in AI. In contrast, column (2) reveals a greater presence of smaller pharmaceutical companies when ranked by size-scaled AI investment. This trend suggests that a growing number of emerging pharmaceutical firms are leveraging AI to gain competitive advantages.

Table 2, Panel B compares high and low AI-intensive firms based on size-scaled AI investment (*Share AI Jobs*). We find that high AI-intensive firms tend to complete trials about 74

days faster and are slightly more likely to complete trials (86.3 percent vs. 84.2 percent). Although their five-day announcement return upon trial completion is similar to that of low AI-intensive, firms, they experience lower seven-day announcement returns on average. There is some evidence that high AI-intensive firms conduct more complex trials, with more conditions and greater enrollment. Table 2, Panel C repeats the comparison based on absolute AI investment (*N AI Jobs*). The patterns are consistent with those observed in panel B. One exception is that the seven-day announcement returns are comparable between high and low AI-intensive firms when partitioned based on absolute AI investment.

The impact of AI on trial efficiency and market reactions

Table 3 presents the results from estimating model (1a). The instrumental variable, *AI Talent Supply*, is significantly positively correlated with *Share AI Jobs* and *N AI Jobs* at the one percent level, suggesting that local AI talent supply is associated with increased AI investment by local firms. The R-square of the first-stage regression is 59.1 percent in column (1) and 30 percent in column (2), indicating good model fit. Further, the Stock-Yogo test generates F-statistics of 528.39 in column (1) and 92.31 in column (2) that far exceeds 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.

Table 4 reports the results from estimating model (1). In columns (1) and (2), the dependent variable is trial duration (*Time to Completion*). We find both *Share AI Jobs* and *N AI Jobs* are positively associated with trial duration and the association is statistically significant at the five percent level or higher. The results suggest that AI adoption increases the time required to complete clinical trials. The coefficient of 199.24 in column (1) means a one standard deviation increase in

AI investment increases trial duration by 199 days, which is 30 percent of the average trial length. Columns (3) and (4) focus on the probability of trial completion. We find that both *Share AI Jobs* and *N AI Jobs* are positively associated with the propensity of trial completion but only *N AI Jobs* reaches statistical significance at the 10 percent level. Columns (5) to (8) examine the effect of AI investment on announcement returns to trial completion. Both *Share AI Jobs* and *N AI Jobs* are negatively associated with five-day announcement returns, though only *N AI Jobs* is statistically significant. When extending the window to seven days, both *Share AI Jobs* and *N AI Jobs* continue to show a negative association with announcement returns and reach statistical significance at the 10 percent level or higher. A one-standard-deviation increase in *Share AI Jobs* is associated with a reduction in seven-day announcement returns by approximately 100 basis points based on the coefficient in column (7). Taken together, these findings suggest that AI negatively impacts the operational efficiency and the market reaction to clinical trials.

Regarding the control variables, it seems trial complexity impacts trial efficiency but is generally not a significant determinant of trial's market reaction. Specifically, intervention trials and those with larger enrollments tend to take less time to complete and have a higher likelihood of completion. In contrast, trials conducted across multiple facilities or involving more conditions require more time and are less likely to be completed. In terms of firm characteristics, firms with higher market-to-book ratios and ROA are more likely to complete trials and they do so faster. Additionally, larger firms tend to have shorter trial durations, and firms with strong sales growth exhibit higher probabilities of completing clinical trials.

The impact of senior management's IT skills

The previous analysis demonstrates that AI, in its current state, negatively impacts the efficiency and market reaction of clinical trials. These findings highlight the importance of investigating how to mitigate the negative impact and amplify the benefits of AI. Recent studies in AI and healthcare point to a lack of trust in AI among senior management and a shortage of professionals with AI skills (Wang et al. 2023; Deloitte 2024). We first explore whether a tech background enables executives to better understand the advantages and limitations of AI and facilitate the integration of professional domain knowledge and AI technologies, thereby maximizing AI's potential to improve the efficiency and market reaction of clinical trials.

We investigate the effect of executives' tech background with model (2), estimated using 2SLS.[10] 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). However, CEOs and CFOs do not act independently; they collaborate on financial-related decisions to deliver desirable business results (Jiang et al. 2010). CFOs are also increasingly involved in strategic management (EgonZehnder 2016). Given that AI investment involves both strategic and financial planning, we focus on both CEOs and CFOs.

$$Outcome_{ijt}=\alpha_0+\alpha_1 AIInvest_{jt}+\alpha_2 TechManager_{jt}+\alpha_3\, AIInvest_{jt}\times TechManager_{jt}+\mathbf{X}_{ijt}+\mathbf{Y}_{jt}+\varepsilon_{ijt} \quad (2)$$

To identify CEOs' and CFOs' professional backgrounds, we extract data on their educational background and career experience from Boardex. An executive is classified as having a tech background if the executive's educational background or career history includes at least one

[10] 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.

tech-related keyword, such as "AI", "software", and "programming."[11] In model (2), *Tech Executive* is an indicator variable that equals one when either the CEO or the CFO has a tech background. We interact *Tech Executive* with *AIInvest* and the coefficient α_3 reflects the effect of AI investment on trial efficiency or the market reaction when executives have a tech background.

Table 5 reports the results of estimating model (2). The sample size for this set of analyses is reduced to 8,784 trials due to the availability of executive data from Boardex. Approximately 45 percent of these trials are conducted by sponsoring firms with tech-savvy executives. As reported in column (1), the coefficient on *Share AI Jobs×Tech Executive* is -330.07 and statistically significant at the one percent level, suggesting that AI significantly reduces trial duration in the presence of executives with a tech background. For firms employing executives with tech background, a one-standard-deviation increase in *Share AI Jobs* is associated with a reduction in trial duration of 369 days (the sum of the coefficients on the interaction term and *Share AI Jobs*, -330.07-38.83), over 50 percent of the average trial duration. The inference using *N AI Jobs* as the proxy for AI investment is similar. The coefficient on *ShareN AI Jobs×Tech Executive* is -338.56 (p-value<0.01), providing further support that AI reduces trial duration with the involvement of tech executives.

Columns (3) and (4) focus on the probability of trial completion. Both *Share AI Jobs×Tech Executive* and *N AI Jobs×Tech Executive* are associated with higher probabilities of trial completion. The associations are statistically significant at the five percent level or higher. In terms of economic impact, a one-standard deviation increase in *Share AI Jobs* (*N AI Jobs*) increases the

[11] 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.

probability of trial completion by 7.1 (6.3) percentage points for firms employing executives with a tech background.

Finally, columns (5) to (8) examine the joint impact of AI investment and tech executives on market reactions to trial completion. We find that both *Share AI Jobs×Tech Executive* and *N AI Jobs×Tech Executive* are associated with higher announcement returns over the two windows examined, although only *N AI Jobs×Tech Executive* is statistically significant at the 10 percent level or higher. The coefficient on *N AI Jobs* in column (8) indicates that a one-standard deviation increase in AI investment results in announcement returns to trial completion that are 31 basis points higher when pharmaceutical companies have executives with a tech background.

Overall, the results in Table 5 demonstrate that executives with a tech background play a crucial role in unlocking the potential of AI. Integration of industry domain knowledge and tech expertise significantly improves the impact of AI on trial efficiency and market reactions.

The impact of long-term horizon

Transformative technologies such as AI are often characterized by significant upfront investment and long payback periods (Crawford 1994). A robust stream of literature has documented that focusing on short-term targets impacts and distorts firms' innovation investment (He and Tian 2013; Guo et al. 2019). Next, we explore whether long-term horizons could facilitate the positive potential of AI.

Competition for capital is a primary cause for focusing on short-term targets instead of long-term goals (Stein 1998; Kraft et al. 2018). As pharmaceutical firms increasingly rely on external capital to fund research and development activities (Enache et al. 2023), they face constant pressures to meet various financial targets, including those that are short-term oriented. Quarterly

analyst forecasts are among the most important short-term targets that managers seek to meet or beat (Graham et al. 2005). On the other hand, when a firm demonstrates the ability to consistently beat analyst forecasts, it proves the managers' ability, which in turn alleviates the pressure to meet short-term targets (Neururer et al. 2018). Therefore, we posit that if a firm demonstrates a consecutive pattern of meeting or beating analyst forecasts, then they are more likely to have a long-term horizon. In model (3), *Long Horizon* is an indicator variable for firms that have consistently met or beat analyst forecasts for at least four consecutive quarters (Kross et al. 2011). *Long Horizon* is equal to one for 45.9 percent of our observations. The interaction term between *AIInvest* and *Long Horizon* reflects the joint effect of AI investment and long-term horizons on AI effectiveness in clinical trials.

$$Outcome_{ijt}=\alpha_0+\alpha_1 AIInvest_{jt}+\alpha_2 LongHorizon_{jt}+\alpha_3\, AIInvest_{jt}\times Long\ Horizon_{jt}+\mathbf{X}_{ijt}+\mathbf{Y}_{jt}+\varepsilon_{ijt} \quad (3)$$

The results of estimating model (3) using 2SLS are presented in Table 6. The sample of the analyses comprises 15,489 trials conducted by firms followed by analysts. In columns (1) and (2), the coefficients on *Share AI Jobs×Long Horizon* and *N AI Jobs×Long Horizon* are -312.71 and -264.49, respectively, both statistically significant at the one percent level. For firms with a long-term horizon, a one-standard deviation increase in *Share AI Jobs* results in a change in trial duration that is 313 days less than firms without a long-term focus. Interestingly, the coefficients on *Share AI Jobs* and *N AI Jobs* are more positive compared to those in Table 2, implying that the horizon simultaneously influences firms' AI investment and trial duration. In columns (3) and (4), the interaction terms are not statistically significant, meaning horizon does not significantly impact the probability of trial completion.

Columns (5) to (8) present the effect of long-term horizon on the market reaction to the clinical trials. The coefficients on *Share AI Jobs×LongHorizon* and *N AI Jobs×LongHorizon* are 0.015 and 0.014 over [-2,+2] (both with *p*-values<0.01), which indicate that clinical trials conducted by firms with long-term horizons are received more positively by investors. The coefficients over [-3,+3] are 0.014 and 0.013, respectively, and both are significant at the five percent level. Economically, the coefficient on *AI Share Jobs* in column (8) suggests that, for a one-standard deviation increase in *Share AI Jobs*, announcement returns are one percentage point higher for firms with a long-term horizon than those focusing on short-term targets. The findings in this section reveal the importance of having a long-term horizon for leveraging the power of AI in clinical trials.

The impact of regulation

The pharmaceutical industry is subject to intensive regulation by various federal and state agencies. The rise of AI has prompted increased regulatory attention. For instance, the Center for Drug Evaluation and Research under the FDA issued a discussion paper on AI in drug manufacturing; the FDA, collaborating with Health Canada and the United Kingdom's Medicines and Healthcare products Regulatory Agency (MHRA), released 10 guiding principles for good machine learning practice (GMLP). Regulation is designed to address market failures and promote welfare (Pigou 1938). Nevertheless, regulation also introduces rent-seeking opportunities (Stigler 1971) and increases the compliance burden on firms (Dambra and Gustafson 2021; Kalmenovitz 2023). In this section, we explore the impact of regulations on the relation between AI and trial efficiency and market reactions using model (4).

$$Outcome_{ijt}=\alpha_0+\alpha_1 AIInvest_{jt}+\alpha_2 HighReg_{jt}+\alpha_3 AIInvest_{jt}\times HighReg_{jt}+\mathbf{X}_{ijt}+\mathbf{Y}_{jt}+\varepsilon_{ijt} \quad (4)$$

In model (4), *HighReg* represents firm-level regulation intensity, proxied by two measures. 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. A higher level of regulation fragmentation indicates a greater compliance burden but also potentially more guidance. We create an indicator variable, *High Reg Frag*, to indicate firm-years where the firm's exposure to regulation fragmentation is greater than or equal to the median sample firm that year, 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). A higher level of regulation intensity suggests a greater compliance burden and closer scrutiny. *High Reg In* is an indicator variable that equals one for firm-years facing higher regulation intensity (greater than or equal to the median sample firm that year), 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 effect of regulation fragmentation. We find the coefficients on *Share AI Jobs× High Reg Frag* and *N AI Jobs× High Reg Frag* are significantly positive at the five percent level or higher in columns (1) and (2). The results suggest that the negative impact of AI on trial efficiency is exacerbated by regulation fragmentation. Note the coefficients on the main effect of AI investment change from significantly positive in Table 2 to significantly negative in panel A of Table 7. This indicates that firm-level AI investment is influenced by regulation fragmentation and AI decreases trial duration after controlling for regulation fragmentation. When regulation fragmentation is low (i.e., *High Reg Frag* = 0), a one-standard-deviation increase in

Share AI Jobs reduces trial duration by approximately 341 days; in contrast, when regulation fragmentation is high, a one-standard-deviation increase in *Share AI Jobs* decreases trial duration by only 53 days (=287.47-341.09). In columns (3) and (4), the dependent variable is the probability of trial completion. Although both *Share AI Jobs* and *N AI Jobs* are significantly related to a higher probability of trial completion, the coefficients on *Share AI Jobs×High Reg Frag* and *N AI Jobs×High Reg Frag* are -0.06 and -0.15 (*p*-values<0.1), respectively, suggesting a lower probability of trial completion under higher regulation fragmentation. Overall, the results in columns (1) to (4) support the notion that the compliance burden from regulations diminishes the positive impact of AI on trial efficiency.

Columns (5) to (6) turn to market reactions to trial completion announcements. The coefficients on *Share AI Jobs×High Reg Frag* and *N AI Jobs ×High Reg Frag* are 0.012 and 0.026 in columns (5) and (6), respectively. Both increase when the window is expanded to [-3,+3] in columns (7) and (8) to 0.011 and 0.026, respectively. (*p*-values<0.01 and 0.05, respectively). The positive coefficients suggest that a one-standard deviation increase in AI investment is associated with higher announcement returns of 1 to 2.6 percent for firms facing a higher degree of regulation fragmentation when compared to those with lower levels. The positive effect aligns with the notion that comprehensive guidance from regulation helps firms conduct clinical trials that are more likely to obtain regulatory approval for commercialization, resulting in favorable market reactions.

Table 7, panel B reports the effect of regulation intensity. We observe in columns (1) to (4) that regulation intensity impedes the potential efficiency benefits of AI as proxied by trial duration (columns (1) and (2)) and the probability of trial completion (columns (3) and (4)), which are consistent with the findings in panel A of Table 6 based on regulation fragmentation. Further, we find regulation intensity mitigates the average negative market reactions to trial completion in

columns (5) to (8), corroborating the results in panel A of Table 7 that regulation serves as a gatekeeper to trials that are more likely to obtain regulatory approval and commercialization.

Additional analyses

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 in models (1) to (4) using three alternative announcement return measures and two alternative time periods. First, in the main analyses, we estimate announcement returns using a market model (CAPM). As a robustness test, in Table 8, we estimate announcement returns using a market-adjusted model ($\beta = 1$) (Panel A), a Fama-French three-factor model (Panel B), and a Fama-Frech-Carhart four-factor model (Panel C). In all three panels, we continue to find that executive tech background, long-term perspective, and regulatory scrutiny facilitate effective AI usage in clinical trials as indicated by positive coefficients on the interaction between AI investment and each of the variables used in the cross-sectional tests in column (7), though the positive impact of regulation intensity fails to reach statistical significance in Panel B and Panel C when *N AI Jobs* is used as the AI investment measure (p-values of 0.123 and 0.266, respectively).

In Table 9, we examine the one week (five trading days) following our initial period (i.e., [-3,+3]), or days [+4,+8] (*Trial CAR[+4, +8]*), and the subsequent week, days [+9,+13] (*Trial CAR[+9, +13]*). In all 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. 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.

Conclusions

This study is among the first to provide insights into the complex role of AI in clinical trials within the pharmaceutical industry. While AI holds the promise of transforming the trial process, our findings indicate that its impact is nuanced. AI adoption tends to reduce trial efficiency and market reaction unless managed by executives with a tech background and a long-term strategic vision. Additionally, our research reveals the double-edged sword of regulatory oversight, which enhances trial market reaction and hampers trial efficiency simultaneously. By highlighting these dynamics, our study contributes to the broader literature on AI's influence on firm productivity and managerial effectiveness. Our results suggest that executives with tech backgrounds and aligning AI adoption with their firms' long-term goals are more effective in maximizing AI's benefits. Moreover, firms should carefully navigate regulatory oversight in the age of AI. These findings offer valuable implications for researchers, practitioners, and policymakers as they seek to harness the transformative power of AI while mitigating its potential downsides.

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Appendix A: Variable Names and Definitions

VARIABLE	**Definition**
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[-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).
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).
Intervention	Indicator variable that equals one if the trial is an interventional study, and zero if it is an observational study.
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.
Share AI Jobs	Ratio of AI-related job postings (from Burning Glass) to total job postings by the sponsor firm in that year.
N AI Jobs	Number of AI-related job postings (from Burning Glass) by the sponsor firm in that year.
AI Talent Supply	Number of individuals aged 18 to 64 with degrees in information technology, normalized by the state-year population.
Tech Executive	Indicator variable that equals one if either the CEO or CFO has a technology-related background, and zero otherwise.
Long Horizon	Indicator variable that equals one if the trial sponsor has consistently met or beaten analyst forecasts for at least four consecutive quarters, 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 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.
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.

Figure 1: AI Job Postings by Year

These figures plots the number of AI-related job postings scaled by total number of AI-related job postings (*Share AI Jobs,* Figure 1a) and the number of AI-related job postings (*N AI Jobs,* Figure 1b) averaged across sponsoring firms by year for the sample period of year 2010 to year 2022. *N AI Jobs* and *Share AI Jobs* are winsorized by year at the top and the bottom one percentile.

Figure 1a: Share AI Jobs

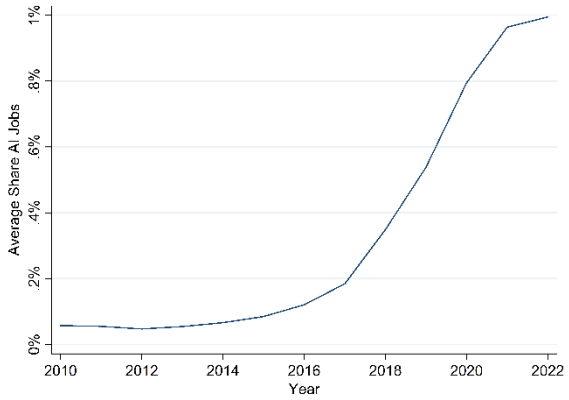


Figure 1b: N AI Jobs

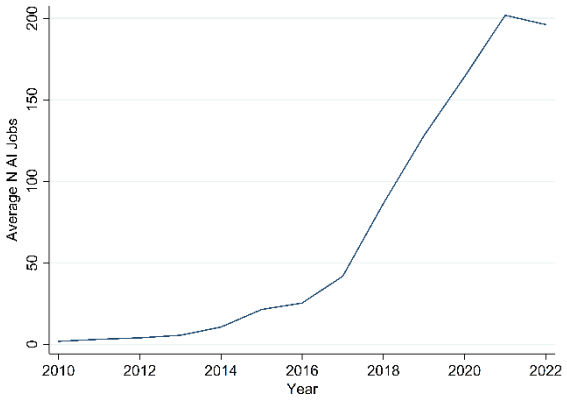


Figure 2: Abnormal turnover surrounding trial completion

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).

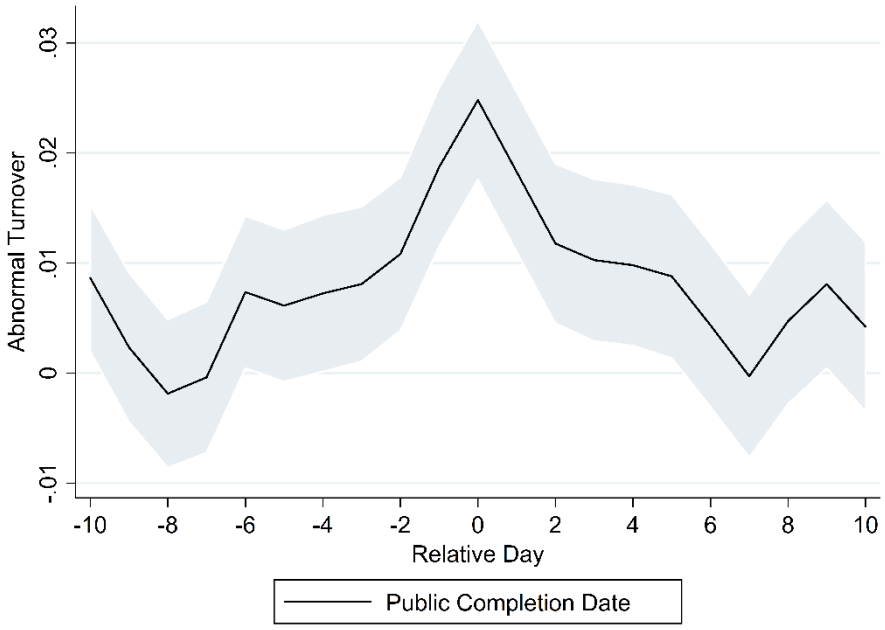


Table 1: Summary Statistics

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

	(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	648.958	639.079	0.000	166.000	453.000	912.000	3370.000
Trial Completed	18,289	0.847	0.360	0.000	1.000	1.000	1.000	1.000
Trial CAR[-2,+2]	14,988	-0.001	0.037	-0.163	-0.018	-0.000	0.018	0.156
Trial CAR[-3,+3]	14,988	-0.001	0.045	-0.210	-0.023	0.000	0.022	0.202
Intervention	18,289	0.862	0.345	0.000	1.000	1.000	1.000	1.000
ln total outcomes	18,289	2.093	0.764	0.000	1.609	2.079	2.639	3.738
ln facilities	18,289	2.176	1.378	0.693	0.693	1.946	3.332	5.024
ln conditions	18,289	0.803	0.262	0.693	0.693	0.693	0.693	2.197
ln enrollment	18,289	4.438	1.657	0.000	3.367	4.290	5.545	9.554
Firm characteristics								
Share AI Jobs	16,165	0.002	0.004	0.000	0.000	0.001	0.003	0.028
N AI Jobs	18,289	51.706	154.863	0.000	0.000	4.000	27.000	1138.000
AI Talent Supply	18,289	0.009	0.003	0.003	0.006	0.009	0.011	0.016
Tech Executive	8,784	0.451	0.498	0.000	0.000	0.000	1.000	1.000
Long Horizon	15,489	0.459	0.498	0.000	0.000	0.000	1.000	1.000
High Reg In	11,873	0.466	0.499	0.000	0.000	0.000	1.000	1.000
High Reg Frag	9,022	0.445	0.497	0.000	0.000	0.000	1.000	1.000
ln assets	18,289	10.055	2.194	3.163	9.472	10.931	11.650	12.269
Cash to assets	18,289	0.237	0.217	0.004	0.103	0.159	0.269	0.967
Market to book	18,289	5.805	7.341	-42.732	2.558	3.852	6.793	63.242
Sales growth	18,289	0.470	6.982	-1.000	-0.021	0.042	0.143	221.792
ROA	18,289	0.087	0.075	0.000	0.039	0.078	0.123	0.495
Net loss	18,289	0.143	0.351	0.000	0.000	0.000	0.000	1.000
R&D intensity	18,289	0.115	0.110	0.010	0.057	0.080	0.133	0.879
Stock return	18,289	0.164	0.483	-0.750	-0.049	0.090	0.229	6.912

Table 2: AI Intensity of Sponsoring Firms

Table 2 provides information about AI intensity of trial sponsoring firms. Panel A presents the top 10 largest trial sponsors based on the average *N AI jobs* (column [1]) and average *Share AI jobs* (column [2]). For comparison, column (3) reports the 10 largest trial sponsors based on the number of trials. Panel B and panel C presents firm characteristics for low and high AI-intensive firms. High (low) AI-intensive firms are those with above-(below-) median *Share AI Jobs* in panel B and *N AI Jobs* in panel C. Differences (High - Low) and *p*-values are reported in columns 7 and 8 of panels B and C. All variables are defined in Appendix A.

Panel A: Top 10 AI-intensive sponsoring firms

	Top AI-intensive sponsoring firms: *N AI Jobs*	**Top AI-intensive sponsoring firms: *Share AI Jobs***	**Top firms with most clinical trials**
Rank	(1)	(2)	(3)
1	JOHNSON & JOHNSON	PROTAGONIST THERAPEUTICS INC	GSK PLC
2	PFIZER INC	TANDEM DIABETES CARE INC	JOHNSON & JOHNSON
3	ASTRAZENECA PLC	VANDA PHARMACEUTICALS INC	PFIZER INC
4	NOVARTIS AG	ALCON INC	NOVARTIS AG
5	GSK PLC	IONIS PHARMACEUTICALS INC	ASTRAZENECA PLC
6	MERCK & CO	INTUITIVE SURGICAL INC	LILLY (ELI) & CO
7	SANOFI	CAREDX INC	SANOFI
8	LILLY (ELI) & CO	KONINKLIJKE PHILIPS NV	BRISTOL-MYERS SQUIBB CO
9	AMGEN INC	IRHYTHM TECHNOLOGIES INC	NOVO NORDISK A/S
10	ABBVIE INC	KARYOPHARM THERAPEUTICS INC	ABBOTT LABORATORIES

Panel B: Comparison of low AI-intensive firms and high AI-intensive firms (Share AI jobs)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Low AI-intensive			**High AI-intensive**			**Diff**	
	N	Mean	Sd	N	Mean	Sd	(5)-(2)	p-value
Trial characteristics								
Time to Completion	6,698	688.877	653.556	6,204	614.918	633.553	-73.959	<0.001
Trial Completed	8,440	0.842	0.365	7,725	0.863	0.344	0.021	<0.001
Trial CAR[-2,+2]	6,777	0.000	0.038	6,612	-0.000	0.028	-0.000	0.470
Trial CAR[-3,+3]	6,777	0.001	0.046	6,612	-0.001	0.035	-0.001	0.050
Intervention	8,440	0.851	0.356	7,725	0.857	0.350	0.006	0.250
ln total outcomes	8,440	2.024	0.749	7,725	2.228	0.759	0.203	<0.001
ln facilities	8,440	2.180	1.367	7,725	2.205	1.403	0.025	0.250
ln conditions	8,440	0.826	0.283	7,725	0.773	0.223	-0.053	<0.001
ln enrollment	8,440	4.393	1.641	7,725	4.563	1.678	0.170	<0.001

Panel C: Comparison of low AI-intensive firms and high AI-intensive firms (N AI jobs)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Low AI-intensive			**High AI-intensive**			**Diff**	
	N	Mean	Sd	N	Mean	Sd	(5)-(2)	p-value
Trial characteristics								
Time to Completion	7,990	673.313	653.133	6,527	619.144	620.190	-54.169	<0.001
Trial Completed	10,073	0.842	0.365	8,216	0.854	0.353	0.012	0.022
Trial CAR[-2,+2]	8,022	-0.001	0.044	6,966	-0.000	0.027	0.001	0.356
Trial CAR[-3,+3]	8,022	-0.001	0.054	6,966	0.000	0.033	0.001	0.414
Intervention	10,073	0.868	0.339	8,216	0.855	0.352	-0.013	0.015
ln total outcomes	10,073	1.977	0.754	8,216	2.235	0.753	0.257	<0.001
ln facilities	10,073	2.156	1.373	8,216	2.201	1.384	0.045	0.028
ln conditions	10,073	0.824	0.281	8,216	0.777	0.234	-0.047	<0.001
ln enrollment	10,073	4.380	1.630	8,216	4.510	1.688	0.129	<0.001

Table 3: Local AI Talent Supply and AI Jobs

This table presents the first stage Ordinary Least Square (OLS) regressions for the 2010-2022 sample period, where the key independent variables are *Share AI jobs* (the ratio of AI-related job postings to total job postings by the sponsor firm in that year.) and *N AI jobs* (the annual number of AI job postings by the firm). The key independent variable is *AI talent supply*, the state-level number of individuals with degrees in information technology, normalized by the state-year population). F-tests for excluded instruments are shown in the last row of the table. All specifications include year fixed effects. Detailed 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.

	(1)	(2)
VARIABLES	*Share AI Jobs*	*N AI Jobs*
AI talent supply	**24.6749*****	**84.8133*****
	(0.000)	**(0.000)**
ln assets	0.1448***	0.1373***
	(0.000)	(0.000)
cash to assets	0.4970***	0.3077***
	(0.000)	(0.000)
MTB	0.0089***	0.0020***
	(0.000)	(0.000)
sales growth	-0.0022***	-0.0022***
	(0.000)	(0.000)
ROA	-0.7666***	-0.9192***
	(0.000)	(0.000)
Net loss	-0.2772***	-0.1633***
	(0.000)	(0.000)
R&D intensity	-0.3389***	0.2548***
	(0.002)	(0.000)
fyear return	0.0163	-0.0114
	(0.493)	(0.355)
Intervention	0.0474***	0.0425**
	(0.002)	(0.026)
ln total outcomes	0.0543***	-0.0083
	(0.000)	(0.369)
ln facilities	-0.0435***	-0.0432***
	(0.000)	(0.000)
ln conditions	-0.1454***	-0.1021***
	(0.000)	(0.000)
ln enrollment	0.0267***	0.0071
	(0.000)	(0.184)
Constant	-1.8271***	-2.0015***
	(0.000)	(0.000)
Year fixed effects	Included	Included
Observations	16,165	18,289
R-squared	0.591	0.300
F-test of excluded instruments	528.59	92.31

Table 4: IV Relationship Between AI and Trial Outcomes

This table presents the second stage results from two-stage least-squares (2SLS) regressions using *AI talent supply* as the instrumental variable for the 2010-2022 sample period. The dependent variables are grouped into two categories: two trial efficiency measures and a trial quality measure. The trial efficiency measures include *Time to Completion* (the number of days between the start and completion dates of the trial) and *Trial Completion* (an indicator equal to one if the trial was completed, and zero otherwise). The market reaction measures include *Trial CAR[-2,+2]* (the CAPM market-model cumulative abnormal return for the five days surrounding the announcement of trial completion) and *Trial CAR[-3,+3]* (the CAPM market-model cumulative abnormal return for the seven days surrounding the announcement of trial completion). The key independent variables are *Share AI jobs* and *N AI jobs*. First stage regression results are available in Table 3. All specifications include year fixed effects. Detailed 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.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Trial Efficiency				**Market Reaction**			
VARIABLES	*Time to Completion*		*Trial Completion*		*Trial CAR[-2,+2]*		*Trial CAR[-3,+3]*	
Share AI jobs	**199.2438*** **		**0.0477**		**-0.0073**		**-0.0102***	
	(0.009)		**(0.287)**		**(0.123)**		**(0.074)**	
N AI jobs		**48.0882****		**0.0214***		**-0.0032****		**-0.0041****
		(0.021)		**(0.081)**		**(0.032)**		**(0.022)**
Intervention	-234.9824***	-221.0576***	0.0824***	0.0899***	0.0010	0.0007	0.0003	0.0006
	(0.000)	(0.000)	(0.000)	(0.000)	(0.279)	(0.480)	(0.762)	(0.624)
ln total outcomes	83.8086***	88.9498***	-0.0041	0.0025	0.0002	-0.0000	0.0002	-0.0003
	(0.000)	(0.000)	(0.337)	(0.463)	(0.592)	(0.922)	(0.732)	(0.601)
ln facilities	224.9450***	213.7999***	-0.0731***	-0.0789***	-0.0006*	-0.0006**	-0.0004	-0.0006*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.073)	(0.020)	(0.236)	(0.064)
ln conditions	244.4583***	242.7254***	-0.0522***	-0.0643***	0.0001	0.0006	0.0019	0.0015
	(0.000)	(0.000)	(0.000)	(0.000)	(0.968)	(0.670)	(0.270)	(0.367)
ln enrollment	-24.0580***	-19.0629***	0.0975***	0.1009***	0.0002	0.0002	0.0002	0.0002
	(0.000)	(0.000)	(0.000)	(0.000)	(0.488)	(0.512)	(0.621)	(0.448)
ln assets	-62.2787***	-31.1912***	-0.0039	-0.0023	0.0013*	0.0010**	0.0013	0.0009*
	(0.000)	(0.000)	(0.583)	(0.403)	(0.098)	(0.017)	(0.187)	(0.080)
cash to assets	-52.3791	-68.9985*	-0.0628*	-0.0257	0.0066	0.0039	0.0055	0.0011
	(0.435)	(0.057)	(0.073)	(0.223)	(0.154)	(0.234)	(0.327)	(0.787)
MTB	-3.0120***	-0.4306	0.0011**	0.0015***	0.0001	0.0001	0.0001*	0.0001
	(0.001)	(0.472)	(0.040)	(0.000)	(0.105)	(0.256)	(0.093)	(0.132)
sales growth	0.1430	-0.1954	0.0013***	0.0011***	0.0001	0.0000	0.0001	0.0001
	(0.772)	(0.658)	(0.000)	(0.000)	(0.455)	(0.626)	(0.386)	(0.260)
ROA	-472.6961***	-494.4295***	0.1583***	0.1086***	-0.0041	0.0018	-0.0093	-0.0040
	(0.000)	(0.000)	(0.000)	(0.002)	(0.468)	(0.715)	(0.171)	(0.499)
Net loss	-11.4441	-34.7196	-0.0211	-0.0242*	-0.0011	0.0009	-0.0028	0.0003
	(0.714)	(0.155)	(0.250)	(0.063)	(0.656)	(0.667)	(0.374)	(0.922)
R&D intensity	-3.7043	-128.3609**	0.0949*	0.0153	-0.0111	-0.0150**	-0.0087	-0.0131
	(0.970)	(0.023)	(0.080)	(0.673)	(0.222)	(0.036)	(0.441)	(0.144)
fyear return	3.8878	14.4828	0.0072	0.0054	-0.0023	-0.0016	-0.0055**	-0.0032**

	(0.821)	(0.159)	(0.459)	(0.391)	(0.160)	(0.194)	(0.014)	(0.029)
Year fixed effects	Included	Included	Included	Included	Included	Included	Included	Included
Observations	12,902	14,517	16,165	18,289	13,389	14,988	13,389	14,988

Table 5: The effect of IT Leadership on the Relationship between AI and Trial Outcomes

This table presents the second stage results from two-stage least-squares (2SLS) regressions using *AI talent supply* as the instrumental variable for the 2010-2022 sample period. The dependent variables are grouped into two categories: two trial efficiency measures and a trial quality measure. The trial efficiency measures include *Time to Completion* and *Trial Completion*. The market reaction measures include *Trial CAR[-2,+2]* and *Trial CAR[-3,+3]*. The key independent variables are *Share AI jobs* and *N AI jobs* and their interactions with *Tech Executive*. *Tech Executive* is an indicator variable that equals one if either the CEO or CFO has a technology-related background, and zero otherwise. First stage regression results are available in Table 3. All specifications include year fixed effects. Detailed 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.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Trial Efficiency				**Market Reaction**			
VARIABLES	*Time to Completion*		*Trial Completion*		*Trial CAR[-2,+2]*		*Trial CAR[-3,+3]*	
Share AI jobs	**-330.0723*** **		**0.0761*** **		**0.0021**		**0.0032**	
×Tech Executive	**(0.000)**		**(0.002)**		**(0.420)**		**(0.292)**	
N AI jobs		**-338.5617*** **		**0.0681** **		**0.0056***		**0.0074** **
×Tech Executive		**(0.000)**		**(0.015)**		**(0.083)**		**(0.048)**
Tech Executive	15.4093	44.3080***	0.0087	-0.0062	-0.0011	-0.0014	-0.0015	-0.0015
	(0.410)	(0.002)	(0.414)	(0.490)	(0.411)	(0.246)	(0.324)	(0.287)
Share AI jobs	-38.8264**		-0.0055		-0.0033**		-0.0052***	
	(0.032)		(0.628)		(0.027)		(0.005)	
N AI jobs		0.3699		-0.0047		-0.0033***		-0.0043***
		(0.975)		(0.557)		(0.007)		(0.003)
Intervention	-187.8622***	-170.9927***	0.0832***	0.0876***	0.0010	0.0004	0.0010	0.0012
	(0.000)	(0.000)	(0.000)	(0.000)	(0.463)	(0.742)	(0.548)	(0.465)
ln total outcomes	77.2361***	77.8440***	-0.0040	-0.0001	-0.0005	-0.0005	-0.0007	-0.0007
	(0.000)	(0.000)	(0.477)	(0.979)	(0.448)	(0.458)	(0.379)	(0.397)
ln facilities	218.9370***	208.7152***	-0.0894***	-0.0937***	-0.0009**	-0.0012***	-0.0008	-0.0015***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.044)	(0.010)	(0.149)	(0.010)
ln conditions	262.3176***	275.8158***	-0.0648***	-0.0714***	0.0024	0.0023	0.0039	0.0016
	(0.000)	(0.000)	(0.000)	(0.000)	(0.266)	(0.301)	(0.159)	(0.564)
ln enrollment	6.1803	3.1063	0.1122***	0.1135***	0.0008*	0.0011**	0.0011**	0.0016***
	(0.403)	(0.640)	(0.000)	(0.000)	(0.084)	(0.016)	(0.040)	(0.004)
ln assets	-7.9655	-11.7509**	0.0021	0.0000	0.0008	0.0007	0.0007	0.0005
	(0.281)	(0.027)	(0.617)	(0.992)	(0.158)	(0.154)	(0.315)	(0.369)
cash to assets	-37.0590	-153.9793***	-0.0264	0.0107	0.0060	0.0043	0.0029	-0.0011
	(0.588)	(0.001)	(0.487)	(0.696)	(0.323)	(0.373)	(0.688)	(0.847)
MTB	0.1040	1.2022*	0.0012***	0.0012***	0.0001	0.0001	0.0001	0.0001
	(0.885)	(0.068)	(0.008)	(0.004)	(0.133)	(0.174)	(0.246)	(0.125)
sales growth	-2.2274**	-1.9651***	0.0016***	0.0011***	0.0004***	0.0002	0.0006***	0.0004**

	(0.012)	(0.003)	(0.000)	(0.000)	(0.000)	(0.216)	(0.000)	(0.013)
ROA	-283.2433	-355.8094***	0.2002**	0.0370	0.0120	0.0140	0.0110	-0.0071
	(0.105)	(0.009)	(0.037)	(0.629)	(0.354)	(0.244)	(0.507)	(0.637)
Net loss	-5.6913	11.9146	-0.0219	-0.0326*	0.0041	0.0026	0.0041	0.0014
	(0.888)	(0.726)	(0.297)	(0.066)	(0.147)	(0.336)	(0.257)	(0.677)
R&D intensity	125.8196	-7.1295	0.0233	-0.0163	-0.0271**	-0.0259***	-0.0257	-0.0218*
	(0.271)	(0.919)	(0.732)	(0.726)	(0.033)	(0.007)	(0.101)	(0.057)
fyear return	23.7941	17.4024	-0.0071	-0.0042	-0.0049**	-0.0029*	-0.0101***	-0.0052***
	(0.269)	(0.119)	(0.560)	(0.574)	(0.048)	(0.058)	(0.002)	(0.004)
Year fixed effects	Included	Included	Included	Included	Included	Included	Included	Included
Observations	5,577	6,903	7,051	8,784	5,795	7,113	5,795	7,113

Table 6: The effect of Long-Term Horizons on the Relationship between AI and Trial Outcomes

This table presents the second stage results from two-stage least-squares (2SLS) regressions using *AI talent supply* as the instrumental variable for the 2010-2022 sample period. The dependent variables are grouped into two categories: two trial efficiency measures and a trial quality measure. The trial efficiency measures include *Time to Completion* and *Trial Completion*. The market reaction measures include *Trial CAR[-2,+2]* and *Trial CAR[-3,+3]*. The key independent variables are *Share AI jobs* and *N AI jobs* and their interactions with *Long Horizon*. *Long Horizon* is an indicator variable that equals one if the trial sponsor has consistently met or beaten analyst forecasts for at least four consecutive quarters, and zero otherwise. First stage regression results are available in Table 3. All specifications include year fixed effects. Detailed 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.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Trial Efficiency				**Market Reaction**			
VARIABLES	*Time to Completion*		*Trial Completion*		*Trial CAR[-2,+2]*		*Trial CAR[-3,+3]*	
Share AI jobs	**-312.7052*****		**0.0475**		**0.0147*****		**0.0140****	
×Long Horizon	**(0.000)**		**(0.277)**		**(0.003)**		**(0.015)**	
N AI jobs		**-264.4883*****		**0.0225**		**0.0134*****		**0.0125****
×Long Horizon		**(0.000)**		**(0.487)**		**(0.001)**		**(0.012)**
Long Horizon	-26.2138	1.5001	0.0017	-0.0038	0.0023**	0.0016*	0.0036***	0.0026**
	(0.197)	(0.910)	(0.862)	(0.596)	(0.042)	(0.085)	(0.008)	(0.019)
Share AI jobs	563.3116***		-0.0696		-0.0269***		-0.0274**	
	(0.001)		(0.452)		(0.009)		(0.025)	
N AI jobs		282.0615***		-0.0128		-0.0152***		-0.0152**
		(0.000)		(0.741)		(0.002)		(0.011)
Intervention	-197.8116***	-186.8418***	0.0881***	0.0917***	0.0005	0.0001	-0.0002	0.0000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.671)	(0.955)	(0.896)	(0.975)
ln total outcomes	66.4453***	84.2919***	0.0045	0.0055	0.0012*	0.0001	0.0011	-0.0000
	(0.000)	(0.000)	(0.424)	(0.145)	(0.076)	(0.785)	(0.165)	(0.957)
ln facilities	242.2070***	222.4371***	-0.0811***	-0.0835***	-0.0013***	-0.0010***	-0.0010*	-0.0009**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.005)	(0.001)	(0.064)	(0.016)
ln conditions	307.8289***	289.3903***	-0.0736***	-0.0756***	-0.0007	0.0010	0.0011	0.0013
	(0.000)	(0.000)	(0.000)	(0.000)	(0.677)	(0.529)	(0.586)	(0.496)
ln enrollment	-28.2000***	-18.6572***	0.1045***	0.1047***	0.0007*	0.0004	0.0006	0.0004
	(0.000)	(0.000)	(0.000)	(0.000)	(0.075)	(0.192)	(0.228)	(0.245)
ln assets	-95.4235***	-41.1836***	0.0077	-0.0011	0.0030**	0.0015***	0.0027*	0.0014**
	(0.000)	(0.000)	(0.456)	(0.736)	(0.011)	(0.002)	(0.053)	(0.016)
cash to assets	-285.1982***	-143.5716***	0.0039	-0.0171	0.0149**	0.0039	0.0121	0.0019
	(0.002)	(0.000)	(0.936)	(0.435)	(0.021)	(0.256)	(0.111)	(0.645)
MTB	-2.2552**	0.7717	0.0018***	0.0016***	0.0002**	0.0001	0.0002*	0.0001
	(0.023)	(0.213)	(0.002)	(0.000)	(0.031)	(0.169)	(0.076)	(0.101)
sales growth	0.5255	-0.2344	0.0011***	0.0010***	0.0000	0.0000	0.0001	0.0001

	(0.344)	(0.608)	(0.000)	(0.000)	(0.584)	(0.561)	(0.391)	(0.218)
ROA	168.7197	-187.8024**	-0.0050	0.0192	-0.0197*	0.0019	-0.0239*	-0.0068
	(0.301)	(0.023)	(0.954)	(0.681)	(0.082)	(0.775)	(0.072)	(0.389)
Net loss	37.5049	-5.6131	-0.0574**	-0.0356***	-0.0041	0.0009	-0.0050	0.0006
	(0.344)	(0.827)	(0.024)	(0.010)	(0.212)	(0.681)	(0.204)	(0.826)
R&D intensity	244.3290*	-43.0313	0.0218	0.0081	-0.0169	-0.0156**	-0.0114	-0.0161*
	(0.053)	(0.480)	(0.729)	(0.830)	(0.117)	(0.036)	(0.381)	(0.084)
fyear return	24.6299	23.2420**	-0.0007	-0.0011	-0.0041**	-0.0021	-0.0080***	-0.0039**
	(0.247)	(0.042)	(0.953)	(0.867)	(0.028)	(0.131)	(0.002)	(0.018)
Year fixed effects	Included	Included	Included	Included	Included	Included	Included	Included
Observations	10,623	12,116	13,533	15,489	11,084	12,570	11,084	12,570

Table 7: The Effect Regulation on the Relationship between AI and Trial Outcomes

This table presents the second stage results from two-stage least-squares (2SLS) regressions using *AI talent supply* as the instrumental variable for the 2010-2022 sample period. The dependent variables are grouped into two categories: two trial efficiency measures and a trial quality measure. The trial efficiency measures include *Time to Completion* and *Trial Completion*. The market reaction measures include *Trial CAR[-2,+2]* and *Trial CAR[-3,+3]*. The key independent variables are *Share AI jobs* and *N AI jobs* and their interactions with *Long Horizon*. *Long Horizon* is an indicator variable that equals one if the trial sponsor has consistently met or beaten analyst forecasts for at least four consecutive quarters, and zero otherwise. First stage regression results are available in Table 3. All specifications include year fixed effects. Detailed 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.

Panel A: Regulation Fragmentation

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Trial Efficiency				**Market Reaction**			
VARIABLES	*Time to Completion*		*Trial Completion*		*Trial CAR[-2,+2]*		*Trial CAR[-3,+3]*	
Share AI jobs	**287.4669*****		**-0.0613***		**0.0119****		**0.0109*****	
×High Reg Frag	**(0.001)**		**(0.097)**		**(0.020)**		**(0.010)**	
N AI jobs		**410.8994****		**-0.1547***		**0.0263***		**0.0256****
×High Reg Frag		**(0.014)**		**(0.097)**		**(0.064)**		**(0.029)**
High Reg Frag	49.7867**	86.2694**	-0.0320***	-0.0524**	0.0020	0.0061	0.0017	0.0057*
	(0.031)	(0.037)	(0.006)	(0.032)	(0.257)	(0.119)	(0.239)	(0.077)
Share AI jobs	-341.0926***		0.0855*		-0.0158**		-0.0129**	
	(0.001)		(0.078)		(0.018)		(0.019)	
N AI jobs		-417.4391**		0.1668*		-0.0285*		-0.0269**
		(0.017)		(0.087)		(0.055)		(0.028)
Intervention	-204.0798***	-212.3755***	0.0671***	0.0762***	0.0009	0.0011	0.0014	0.0010
	(0.000)	(0.000)	(0.000)	(0.000)	(0.572)	(0.489)	(0.255)	(0.417)
ln total outcomes	72.3835***	77.0467***	0.0065	0.0114**	-0.0002	-0.0004	-0.0002	-0.0003
	(0.000)	(0.000)	(0.181)	(0.011)	(0.769)	(0.578)	(0.767)	(0.592)
ln facilities	221.8128***	217.3706***	-0.0858***	-0.0914***	-0.0007	-0.0012**	-0.0007*	-0.0011***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.146)	(0.012)	(0.067)	(0.006)
ln conditions	312.6812***	327.0788***	-0.0830***	-0.0920***	0.0033	0.0017	0.0012	0.0013
	(0.000)	(0.000)	(0.000)	(0.000)	(0.153)	(0.476)	(0.509)	(0.489)
ln enrollment	11.5704*	4.6841	0.1094***	0.1121***	0.0006	0.0009*	0.0004	0.0007*
	(0.072)	(0.418)	(0.000)	(0.000)	(0.198)	(0.053)	(0.284)	(0.100)
ln assets	-10.8595	-15.4148**	-0.0040	-0.0034	0.0012	0.0010*	0.0013**	0.0012**
	(0.293)	(0.013)	(0.420)	(0.322)	(0.126)	(0.092)	(0.038)	(0.014)
cash to assets	42.2539	-130.3718***	-0.0598*	-0.0059	0.0044	-0.0032	0.0063	0.0008
	(0.505)	(0.001)	(0.075)	(0.790)	(0.461)	(0.477)	(0.201)	(0.839)
MTB	2.1902**	1.5236**	0.0010*	0.0014***	0.0001	0.0001*	0.0001*	0.0001
	(0.010)	(0.016)	(0.055)	(0.001)	(0.113)	(0.093)	(0.066)	(0.144)

sales growth	-0.8440	-0.3017	0.0013***	0.0010***	0.0001	0.0001	0.0001	0.0000
	(0.108)	(0.487)	(0.000)	(0.000)	(0.352)	(0.242)	(0.468)	(0.605)
ROA	-44.0982	-86.5952	0.0823	0.0210	0.0017	0.0019	0.0089	0.0150*
	(0.713)	(0.398)	(0.191)	(0.706)	(0.863)	(0.839)	(0.267)	(0.058)
Net loss	-11.3178	5.8420	-0.0281	-0.0376**	-0.0011	0.0006	0.0004	0.0020
	(0.729)	(0.834)	(0.100)	(0.012)	(0.733)	(0.836)	(0.878)	(0.381)
R&D intensity	-134.1393	-90.2011	0.0483	0.0027	-0.0057	-0.0129	-0.0097	-0.0147*
	(0.185)	(0.144)	(0.383)	(0.944)	(0.643)	(0.184)	(0.325)	(0.057)
fyear return	0.1645	7.7115	0.0024	0.0058	-0.0074***	-0.0043***	-0.0035*	-0.0024*
	(0.994)	(0.487)	(0.821)	(0.386)	(0.004)	(0.007)	(0.075)	(0.067)
Year fixed effects	Included	Included	Included	Included	Included	Included	Included	Included
Observations	7,788	9,213	9,993	11,873	8,021	9,437	8,021	9,437

Table 7 (continued)
Panel B: Regulatory Intensity

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Trial Efficiency				**Market Reaction**			
VARIABLES	*Time to Completion*		*Trial Completion*		*Trial CAR[-2,+2]*		*Trial CAR[-3,+3]*	
Share AI jobs	**652.6750*****		**-0.1881***		**0.0193****		**0.0241*****	
×High Reg In	**(0.003)**		**(0.061)**		**(0.011)**		**(0.010)**	
N AI jobs		**2,073.7800***		**-1.2438**		**0.0699***		**0.0964***
×High Reg In		**(0.079)**		**(0.260)**		**(0.082)**		**(0.054)**
High Reg In	65.2873***	330.5927**	0.0170*	-0.1367	0.0002	0.0086	-0.0004	0.0121*
	(0.000)	(0.026)	(0.056)	(0.323)	(0.842)	(0.105)	(0.708)	(0.068)
Share AI jobs	-929.8512***		0.2299*		-0.0251***		-0.0315***	
	(0.001)		(0.072)		(0.010)		(0.008)	
N AI jobs		-2,353.1677*		1.3523		-0.0772*		-0.1072*
		(0.070)		(0.262)		(0.079)		(0.050)
Intervention	-256.1814***	-260.2754***	0.0676***	0.0812***	0.0011	0.0005	0.0005	0.0002
	(0.000)	(0.000)	(0.000)	(0.000)	(0.374)	(0.723)	(0.736)	(0.907)
ln total outcomes	129.1430***	182.9387***	0.0022	-0.0377	0.0006	0.0026	0.0007	0.0036
	(0.000)	(0.000)	(0.781)	(0.430)	(0.399)	(0.142)	(0.423)	(0.107)
ln facilities	216.6751***	191.4056***	-0.0785***	-0.0684***	-0.0010**	-0.0020***	-0.0006	-0.0020**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.019)	(0.009)	(0.212)	(0.027)
ln conditions	280.0595***	285.0933***	-0.0692***	-0.0448	-0.0009	-0.0013	0.0008	-0.0017
	(0.000)	(0.000)	(0.001)	(0.246)	(0.643)	(0.570)	(0.746)	(0.583)
ln enrollment	12.0279	14.3445	0.1075***	0.1065***	0.0003	0.0006	0.0002	0.0007
	(0.166)	(0.204)	(0.000)	(0.000)	(0.465)	(0.195)	(0.632)	(0.260)
ln assets	104.4163***	107.3962*	-0.0268	-0.0618	0.0037***	0.0043**	0.0043***	0.0058**
	(0.005)	(0.096)	(0.116)	(0.282)	(0.005)	(0.041)	(0.008)	(0.027)
cash to assets	314.9749**	21.0976	-0.1176**	-0.0254	0.0043	-0.0001	0.0050	-0.0010
	(0.017)	(0.807)	(0.033)	(0.577)	(0.470)	(0.982)	(0.484)	(0.855)
MTB	-0.2336	-5.9091	0.0018***	0.0067	0.0000	-0.0002	0.0000	-0.0003
	(0.828)	(0.219)	(0.002)	(0.133)	(0.852)	(0.176)	(0.804)	(0.243)
sales growth	-4.5600*	-3.2326	0.0017***	0.0023*	0.0004***	0.0003***	0.0005***	0.0005***
	(0.062)	(0.157)	(0.006)	(0.095)	(0.000)	(0.001)	(0.000)	(0.000)
ROA	-229.4337	-538.4370*	0.1734**	0.3602	-0.0064	-0.0114	-0.0155	-0.0280
	(0.259)	(0.088)	(0.050)	(0.212)	(0.508)	(0.420)	(0.197)	(0.106)
Net loss	44.9601	158.2473*	-0.0386*	-0.0976	0.0026	0.0057*	0.0014	0.0060
	(0.366)	(0.078)	(0.058)	(0.142)	(0.295)	(0.085)	(0.652)	(0.153)
R&D intensity	-277.8535	-925.4456	0.2354**	0.5689	-0.0181	-0.0469**	-0.0294*	-0.0722**
	(0.319)	(0.111)	(0.036)	(0.256)	(0.173)	(0.038)	(0.080)	(0.012)

fyear return	174.5087***	84.2225*	-0.0185	-0.0180	-0.0012	-0.0018	-0.0020	-0.0028
	(0.003)	(0.097)	(0.480)	(0.649)	(0.656)	(0.447)	(0.542)	(0.327)
Year fixed effects	Included	Included	Included	Included	Included	Included	Included	Included
Observations	6,485	7,388	7,923	9,022	6,489	7,363	6,489	7,363

Table 8: Robustness Tests using Alternate Market Reaction Measures

This table presents the second stage results from two-stage least-squares (2SLS) regressions using *AI talent supply* as the instrumental variable for the 2010-2022 sample period. In panel A, the dependent variable is the market-adjusted (β=1) cumulative abnormal return (*CAR*) for the seven days surrounding the announcement of trial completion, [-3,+3]. In panel B, the dependent variable is Fama-French cumulative abnormal return for the same seven-day period. In panel C, the dependent variable is Fama-French-Carhart cumulative abnormal return for the same seven-day period. The key independent variables are the two AI measures, *Share AI Jobs* and *N AI Jobs*. Additionally, the following variables from the previous tables and their interaction terms with *Share AI Jobs* or *N AI Jobs* are included: *Tech Executive*, *Long Horizon*, *High Reg In*, and *High Reg Frag*. First stage regression results are available in Table 3. 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 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, MTB, sales growth, ROA, Net loss, R&D intensity,* and *fyear 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.

Panel A: Market-Adjusted (β=1) CAR[-3,+3]

(1) AI	(2) Variable	(3) AI	(4) p-value	(5) Variable	(6) p-value	(7) AI×Variable	(8) p-value	(9) Year fixed effects	(10) Observations
Share AI Jobs		-0.0137**	(0.020)					Included	13,389
	Tech Executive	-0.0078***	(0.000)	-0.0012	(0.411)	0.0055*	(0.061)	Included	5,795
	Long Horizon	-0.0364***	(0.006)	0.0045***	(0.002)	0.0178***	(0.005)	Included	11,084
	High Reg Frag	-0.0174**	(0.010)	0.0013	(0.475)	0.0113**	(0.029)	Included	8,021
	High Reg In	-0.0370***	(0.003)	0.0001	(0.930)	0.0280***	(0.004)	Included	6,489
N AI Jobs		-0.0048***	(0.009)					Included	14,991
	Tech Executive	-0.0058***	(0.000)	-0.0014	(0.302)	0.0079**	(0.031)	Included	7,116
	Long Horizon	-0.0187***	(0.002)	0.0032***	(0.004)	0.0154***	(0.002)	Included	12,573
	High Reg Frag	-0.0293**	(0.049)	0.0055	(0.165)	0.0263*	(0.066)	Included	9,440
	High Reg In	-0.1313**	(0.022)	0.0150**	(0.031)	0.1183**	(0.024)	Included	7,363

Panel B: Fama-French CAR[-3,+3]

(1) AI	(2) Variable	(3) AI	(4) p-value	(5) Variable	(6) p-value	(7) AI×Variable	(8) p-value	(9) Year fixed effects	(10) Observations
Share AI Jobs		-0.0088	(0.114)					Included	13,389
	Tech Executive	-0.0052***	(0.004)	-0.0019	(0.195)	0.0044	(0.125)	Included	5,795
	Long Horizon	-0.0252**	(0.032)	0.0034***	(0.009)	0.0131**	(0.020)	Included	11,084
	High Reg Frag	-0.0153**	(0.019)	0.0023	(0.179)	0.0117**	(0.019)	Included	8,021
	High Reg In	-0.0257**	(0.025)	-0.0006	(0.606)	0.0201**	(0.025)	Included	6,489
N AI Jobs		-0.0038**	(0.034)					Included	14,988
	Tech Executive	-0.0042***	(0.004)	-0.0023*	(0.099)	0.0086**	(0.017)	Included	7,113
	Long Horizon	-0.0137**	(0.018)	0.0024**	(0.027)	0.0113**	(0.021)	Included	12,570
	High Reg Frag	-0.0241	(0.103)	0.0053	(0.179)	0.0219	(0.123)	Included	9,437
	High Reg In	-0.0825	(0.115)	0.0091	(0.151)	0.0743	(0.120)	Included	7,363

Table 8 (continued)

Panel C: Fama-French-Carhart CAR[-3,+3]

(1) AI	(2) Variable	(3) AI	(4) p-value	(5) Variable	(6) p-value	(7) AI×Variable	(8) p-value	(9) Year fixed effects	(10) Observations
Share AI Jobs		-0.0094*	(0.097)					Included	13,389
	Tech Executive	-0.0052***	(0.005)	-0.0018	(0.221)	0.0029	(0.318)	Included	5,795
	Long Horizon	-0.0241**	(0.041)	0.0035***	(0.008)	0.0123**	(0.029)	Included	11,084
	High Reg Frag	-0.0142**	(0.032)	0.0022	(0.215)	0.0105**	(0.039)	Included	8,021
	High Reg In	-0.0250**	(0.032)	-0.0006	(0.590)	0.0196**	(0.032)	Included	6,489
N AI Jobs		-0.0040**	(0.027)					Included	14,988
	Tech Executive	-0.0038**	(0.011)	-0.0023*	(0.090)	0.0071**	(0.048)	Included	7,113
	Long Horizon	-0.0128**	(0.029)	0.0024**	(0.025)	0.0101**	(0.040)	Included	12,570
	High Reg Frag	-0.0186	(0.224)	0.0040	(0.325)	0.0164	(0.266)	Included	9,437
	High Reg In	-0.0797	(0.131)	0.0085	(0.181)	0.0717	(0.137)	Included	7,363

Table 9: Robustness Tests of Short-Term Stock Price Reversals

This table presents the second stage results from two-stage least-squares (2SLS) regressions using *AI talent supply* as the instrumental variable for the 2010-2022 sample period. In panel A, the dependent variable is *Trial CAR [+4, +8]*—the cumulative abnormal return (*CAR*) for the first week (five trading days following the original event window, [-3,+3]. In panel B, the dependent variable is *Trial CAR [+9,+13]*—the cumulative abnormal return for the second week (five trading days) following the original event window, [-3,+3]. All CARs are estimated using market-model (CAPM). The key independent variables are the two AI measures, *Share AI Jobs* and *N AI Jobs*. Additionally, the following variables from the previous tables and their interaction terms with *Share AI Jobs* or *N AI Jobs* are included: *Tech Executive*, *Long Horizon*, *High Reg In,* and *High Reg Frag*. First stage regression results are available in Table 3. 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 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, MTB, sales growth, ROA, Net loss, R&D intensity,* and *fyear 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.

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) Year fixed effects	(10) Observations
Share AI Jobs		0.0051	(0.248)					Included	13,366
	Tech Executive	0.0012	(0.380)	0.0015	(0.231)	0.0012	(0.617)	Included	5,788
	Long Horizon	0.0131	(0.146)	-0.0008	(0.441)	-0.0059	(0.172)	Included	11,063
	High Reg Frag	-0.0003	(0.948)	0.0011	(0.414)	0.0003	(0.928)	Included	8,006
	High Reg In	0.0006	(0.952)	-0.0020**	(0.028)	0.0012	(0.867)	Included	6,484
N AI Jobs		-0.0004	(0.785)					Included	14,961
	Tech Executive	-0.0016	(0.154)	0.0016	(0.176)	0.0019	(0.549)	Included	7,103
	Long Horizon	0.0019	(0.684)	0.0004	(0.619)	-0.0027	(0.485)	Included	12,548
	High Reg Frag	-0.0054	(0.636)	0.0021	(0.494)	0.0036	(0.745)	Included	9,419
	High Reg In	-0.0117	(0.768)	-0.0005	(0.924)	0.0117	(0.746)	Included	7,356

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) Year fixed effects	(10) Observations
Share AI Jobs		0.0020	(0.658)					Included	13,332
	Tech Executive	-0.0015	(0.288)	-0.0026**	(0.041)	-0.0008	(0.750)	Included	5,772
	Long Horizon	-0.0018	(0.837)	0.0008	(0.442)	0.0016	(0.700)	Included	11,031
	High Reg Frag	-0.0117**	(0.029)	0.0016	(0.253)	0.0094**	(0.021)	Included	7,984
	High Reg In	-0.0165*	(0.088)	-0.0009	(0.339)	0.0123	(0.100)	Included	6,475
N AI Jobs		0.0006	(0.708)					Included	14,921
	Tech Executive	-0.0010	(0.406)	-0.0006	(0.631)	-0.0007	(0.844)	Included	7,084
	Long Horizon	-0.0024	(0.608)	0.0009	(0.305)	0.0028	(0.474)	Included	12,510
	High Reg Frag	-0.0093	(0.436)	0.0005	(0.871)	0.0083	(0.472)	Included	9,392
	High Reg In	-0.0470	(0.268)	0.0033	(0.523)	0.0421	(0.277)	Included	7,345