Pipeline Depth and Stock Price Reactions to Clinical Trial Announcements

An Event Study of US-Listed Small-Cap Pharmaceutical Development Firms, 2014-2024

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Abstract

This thesis explores the relation between US-listed small-cap pharmaceutical development firms' pipeline diversification and the magnitude of share price reactions following the announcement of clinical trial results. We conduct an event study with 739 events across 270 unique companies linked with trial data and stock prices during the period 2014-2024 with the aim of capturing differing abnormal return patterns between firms with broad and narrow research pipelines. We suggest that the higher the number of concurrent trials, the lower the expected magnitude of the effect on the company's share price following the announcement of clinical trial results. We find that the share prices of companies with larger clinical pipelines are significantly less impacted by negative news events relating to the conduct of their clinical trials. Overall, we find mixed evidence that the number of concurrent trials has a significant impact on company stock prices following the announcement of clinical trial outcomes.

Keywords: Biotechnology, Real Options, Portfolio Diversification, Event Study, Clinical Trial Announcements

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1. Introduction

The Pharmaceutical industry develops, manufactures and distributes treatment for human diseases and is one of the most R&D intensive industries in the global economy; DiMasi et al. (2003) estimate that pharmaceutical firms account for roughly 20% of all private-sector R&D spending. We focus our analysis on early-stage, R&D-focused firms – the smallest, listed pharmaceutical development and biotechnology firms – whose value, in contrast to larger, more diversified pharmaceutical companies, derives almost entirely from their pipeline of drugs in development (Thakor et al., 2017), which carries a high probability of failure at every clinical trial stage but a large potential payoff if successful. This feature of the biotechnology sector provides a rich source of events with largely binary outcomes suited to event study analysis.

Myers (1977) establishes that a significant part of firm value is reflected in their growth options, which is the right to make future investments without the obligation to do so. The drug development process follows a similar logic where each clinical trial acts as an option for firms to commit capital in exchange for the potential right to commercialize a treatment or drug if trials succeed. Dixit & Pindyck (1994) later formalizes a general framework for irreversible investments under uncertain conditions which provides a set of options that maps perfectly to biotech investments and clinical trials where the options are to wait, expand investments, or abandon research on a drug. Drug development provides a clear empirical setting for this framework with clearly defined, publicly observable options that resolve in a largely discrete and observable manner.

While the single-option framework captures the value of an individual research program, many biotech firms run several programs concurrently across different therapeutic areas or mechanisms of action. Vassolo et al. (2004) show that for biotechnology firms, a portfolio of imperfectly correlated, non-redundant R&D programs reduces risk relative to any individual program, as independent programs are less likely to fail simultaneously for shared reasons. Applying this logic to clinical development, a firm running trials across different therapeutic areas holds a portfolio where biological, regulatory, and commercial risks are largely independent. It follows that, ceteris paribus, a firm holding a larger portfolio of assets in clinical development should experience lower volatility following the announcement of any given trial result. This result is both intuitive and a direct extension of classical diversification theory applied at the firm level: just as holding uncorrelated financial assets reduces portfolio variance (Markowitz, 1952), holding imperfectly correlated R&D programs should reduce the probability of simultaneous failure of pipeline assets and thereby reduce asset price volatility. Another way to frame this logic is to say that each individual trial represents a larger share of total firm value in a firm with fewer clinical programs than in a firm with many concurrent programs, and therefore that the same trial result should generate a larger market reaction in the former than in the latter.

Extensive empirical work has examined how individual trial announcements affect stock prices

around the event date. Singh et al. (2022) conducted the most comprehensive study, analyzing 13,807 trials between 2000 and 2020, confirming prior findings of significant abnormal returns around both positive and negative announcements and establishing that earlier-stage biotech companies experience the largest effects. However, limited attempts have been made in academic literature to establish the impact that the optionality of an R&D portfolio has on stock prices following the announcement of trial results, or how a negative trial outcome affects the stock price of a biotechnology firm with a single or few assets in their pipeline compared with firms with more extensive pipelines.

This paper contributes to the literature by examining whether pipeline depth — as measured by the number of concurrent clinical trials a company has ongoing at the time of the announcement of a trial's result—impacts the magnitude of abnormal returns in a sample of US-listed small-cap biotech firms over the ten-year period June 2014 to June 2024. If the portfolio logic of Vassolo et al. (2004) holds, then the abnormal returns for firms with diversified pipelines should be systematically smaller following trial result announcements.

2. Background

2.1 Biotechnology and Pharmaceutical Development Industries

The Pharmaceutical industry develops, manufactures, and distributes treatments against human diseases. Within this broad definition there are distinctions and sub-sectors such as biopharmaceuticals, biotechnology, and specialty pharmaceuticals with definitions that are applied loosely and differ depending on context and audience making it difficult to provide singular neat definitions. Firms exist along a continuum and industry and sector definitions vary from source to source. For the purposes of our research, we focus on companies developing medicines and treatments that require FDA approval before being marketed in the United States.

Pharmaceutical development is extremely capital intensive, and since the 1980s, the R&D expense burden and the actors that account for productive and successful drug discovery and development has been in constant flux historically. Until the 1980s, pharmaceutical R&D spending and innovation was almost entirely centralized within the major US and European Pharmaceutical companies, collectively known as 'Big Pharma'. These large, vertically integrated, companies relied almost entirely on internal R&D teams to discover, develop, and bring their product offerings to market. The definitive paper, (Munos, 2009), explains the history of drug development over the 60 years prior: from the 1950s through the 1980s, Big Pharma (under Munos' definition, the largest 15 global pharmaceutical companies) accounted for approximately 75% of New Molecular Entities registrations (NMEs - drug compounds not previously approved by the FDA, including both small-molecules, new chemical entities (NCEs) and biologics, new biological entities (NBEs)). This share has been steadily declining since 1980 and Big Pharma

accounted for approximately 35% of NMEs in 2009. Conversely, over the same period, the mean annual NME output per small pharmaceutical company increased from approximately 0.02 to 0.12 per annum. A 2019 industry report by the IQVIA Institute for Human Data Science (2019) supports this trend with the share of New Active Substances registered with the FDA owned by 'Emerging Biopharma' companies (defined as companies with revenues below $500 million, or estimated R&D spends below $200 million) increasing from 33% in 2010 to 47% in 2018, while the share of NAS patents originally attributable to Emerging Biopharma companies increased from 50% to 64%. This suggests that 64% of new medications that make it to the US market originate from small biotech firms and shows a dramatic reversal from the 1980s when 75% of new medications were developed in-house at the top 15 pharmaceutical companies alone. While the number of NMEs per year has remained essentially flat since 1980, fluctuating between 20-30 each year, the cost of a new NME has grown at an annualized rate of 13.4% since 1950, outpacing Big Pharma annualized R&D spending which has grown at an average compounding rate of 12.4% since 1970 (Munos (2009)). Munos cites survey data from several Big Pharma companies suggests that their pipeline targets are set at 2-3 NMEs each year - targets which far exceed their own internal R&D capabilities, which necessitates Big Pharma to engage in licensing and M&A in order to achieve their growth targets.

Smaller, more agile, usually venture-backed firms have risen to fill the R&D gap left by Big Pharma and today account for an ever-increasing share of NMEs. Big Pharma then steps in and acquires assets from smaller firms at any stage of development, from preclinical assets to approved and marketed assets, in effect outsourcing a significant portion of their R&D to smaller, more focused firms. A more recent development is the emergence of what a report from McKinsey & Company (2021) calls the biotech 'portfolio model' employed by companies such as Roivant and ElevateBio. These companies develop, acquire, and finance a curated portfolio of single-asset/highly focused companies in strategic therapeutic areas, leveraging scale and shared facilities to reduce costs and improve development efficiency, while benefiting from the reduced risk of a diversified portfolio of clinical assets. These 'portfolio model' companies are independent actors but frequently acquire small firms and subsequently sell assets onward to Big Pharma. This model is emerging as a relatively new and productive class of actor in the pharmaceutical development space. Though our dataset is designed to examine the very smallest, US-listed, pharmaceutical development firms and the Emerging Biopharma definition used by IQVIA will include firms much larger than our $2 billion initial market capitalization cutoff, the difference in degree of productivity between Big and Emerging Pharma provides color on our dataset: these are the relatively small firms that together account for a large portion of NMEs that make it to the market.

2.2 FDA Drug Development Process

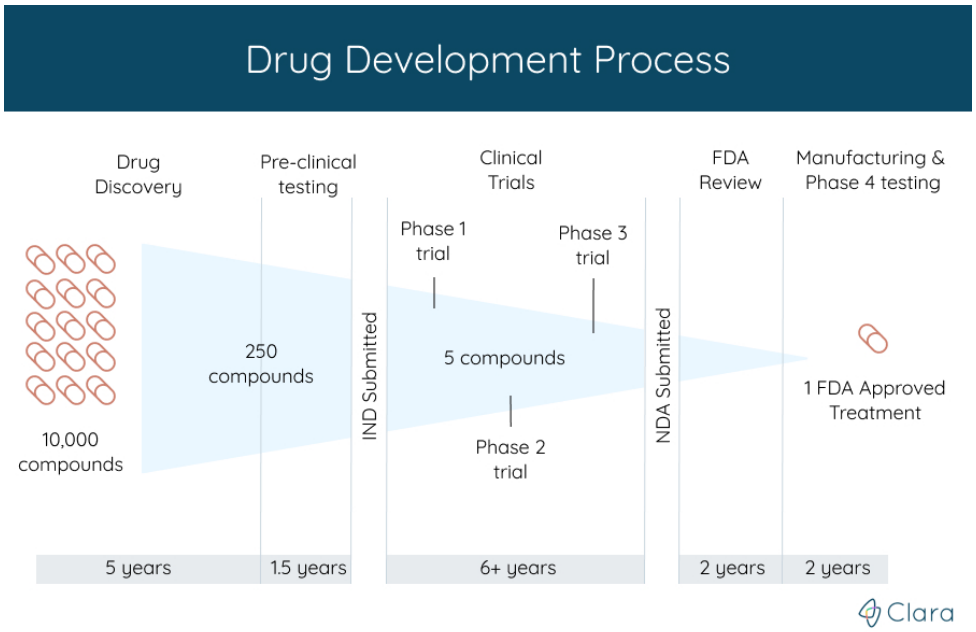

Figure 1. Drug development funnel

Figure 1 shows a simplified diagram of the regulatory process required to bring a new drug to market in the US. The FDA lists five main steps in the drug development process on its website: (1) Discovery and Development, (2) Preclinical Research, (3) Clinical Research, (4) FDA Review, and (5) FDA Post-Market Safety Monitoring. Some firms in our study will engage in all stages of the drug development process, and others will specialize in different stages, but as a rule, since we select the smallest listed firms, they will tend to operate mostly in the earlier stages of development: the more advanced the stage of development, the larger and costlier the clinical trials required to proceed and the more concentrated the pharmaceutical industry becomes. We only include firms that are Lead Sponsors for clinical trials in our study - that is to say we study events for companies engaging in the third step of drug development, (3) Clinical Research.

3. Literature Review

Our thesis relates primarily to four main areas of financial literature. First, it relates to the theory of real options, which allows us to frame our analysis of investment opportunities as options that firms can choose to continue to invest in or to abandon. We apply this theory to the pharmaceutical development sector using methodologies informed by previous research papers. Second, it relates to event study literature and specifically literature focused on stock price reactions to clinical trial outcomes. Third, it relates to literature on portfolios of real options, which examines how the joint value of multiple options differs from their sum of parts. We

extend this literature to the biotech sector by proposing and testing whether option value accrues to firms with larger pipeline sizes, all else equal.

3.1 Real Options within Biotech

Myers (1977) was amongst the first to apply the logic of financial options theory (Black & Scholes, 1973) to real investment decisions, arguing that firm value—especially for R&D-heavy firms—is more tied to investment opportunities which resemble call options, where firms have the right but no obligation to undertake an investment or to abandon a research project. Dixit & Pindyck (1994) later formalize this in a general framework for irreversible investments under conditions of uncertainty, identifying the option to wait, expand, or abandon a project and showing that the economic option value increases with uncertainty. Berk et al. (1999) extend this literature to asset pricing, suggesting that firms whose value is primarily determined by growth options have a fundamentally different systematic risk profile compared to asset heavy firms and should therefore also have a different return profile. With the shift in systematic risk occurring when the growth options are exercised.

The biotech sector offers a particularly pure real-world setting for studying real options, as growth options are relatively clearly defined, and observable through each firm's clinical trial pipeline. Kellogg & Charnes (2000) and Schwartz (2004) confirm this, showing that the majority of biotech firm value derives from growth options and that traditional valuation methods such as discounted cash flow models systematically undervalue early-stage drug development firms. A more appropriate approach is to view a biotech firm as a portfolio of real options where each clinical trial represents an option that can be continued, abandoned, or expanded depending on outcomes.

3.2 Clinical Trial Announcements and Market Reactions

Having established that biotech R&D projects behave like real options, we would expect large movements in stock prices to occur when a clinical trial announcement is released, signaling to the market a firm's intentions to either continue investments, halt, or abandon a research project.

Sharma & Lacey (2004) represents one of the early examples of clinical trial event study literature, examining a closed-ended sample of clinical trials covering 344 drug approvals and 41 FDA rejections. They find statistically significant evidence that trials with positive outcomes record on average a three-day cumulative abnormal return (CAR) of $+1.5\%$, while failures averaged a three-day CAR of -21.0%. The paper also concludes that abnormal returns are entirely concentrated within the three-day window, with no pre- or post-event drift. However, as they focus on final, conclusive events - that is to say approval or rejection - gathered from FDA documentation and company announcements, they risk selection bias, as the FDA does

not publicly announce rejections. This is evident in their sample size having over eight times more approval events than rejections, while fewer than 10% of new drugs reach the market. Furthermore, there is little new information provided by a final FDA approval (i.e. BLA/NDA) as 90.6% of drugs receive final approval following successful pivotal trials, according to recent academic literature (Schuhmacher et al., 2025). This means the most important informational event in a drug's final stages of development— usually a pivotal Phase III trial approval or rejection, which is far less certain and succeeds at rates between 49.8% and 52.4% is excluded in their sample, which is reflected in the relatively modest positive CAR of only $+1.5\%$.

Hwang (2013) tries to solve this by using data queried from clinical trial registrations and results posted to ClinicalTrials.gov, an approach we adopt similarly but at a much larger scale. Conducting an event study around Phase II and III outcome disclosures, Hwang (2013) finds very similar results to Sharma & Lacey (2004), though the small sample size of only 24 announcement events for seven, large, publicly traded, US pharmaceutical companies constrained statistical significance.

Singh et al. (2022) corrects the earlier papers in what is, to our knowledge, the most comprehensive study to date, analyzing 379 publicly traded US pharmaceutical and biotech companies across 13,807 clinical trial outcomes between 2000 and 2020. They confirm the prior findings of papers such as Hwang (2013) and Rothenstein et al. (2011) and show significant cumulative abnormal returns around clear positive or negative announcements for the entire sample. They also find that early-stage biotech firms display outsized reactions to trial announcements, which confirms our choice of using smaller firms as our main sample. The paper uses the Fama–French 5 factor models to estimate abnormal returns, which is appropriate for biotech firms given their well-documented heavy loading on the SMB factor (Bruneo et al., 2024). By treating each trial as an independent event and each firm as a homogeneous unit at the time of announcement, Singh et al. (2022) does not however take into account the number of concurrent trials that a firm has at a specific point in time. Theoretically, the effect of a trial announcement should be smaller the larger the number of concurrent trials a firm holds, as the firm has a lesser dependence on the success of any individual trial. Their model allows for this possibility as it leaves a statistically significant unexplained constant after controlling for the effects of trial announcements and specific company characteristics.

3.3 Portfolio of R&D Options

While real options provide a good framework to understand individual clinical trials, in practice biotech companies typically hold multiple concurrent clinical programmes across different therapeutic areas using different biomarkers. Firm value for firms with multiple assets is thus better understood as a portfolio of real options rather than singular real options in isolation.

Markowitz (1952) first established the theory of portfolio diversification, showing that portfolios with imperfect return correlation reduce portfolio variance below that of individual securities. Trigeorgis (1993) puts forth the theory on the diversification benefits of real options, arguing that beyond a financial sense, a portfolio of real options can create complementary super-additive effects that aid in the projects' mutual development. However, it was unclear how this framework applied to the biotech setting specifically.

Vassolo et al. (2004) builds upon Trigeorgis (1993) and apply their framework within a biotech context, showing that a portfolio of non-redundant R&D options is worth more than any single program in isolation, with independent programs in different technological areas compounding in value. Vassolo argues that this compounding effect emerges partly through the accumulation of fungible skills and knowledge across different clinical programs.

3.4 Factor Models in Asset Pricing

Asset pricing factor models provide the empirical benchmark against which abnormal returns are measured in this thesis. The CAPM proposed by Sharpe (1964) attributes all expected returns to a company's beta (β) exposure to the market factor. Fama & French (1993) addresses this problem through a more empirical approach rather than the theoretical lens of Sharpe, adding size (SMB) and value (HML) as two fundamental factors that capture return premia that the CAPM leaves unexplained, though critics argue that the value factor reflects investor overreaction rather than rational risk compensation. Fama & French (2015) responds to the critics by extending the model to include 5 factors, adding profitability (RMW) and investment (CMA). The choice of factor-model is consequential, as the firms in our sample are smaller by nature and have heavy loading on the SMB factor, and at the same time negative profitability and aggressive investments generate loading on the RMW and CMA factors. We decide to follow in the footsteps of Singh et al. (2022) in adopting the FF5 method as our primary specification.

3.5 Motivation and Research Question

While the literature has established that clinical trial announcements generate significant abnormal returns for biotech firms, and that holding a portfolio of real assets would theoretically reduce idiosyncratic risk, a direct examination of how pipeline size affects stock price reactions to trial announcements remains absent. We address this gap by conducting an event study on a sample of small-cap US-listed biotech firms over the period 2014–2024, testing whether firms with larger concurrent trial portfolios exhibit systematically smaller abnormal returns and lower volatility around clinical trial announcement events than firms with fewer active trials.

H_1: The absolute magnitude of cumulative abnormal returns (CARs) for firms around clinical trial results announcement is negatively related to the number of concurrent trials

ongoing at the time of the event.

H_2: Single-trial firms will experience larger share price losses following negative clinical trial announcements.

4. Data and Methodology

To gather the data for our event study we needed to link different kinds of data from several sources, a number of which did not use shared, relatable, or even any form of unique identifier. At each step of gathering data we used as broad, varied search terms and screening criteria as possible to ensure we gathered all available and pertinent data. This broad approach necessarily led to false positive matches that called for a great deal of manual data cleaning and even qualitative judgment, but was necessary to ensure that our final dataset (which in practice required simultaneous matching across three filtered data sources) was as large and complete as possible.

4.1 Sample Selection

4.1.1 Identifying Pertinent Companies

Our intent in sample selection was to identify biotech companies that were small at the outset of our observation window and to follow their fortunes over our ten-year window. With this in mind we begin our screening process on S&P Capital IQ, selecting companies that were classified in the S&P GICS primary industry classifier Health Care (35) and were at some point during the period 2014-06-01 to 2024-06-01 publicly listed on New York stock exchanges (NYSE, NASDAQ CM, NASDAQ GM, NASDAQ GS). We begin with as broad an industry screen as possible as we found that with more specific industry classifiers such as Biotechnology (35201010) or Pharmaceuticals (35202010), we excluded many relevant companies conducting clinical trials during the period that were positioned differently in the GICS taxonomy. Specifically, we found many companies in the primary sector 3510, Health Care Equipment & Services, that also actively conducted interventional clinical trials during our period. Conversely, when we omitted industry from our screen entirely, we identified clinical trials related to irrelevant companies in sectors such as Industrial Conglomerates (20105010) or Packaged Foods & Meat (30202030).

We then excluded companies with a market capitalization above $2 billion at the start of our period to narrow our focus on smaller, and therefore predominantly early- and development-stage companies. We focus on small-cap firms because they are predominantly pre- or low-revenue and therefore their market capitalizations are more closely tied to the strength of their clinical

pipelines. We defined small-cap as having a market capitalization of less than $2 billion, which corresponds to the conventional small-cap definition used in asset pricing literature and by small-cap index funds such as Russell 2000 and S&P SmallCap 600. To capture the entire population of biotech firms during the period, we added firms that had an IPO during 2014-06-01 to 2024-06-01 that had an initial IPO market capitalization under $2 billion. We chose not to implement any maximum market capitalization screen so as not to exclude companies that grew and became mid- or large-cap during the period. Finally, we included companies that have been delisted or acquired during our observation period to minimize selection bias.

These screening criteria produce a list of 1,830 companies in the Health Care industry that were at some point listed on a major US exchange and had a market cap below $2 billion at the outset of our period or at IPO, allowing for acquisitions, liquidations, delistings, and reorganizations. These criteria did however include approximately 700 companies whose last SEC filing was before 2014, which we were unable to exclude using screening filters on Capital IQ. Using a combination of ISIN and CUSIP numbers from Capital IQ we further query the Refinitiv Eikon/LSEG database to exclude these extraneous data. The result is a final list of 1,037 companies.

4.1.2 Identifying Clinical Trials Linked to Sample Companies

We source our clinical trials data by querying the ClinicalTrials.gov API, which is maintained by the National Institutes of Health. ClinicalTrials.gov is designed with the specific purpose of registering and tracking trials for regulatory compliance and public transparency, and is not designed as a database to output information linking trials to publicly listed companies in a one-to-one mapping. As such, naming convention is not strict and allows name variants and abbreviations, and the database does not include a unique corporate identifier such as ISIN, CUSIP, or CIK to query. Furthermore, there are many different fields under which companies with a relationship to a trial can be listed.

We decided to query the `LeadSponsor` field as it is the least ambiguous option, but there are other fields to which we could match our companies to such as `ResponsibleParty` or `Organization` that follow somewhat loose conventions. There is no field that concisely expresses "final corporate backer", and to complicate things, `LeadSponsor` can even name a specific scientist or team rather than a company. To generate our query, we take the Entity Name field output from Capital IQ and perform various cleaning steps to produce reasonable variations on the company's name. This was done manually in Excel and mostly consisted of removing appended exchange and ticker information, as well as extraneous punctuation and corporate suffixes such as "inc." and "corp". We retain all variations and then use this list to query the SEC EDGAR API and output the `formerNames` field as well as CIK identifiers and other fields such as first filing date and most recent filing to help us identify mismatches.

Using a combination of ISIN and CUSIP numbers from Capital IQ we further query the Refinitiv Eikon/LSEG database for subsidiary names associated with our list of parent companies. The result is a list of approximately 15,000 current, former, and subsidiary names, which we then use to query the ClinicalTrials.gov API.

The ClinicalTrials.gov API has its own fuzzy string-matching capability which works both in our favor and to our detriment—the fuzzy string-matching helps pick up on trials with typing errors or common abbreviations in the place of `LeadSponsorName` but also produced many false-positive matches. This produced a list of approximately 26,000 unique trials, linked to 698 of the 1,037 companies in our screen, each identified by a unique NCTID (National Clinical Trial ID) number. After manual cleaning, the resulting database has 5,805 interventional clinical trials that we can confidently link through the `LeadSponsor` field to 447 of the 698 companies to which we had initially matched trials. Trial data are then aggregated on a monthly basis at the firm-level based on trial start and end dates, resulting in firm-month observations of the number of concurrent active trials.

4.1.3 Selecting and labelling Relevant Events

Separately we clean a list of events using data from S&P Capital IQ. Using the list of 447 companies for which we have clinical trial data, we clean and filter the Key Development Type & Category field from S&P Capital IQ for each of our companies. This provides a list of all events during our period, accompanied by a date and categorization (e.g. Conference, Private Placement, Product-related Announcement, Strategic Alliance, etc.) for each company in our sample, 274,735 events in total (approximately 55 events per year, per company). There are several categories of announcements that frequently produce abnormal returns, but our focus is a cleaned subset of Product-related Announcements (27,331 events) which contains announcements related to trial initiations, first patients dosed, patient recruitment, preclinical developments, other regulatory events, announcements related to non-pharmaceutical or unregulated products, conference participation, and many other announcements. For this cleaned subset, we choose the first announcement (if there are multiple clearly relating to the same clinical program or trial) indicating trial conclusion and dissemination of clinical data. As an example, we exclude interim readouts and include announcements where the primary endpoint is met or "announces Phase 2 results". The guiding principle of our selection is to select the first announcement of a material and binary change in the company's prospects with respect to any given clinical trial or pipeline asset.

This produces 1,256 events for 451 companies, which we then match the subset of firms for which we have concurrent clinical pipeline data. This produces a cleaned, primary dataset consisting of 806 announcements from 288 companies that we judge to be the first announcement of a decisive outcome, positive or negative, of a clinical trial, when we are confidently able to

label the phase of the underlying trial, and match to our selection of companies. Our final sample excludes additional events that occur before the firm's IPO or before the firm has been listed for a calendar year as there are insufficient trading days to establish a robust estimation window leading to a final total of 739 events and 270 companies.

4.2 Financial Data

Stock market data, including the daily closing price and trading volume, are sourced from the Refinitiv Eikon/LSEG database, matched using firm ISIN and CUSIP numbers. Monthly returns are then calculated from the change in daily closing price over each calendar month. A list of all subsidiaries, affiliates and joint ventures for our sample firms are sourced since biotechnology firms sometimes conduct trials using subsidiary firms or in joint ventures with another firm.

Financial data used in our factor models are collected through Refinitiv Eikon/LSEG and linked with the stock market data using the ISIN and CUSIP identifiers. Annual financial data including total assets, cash and cash equivalents, total debt, and total revenues are included.

4.3 Sample Statistics

Table 1. Panel A — Sample Overview

Panel A — Sample Overview	
Time period	
Sample start	2014-05-31
Sample end	2024-05-31
Raw sample	
Events (raw)	1,256
Unique firms (raw)	451
Matched sample	
Matched to trial data	806
Unique firms (matched)	288
Final sample	
Events included	739
Events excluded	67
Unique firms (final)	270
Events per firm	
Mean	2.73
Median	2.00
Minimum	1
Maximum	15

4.4 Event Study Design

To test whether the magnitude of a trial announcement's effect on stock prices varies between firms with different sizes of project pipelines, our paper employs a standard short event study following the study methodology found in Brown and Warner (1985) and MacKinlay (1997) to isolate the stock price reaction to clinical trial announcements and from broader market movements. Following the methodology used by Singh et al. (2022), the event date is defined as the date of first public disclosure.

We define a standard event estimation window of [-250, -11] trading days before the event date, which provides daily returns from the previous full calendar year. The pre-event date window is defined as [-10,-2] trading days before the event, which is intended to prevent anticipatory price movements or information leakage in the days leading up to the event. The event window is defined as [-1, +1] trading days around the event date, capturing both the announcements, and the adjacent trading days accounting for pre-market or after-hours trial announcements. We have chosen to report results for the wider [-3, +3] as additional robustness checks.

Abnormal returns are estimated using the Fama-French (FF5) model, which extends the FF3 model by adding profitability and investment factors and is well-suited to the development-stage biotech industry, given its loss-making and its high degree of investment intensity.

$$R_{it} = \alpha_i + \beta_{1i} MKT_t + \beta_{2i} SMB_t + \beta_{3i} HML_t + \beta_{4i} RMW_t + \beta_{5i} CMA_t + \epsilon_{it} \tag{1}$$

Where R_{it} is the excess return of firm i on day t and the Fama-French factors on the right.

$$AR_{it} = R_{it} - \hat{\alpha}_i - \hat{\beta}_{1i} MKT_t - \hat{\beta}_{2i} SMB_t - \hat{\beta}_{3i} HML_t - \hat{\beta}_{4i} RMW_t - \hat{\beta}_{5i} CMA_t \tag{2}$$

Cumulative abnormal returns (CAR) are then calculated by summing daily abnormal returns over the event window

$$CAR_i(t_1, t_2) = \sum_{t=t_1}^{t_2} AR_{it} \tag{3}$$

Cumulative abnormal returns (CAR) and Absolute Cumulative abnormal returns (|CAR|) are included in our event design to test both the direction and magnitude of stock market reactions. The signed CAR measure preserves the direction of the market reaction and shows whether announcements, on average, increase or decrease share price. |CAR| shows the magnitude of the price change regardless of sign which is useful since our dataset does not include sentiment labels.

To examine whether pipeline size influences post-announcement returns, we first divided our

sample into two groups, single-trial firms and multi-trial firms. This divide provides us with an initial test on whether the number of concurrent trials has any effect on the stock price. We then further divide the sample into Quartiles, to test not only if the effect of the number of concurrent trials exists, but also to evaluate what kind of relation it has with the size of stock prices movements following clinical trial announcements. We split the sample into Quartiles by ranking the firms by their number of concurrent trials and by dividing the sample into groups that were as balanced as possible. Q1 is comprised of companies that only have a single trial active, Q2 contains firms with two to three concurrent trials, Q3, firms with four to six trials active, and Q4, firms with seven or more trials active. The Quartiles are assigned on a monthly basis, reflecting the fact that the number of concurrent trials for each firm fluctuates over the ten-year observation period as firms conclude and initiate new trials.

5. Results

5.1 Mean CARs for single vs multi-trial firms

Table 2. FF5 Mean CARs: Single- vs. Multi-Project Firms with Difference Test

		CAR$[-1,+1]$			**CAR**$[-3,+3]$		
Group	n	**Mean**	**SE**	**95% CI**	**Mean**	**SE**	**95% CI**
Single	111	-0.0013	0.0366	$[-0.074,\ +0.071]$	-0.0085	0.0399	$[-0.088,\ +0.071]$
Multi	628	0.0402^{**}	0.0201	$[+0.001,\ +0.080]$	0.0423^{**}	0.0203	$[+0.002,\ +0.082]$
Difference (S$-$M)		-0.0415	0.0418	$[-0.124,\ +0.041]$	-0.0508	0.0448	$[-0.139,\ +0.038]$

Notes: Mean CARs estimated using the Fama–French five-factor model. Single and Multi rows report one-sample t-tests of H_0: CAR $= 0$; SE is the standard error of the mean. The Difference row reports a Welch two-sample t-test of H_0: $\text{CAR}_{\text{single}} = \text{CAR}_{\text{multi}}$, with SE computed under unequal variances. CARs expressed as decimals. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.10$.

Table 2 reports the mean Cumulative Abnormal Returns (CARs) for single-trial and multi-trial firms across event windows of 1 and 3 days, before and after the event, as estimated by the Fama-French five-factor model. This naive approach leads to very slightly negative mean CARs for single-trial firms and slightly positive CARs for multi-trial firms, but we cannot make any solid conclusions about the magnitude of these CARs as the differences in mean between single-trial and multi-trial firms are not statistically significant at any conventional significance level for any estimation window. The positive mean CAR of 4.0% and 4.2% for multi-trial firms is significant at p<0.05 in both estimation windows.

This null result is unsurprising, however, as our dataset does not include sentiment analysis and therefore our events include a mixture of positive and negative results for both groups. Our event data features 63 events with positive returns and 48 with negative returns for single-trial firms, and 320 positive-return events and 308 negative-return events for multi-trial firms. Despite the

statistical insignificance of the result, the difference between single and multi-trial groups even at this level follows our intuition: we expect negative results for single-trial firms to produce extreme negative stock returns and we expect multi-trial firms to, on average, exhibit smaller negative returns in the event of negative trial outcomes due to diversification benefits and option value.

5.2 Mean |CAR| for single vs multi-trial firms

Table 3. FF5 Mean $|\text{CAR}|$: Single- vs. Multi-Project Firms

		$\lvert\textbf{CAR}\rvert[-1,+1]$		$\lvert\textbf{CAR}\rvert[-3,+3]$	
Group	n	**Mean (SE)**	**95% CI**	**Mean (SE)**	**95% CI**
Single	111	0.2428^{***} (0.0284)	$[+0.187,\ +0.299]$	0.2824^{***} (0.0295)	$[+0.224,\ +0.341]$
Multi	628	0.2391^{***} (0.0178)	$[+0.204,\ +0.274]$	0.2565^{***} (0.0176)	$[+0.222,\ +0.291]$
Difference (S−M)		0.0037 (0.0335)	$[-0.062,\ +0.070]$	0.0258 (0.0344)	$[-0.042,\ +0.094]$

Notes: Mean absolute CARs estimated using the Fama–French five-factor model. Standard errors in parentheses. Single and Multi rows report one-sample t-tests of H_0: $|\text{CAR}| = 0$. The Difference row reports a Welch two-sample t-test of H_0: $|\text{CAR}|_{\text{single}} = |\text{CAR}|_{\text{multi}}$, with 95% CI computed under unequal variances. Neither difference is statistically significant at conventional levels. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.10$.

Table 3 reports mean absolute cumulative abnormal returns, |CARs|, which shows the magnitude of the price reaction, whether positive or negative, for the same groups and event windows. The returns data from both single and multi-trial firms now significantly different from zero at p<0.01 and range between $23.9 - 28.2\%$, with single-trial firms experiencing higher |CARs| following trial announcements. The 3-day window shows higher mean |CARs| than the 1-day window, which we would expect even in the absence of an event due to accumulation of trading noise. These |CARs| are mechanically larger compared with the mean CARs in the previous table as the negative returns no longer offset the positive returns. The difference between single and multi-project firm mean |CARs| are still not significant at conventional significance levels, and the p-values are now larger than in the Mean CAR case (Table 2).

5.3 Differences in CAR and |CARs| for firms split by Trial Count Quartiles

Table 4. FF5 Signed CAR by Trial Count Quartile

		CAR$[-1,+1]$		**CAR**$[-3,+3]$	
Group	n	**Mean (SE)**	**95% CI**	**Mean (SE)**	**95% CI**
Q1: 1	111	-0.0013 (0.0366)	$[-0.074,\ +0.071]$	-0.0085 (0.0399)	$[-0.088,\ +0.071]$
Q2: 2–3	307	0.0425 (0.0359)	$[-0.028,\ +0.113]$	0.0493 (0.0362)	$[-0.022,\ +0.120]$
Q3: 4–6	198	0.0239 (0.0276)	$[-0.030,\ +0.078]$	0.0245 (0.0285)	$[-0.032,\ +0.081]$
Q4: 7+	123	0.0607^{**} (0.0235)	$[+0.014,\ +0.107]$	0.0536^{**} (0.0243)	$[+0.005,\ +0.102]$
Pairwise differences vs. Q1					
Q1 − Q2		-0.0439 (0.0513)	$[-0.145,\ +0.057]$	-0.0578 (0.0539)	$[-0.164,\ +0.048]$
Q1 − Q3		-0.0252 (0.0458)	$[-0.116,\ +0.065]$	-0.0330 (0.0490)	$[-0.130,\ +0.064]$
Q1 − Q4		-0.0620 (0.0435)	$[-0.148,\ +0.024]$	-0.0621 (0.0468)	$[-0.154,\ +0.030]$

Notes: Mean signed CARs estimated using the Fama–French five-factor model, reported by trial count Quartile. Standard errors in parentheses. Quartile rows report one-sample t-tests of H_0: CAR $= 0$. Difference rows report Welch two-sample t-tests of equality of means between Q1 and each other Quartile, with 95% CIs computed under unequal variances. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.10$.

We now split our data into four Quartiles, constructed to produce as balanced an n as possible, along the concurrent trial count dimension. This results in Quartiles containing companies with 1 clinical trial, 2-3, 4-6, and 7+ clinical trials. We then conduct the event study as before, using the FF5 model, examining CAR in Table 4 and |CAR| in Table 5.

Table 4 predictably produces the same Mean and Standard Error for Q1 as was produced for the set of Single firms in Table 2 because Q1 is the same as the set of firms with only one concurrent clinical trial. Mean CAR generally rises across quartiles though the Q3 declines relative to Q2 across both estimation windows. The mean estimate for Q4 is significant in both estimation windows but the pairwise difference with Q1 is insignificant so we cannot make any inference that there is a statistically significant difference between the mean CARs of firms that have only a single asset in development and those firms that have more than 7 assets in development.

Table 5. FF5 Absolute |CAR| by Pipeline Quartile

		$\lvert\mathbf{CAR}\rvert[-1,+1]$		$\lvert\mathbf{CAR}\rvert[-3,+3]$	
Group	n	**Mean (SE)**	**95% CI**	**Mean (SE)**	**95% CI**
Q1: 1	111	0.2428^{***} (0.0284)	$[+0.187,\ +0.299]$	0.2824^{***} (0.0295)	$[+0.224,\ +0.341]$
Q2: 2–3	307	0.2769^{***} (0.0323)	$[+0.213,\ +0.340]$	0.3000^{***} (0.0320)	$[+0.237,\ +0.363]$
Q3: 4–6	198	0.2346^{***} (0.0220)	$[+0.191,\ +0.278]$	0.2457^{***} (0.0225)	$[+0.201,\ +0.290]$
Q4: 7+	123	0.1522^{***} (0.0198)	$[+0.113,\ +0.191]$	0.1664^{***} (0.0197)	$[+0.127,\ +0.205]$
Pairwise differences vs. Q1					
Q1 − Q2		-0.0340 (0.0430)	$[-0.119,\ +0.051]$	-0.0176 (0.0435)	$[-0.103,\ +0.068]$
Q1 − Q3		0.0082 (0.0359)	$[-0.063,\ +0.079]$	0.0367 (0.0371)	$[-0.036,\ +0.110]$
Q1 − Q4		0.0906^{***} (0.0346)	$[+0.022,\ +0.159]$	0.1160^{***} (0.0355)	$[+0.046,\ +0.186]$

Notes: Mean absolute CARs estimated using the Fama–French five-factor model, reported by pipeline Quartile. Standard errors in parentheses. Quartile rows report one-sample t-tests of H_0: $|\text{CAR}| = 0$. Difference rows report Welch two-sample t-tests of equality of means between Q1 and each other Quartile, with 95% CIs computed under unequal variances. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.10$.

The absolute CARs shown in Table 5 provide the first evidence of a statistically significant difference in reaction magnitudes between cohorts of differing portfolio depths. The |CARs| are significantly different from zero in every Quartile, in both estimation windows, and peak in Q2 and reach their nadir in Q4. However, only the pairwise Welch test between Q1 and Q4 emerges as significant with a $p< 0.01$ result, indicating the existence of a diversification benefit that emerges between firms with only one asset and those with diversified portfolios. It is both promising and concerning that the first data to emerge that supports our hypothesis is in the difference between Q1 and Q4 - where theory would suggest the differential is largest but also where the most confounding size and other similar factors can accrue.

5.4 Difference in Mean CAR for positive vs. negative events for single vs multi-trial firms

Table 6 shows another variation on the same data, this time disaggregating events that produce positive stock reactions (Panel A) entirely from events that produce negative stock reactions (Panel B). This is interesting from a theoretical framework because we now examine events that engender a negative stock reaction regardless of the sentiment of the headline. That is to say - if the market anticipates very positive news and only receives a somewhat positive news item, the stock price return may be negative even when a manual sentiment analysis of the news item would have classified the event as positive. The analysis was first conducted for the full sample (Appendix, Table 10), which showed strongly significant reactions in both directions in line with the announcement, with positive events averaging $+22.2\%$ and negative

events averaging -16.8% over the $[-1,+1]$ window, while the full sample CAR was marginally significant reflecting the offset between the two types of events.

Panel A shows that all four Quartiles exhibit positive mean CARs significantly different from zero when conditioned on news that provide positive returns. This result is a direct consequence of conditioning and while significant does not provide much scope for theoretical analysis as no pair of differences in Quartile results is significant in either sampling window. We cannot say that portfolio depth impacts stock price reactions following positive news.

The negative outcomes found in Panel B however show clear and statistically significant differences in the magnitudes of negative reactions following stock events when conditioned on portfolio depth. The average CAR reactions are all statistically significant across both windows and tend to be monotonic down ranging from -23.7% for single-trial firms to -7.4% for firms with more than 7 concurrent pipeline assets. All pairwise comparisons with the fourth Quartile show that firms with wider pipelines experience statistically significant smaller price drops following negative trial outcomes than firms with fewer concurrent clinical trials.

Table 6. FF5 CAR by Trial Count Quartile — Positive and Negative Reactions

		CAR$[-1,+1]$			**CAR**$[-3,+3]$		
Group	n	**Mean (SE)**		**95% CI**	**Mean (SE)**		**95% CI**
Panel A: Positive reactions							
Q1: 1	63	0.1784^{***}	(0.0437)	$[+0.091, +0.266]$	0.1888^{***}	(0.0473)	$[+0.094, +0.283]$
Q2: 2–3	153	0.2720^{***}	(0.0630)	$[+0.147, +0.397]$	0.2735^{***}	(0.0632)	$[+0.149, +0.398]$
Q3: 4–6	97	0.2137^{***}	(0.0430)	$[+0.128, +0.299]$	0.2149^{***}	(0.0449)	$[+0.126, +0.304]$
Q4: 7+	70	0.1630^{***}	(0.0342)	$[+0.095, +0.231]$	0.1570^{***}	(0.0355)	$[+0.086, +0.228]$
Pairwise differences — Positive reactions							
Q1 − Q2		-0.0936	(0.0767)	$[-0.245, +0.058]$	-0.0848	(0.0789)	$[-0.240, +0.071]$
Q1 − Q3		-0.0353	(0.0613)	$[-0.156, +0.086]$	-0.0262	(0.0652)	$[-0.155, +0.103]$
Q1 − Q4		0.0154	(0.0555)	$[-0.094, +0.125]$	0.0318	(0.0592)	$[-0.085, +0.149]$
Q2 − Q3		0.0583	(0.0763)	$[-0.092, +0.209]$	0.0586	(0.0775)	$[-0.094, +0.211]$
Q2 − Q4		0.1091	(0.0717)	$[-0.032, +0.250]$	0.1166	(0.0725)	$[-0.026, +0.259]$
Q3 − Q4		0.0507	(0.0549)	$[-0.058, +0.159]$	0.0580	(0.0573)	$[-0.055, +0.171]$
Panel B: Negative reactions							
Q1: 1	48	-0.2372^{***}	(0.0432)	$[-0.324, -0.150]$	-0.2674^{***}	(0.0474)	$[-0.363, -0.172]$
Q2: 2–3	154	-0.1855^{***}	(0.0231)	$[-0.231, -0.140]$	-0.1735^{***}	(0.0249)	$[-0.223, -0.124]$
Q3: 4–6	101	-0.1584^{***}	(0.0236)	$[-0.205, -0.112]$	-0.1584^{***}	(0.0242)	$[-0.206, -0.111]$
Q4: 7+	53	-0.0744^{***}	(0.0184)	$[-0.111, -0.037]$	-0.0830^{***}	(0.0193)	$[-0.122, -0.044]$
Pairwise differences — Negative reactions							
Q1 − Q2		-0.0517	(0.0490)	$[-0.149, +0.046]$	-0.0939^{*}	(0.0536)	$[-0.201, +0.013]$
Q1 − Q3		-0.0788	(0.0492)	$[-0.177, +0.019]$	-0.1089^{**}	(0.0532)	$[-0.215, -0.003]$
Q1 − Q4		-0.1628^{***}	(0.0470)	$[-0.257, -0.069]$	-0.1844^{***}	(0.0512)	$[-0.287, -0.082]$
Q2 − Q3		-0.0271	(0.0330)	$[-0.092, +0.038]$	-0.0150	(0.0347)	$[-0.083, +0.053]$
Q2 − Q4		-0.1111^{***}	(0.0295)	$[-0.169, -0.053]$	-0.0905^{***}	(0.0315)	$[-0.153, -0.028]$
Q3 − Q4		-0.0840^{***}	(0.0299)	$[-0.143, -0.025]$	-0.0755^{**}	(0.0309)	$[-0.137, -0.014]$

Notes: Mean signed CARs estimated using the Fama–French five-factor model, reported by trial count Quartile separately for positive (Panel A) and negative (Panel B) market reactions. Standard errors in parentheses. Quartile rows report one-sample t-tests of H_0: CAR $= 0$. Difference rows report Welch two-sample t-tests with 95% CIs computed under unequal variances. Panel A shows no significant pairwise differences across Quartiles for positive reactions. Panel B shows a clear monotonic pattern, with larger pipelines associated with significantly smaller negative CARs, particularly for Q1 − Q4 comparisons. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.10$.

5.5 Robustness to firm size

Before conducting our event study, a key methodological concern we identified was that our measure of pipeline depth would likely exhibit strong correlation with and be confounded by other simple factors such as firm size and liquidity. All else equal, firms that have more trials tend to be larger than firms that have fewer, and such firms may exhibit smaller price reactions for reasons other than development pipeline depth, such as access to alternate revenue streams, deeper access to capital markets, and more widespread and available analyst coverage. To test whether the relationship found in Tables 6 and 5 persists when accounting for measures of firm size and liquidity, we re-estimate the |CAR| regression using the Fama-French five-factor model including logs of Total Assets and Cash and Cash Equivalents as regressors. Unfortunately we did not have these financial data for all firms so we re-estimate our baseline |CAR| model on this subset of 585 announcements to ensure a fair and valid comparison.

This robustness test (Table 7) shows that the concurrent trials count is not a significant predictor of the magnitude of cumulative abnormal returns when including assets as a factor. The statistically significant negative relationship between log(trial count) and |CAR| loses significance and is attenuated from -0.041 in the baseline case to -0.023 when we control for log(assets) and the assets variable is negative and significant at a p-level of $p<0.01$, indicating that the effect we previously attribute to pipeline depth is better captured by assets than portfolio depth. When we instead control for log(cash) the relationship between trial count and |CAR| falls to -0.032 but remains significant at $p<0.05$. Different from trial count and assets, the coefficient on cash (significant at $p<0.01$) is positive, which is intuitive as, ceteris paribus, firms that are better funded are better positioned to finance their next steps without slowing down or diluting existing owners, whether that be pursuing the next clinical trial in the case of positive results or refocusing efforts on other assets following negative outcomes. The negative coefficient for trial count suggests that the number of clinical trials count has a negative relation to abnormal returns, consistent across all four regressions. In the model where we include both cash and assets both cash and assets remain significant. We choose to check for multicollinearity due to suspected correlation between pipeline size, assets and cash: trial count does not exhibit a multicollinearity problem with either assets or cash alone with no VIF score exceeding 1.25, but when both assets and cash are included the VIFs for both assets and cash exceed 10 indicating a severe multicollinearity problem - this is unsurprising as cash is a component of assets.

Table 7. Cross-Sectional OLS: |CAR| on Log Trial Count with Controls (FF5)

Variable	**(1) Baseline**	**(2) + log(assets)**	**(3) + log(cash)**	**(4) + log(assets) + log(cash)**
log(trial count)	-0.0413^{***}	-0.0228	-0.0320^{**}	-0.0164
	(0.0142)	(0.0157)	(0.0144)	(0.0157)
Volatility (σ)	0.8761	0.3597	0.7903	0.3424
	(0.6287)	(0.6691)	(0.6222)	(0.6585)
log(total assets)	—	-0.0272^{***}	—	-0.0239^{***}
		(0.0083)		(0.0086)
log(cash)	—	—	0.0990^{***}	0.0916^{***}
			(0.0237)	(0.0236)
Phase FE	Yes	Yes	Yes	Yes
N	585	585	585	585
R^2	0.035	0.048	0.055	0.065
Adj. R^2	0.023	0.035	0.042	0.050

Variance Inflation Factors (VIF)

Variable	**(1) Baseline**	**(2) + log(assets)**	**(3) + log(cash)**	**(4) + log(assets) + log(cash)**
log(trial count)	1.02	1.22	1.16	1.23
Volatility (σ)	1.02	1.11	1.09	1.11
log(total assets)	—	1.32	—	11.53
log(cash)	—	—	1.24	10.84

Notes: OLS estimates of $|\text{CAR}[-1,+1]|$ on log(trial count) and firm-level controls using Fama–French five-factor abnormal returns. All specifications include phase fixed effects and HC3 heteroskedasticity-robust standard errors in parentheses. All columns are estimated on the same balanced sample of 585 observations. The cash variable enters in log form. VIF values are reported per specification. The elevated VIF values for log(total assets) and log(cash) in column (4) (11.53 and 10.84, respectively) indicate substantial multicollinearity between these two variables when entered jointly, suggesting results from that specification should be interpreted with caution. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.10$.

5.6 Diversification benefits graphs

As shown in the Appendix, Figure 2 (left) shows that mean CAR for negative outcome days becomes steadily more negative as the number of concurrent ongoing trials decreases, showing that the mean negative CAR for firms with fewer concurrent trials is larger than for firms with more concurrent trials. Appendix Figure 2 (right) shows that the distribution of CARs for quartile 1 firms exhibits a higher degree of kurtosis, on both sides of the distribution, than quartile 4 firms,

and exhibit more extreme values particularly on the negative side of the distribution.

Both graphs are supportive of a portfolio theory of real options delivering diversification, decreasing the volatility of stock returns.

6. Discussion and Limitations

6.1 Event Study Result

Firstly, our findings using |CAR| confirm previous research connecting clinical trial announcements and biotech stock prices, showing significant volatility following announcements of trial results, and we also show that portfolios with a larger pipeline have a statistically significantly lower degree of volatility in stock price reaction surrounding announcement dates.

Although there is no significant relation across the Quartile groups to positive news announcements, the firms with largest pipelines (Q4), and the smallest Quartile (Q1) react quite differently to the failure of trials. The fourth Quartile, companies with 7+ concurrent trials, displays stock price declines one third of the magnitude of those of the single-trial Quartile, 7.4% vs 23.7%. This highlights the nature of diversification benefits, with firms with larger pipelines being able to continue the development of their other drug candidates should one of their flagship drugs fail, whilst for single-trial biotechs, a failed clinical trial puts the future of the organization into question. This further reinforces the point that having portfolio diversity in biotech can act as downside protection while not necessarily increasing the magnitude of returns following positive outcomes.

Although only approaching statistical significance, it is worth noting that multi-trial companies exhibit an average CAR of approximately 4%, whilst single-trial companies scatter around 0% suggesting possible systematic outperformance. This connects well to Vassolo et al. (2004), who argues that multi-trial companies are better positioned to obtain fungible knowledge, building and operating across different research areas simultaneously and accumulating an information base that future investments can draw upon, effectively compounding the value of each marginal trial.

Guedj & Scharfstein (2004) shows that early stage biotech companies with singular products are often more aggressive than mature competitors in pursuing later stage trials. This is because management are often unwilling to pull the plug on their only viable drug and are therefore willing to advance drug candidates with weaker experimental results, whilst larger companies are much more willing to terminate unpromising assets. We test this theory with our sample (Appendix, Table 9) but find no significant differences in the percentage of concurrent trials from Quartile 1 and Quartile 4 that ended in failure across any development stage.

6.2 Dataset Limitations

We attempted to gather as comprehensive and accurate a dataset as possible, but our dataset has several limitations that impact our analysis and the degree of certainty with which we can discuss our results. In practice, solving these limitations would require adopting completely different methodology from the outset in gathering data. The weakest point of our dataset is likely the completeness of our simultaneous clinical trials dataset: missing a trial can change which Quartile a firm appears in and can affect whether we consider a company a single- or multi-trial firm. This is further complicated by the time-series nature of this measure, meaning that we need multiple observations. Furthermore, there are many situations that lead to edge cases which are difficult to resolve: one such issue is for trials run by firms that have then been acquired by other firms in our sample and subsequently dissolved (so they do not appear as a subsidiary of the new parent) and whether trials are appropriately linked to the new parent. The best way to gather this data would be to trade the number of firm observations for higher quality data by surveying a subset of firms and asking them to provide all current and historic NCTIDs that are associated with their company - grey areas will likely still exist using this definition, but the data quality issues would be much more tractable. A smaller subset would also allow for more thorough characterization of event data.

7. Conclusion

In this thesis, we examine whether firms with different concurrent clinical trial counts experience significantly different stock price reactions to individual clinical trial announcements. To test this, we conduct an event study covering 739 trial announcements from 270 US-listed small-cap biotech firms between 2014 and 2024. We estimate the abnormal returns using the Fama-French five-factor model and tests whether a larger pipeline reduces the price impact of any single trial result.

Our main finding is mixed, showing that pipeline size has little effect on how stock prices react to positive trial news, while it does significantly affect how stocks react to negative trial news. The stock prices of firms with only one active trial fall on average -23.7% following negative announcements, compared to firms with seven or more active trials, which lose only -7.4%. This difference is statistically significant and observable across all event windows. However, when we control for firm assets in our robustness checks, the pipeline effect loses significance. Pipeline size and firm size are correlated in our sample, and we cannot fully separate the effects of the two. Controlling for cash reduces the magnitude of the negative effect of pipeline size on magnitude of reaction but pipeline size remains significant.

While our findings do provide early suggestive evidence that pipeline size has an effect on stock price reactions to individual clinical trial announcements in some event scenarios, the

aforementioned limitations stand, and need to be addressed in future research to better isolate the effect of pipeline size on stock price reactions. A study on a larger dataset that better ensures completeness by surveying companies and gathering human-labeled data rather than pulling data from public databases could establish whether this effect remains significant when controlling for different measures of firm size.

8. References

References

Berk, J. B., Green, R. C., & Naik, V. (1999). Optimal investment, growth options, and security returns. *The Journal of Finance*, *54*(5), 1553–1607. https://doi.org/10.1111/0022-1082.00161

Black, F., & Scholes, M. (1973). The pricing of options and corporate liabilities. *Journal of Political Economy*, *81*(3), 637–654. https://doi.org/10.1086/260062

Bruneo, H., Giacomini, E., Iannotta, G., Murthy, A., & Patris, J. (2024). Risk and return in the biotech industry. *International Journal of Productivity and Performance Management*, *73*(6), 1926–1947. https://doi.org/10.1108/IJPPM-04-2023-0179

Carhart, M. M. (1997). On persistence in mutual fund performance. *The Journal of Finance*, *52*(1), 57–82. https://doi.org/10.1111/j.1540-6261.1997.tb03808.x

DiMasi, J. A., Hansen, R. W., & Grabowski, H. G. (2003). The price of innovation: New estimates of drug development costs. *Journal of Health Economics*, *22*(2), 151–185. https://doi.org/10.1016/S0167-6296(02)00126-1

Dixit, A. K., & Pindyck, R. S. (1994). *Investment under uncertainty*. Princeton University Press.

Fama, E. F., & French, K. R. (1993). Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics*, *33*(1), 3–56. https://doi.org/10.1016/0304-405X(93)90023-5

Fama, E. F., & French, K. R. (2015). A five-factor asset pricing model. *Journal of Financial Economics*, *116*(1), 1–22. https://doi.org/10.1016/j.jfineco.2014.10.010

Guedj, I., & Scharfstein, D. (2004). *Organizational scope and investment: Evidence from the drug development strategies and performance of biopharmaceutical firms* (NBER Working Paper No. 10933). National Bureau of Economic Research. https://doi.org/10.3386/w10933

Hwang, T. J. (2013). Stock market returns and clinical trial results of investigational compounds:

An event study analysis of large biopharmaceutical companies. *PLOS ONE*, *8*(8), e71966. https://doi.org/10.1371/journal.pone.0071966

IQVIA Institute for Human Data Science. (2019). *The changing landscape of research and development*. IQVIA. https://www.iqvia.com/insights/the-iqvia-institute/reports-and-publications/reports/the-changing-landscape-of-research-and-development

McKinsey & Company. (2021). *A new portfolio model for biotech*. https://www.mckinsey.com/industries/life-sciences/our-insights/a-new-portfolio-model-for-biotech

Kellogg, D., & Charnes, J. M. (2000). Real-options valuation for a biotechnology company. *Financial Analysts Journal*, *56*(3), 76–84. https://doi.org/10.2469/faj.v56.n3.2362

Markowitz, H. (1952). Portfolio selection. *The Journal of Finance*, *7*(1), 77–91. https://doi.org/10.1111/j.1540-6261.1952.tb01525.x

Munos, B. (2009). Lessons from 60 years of pharmaceutical innovation. *Nature Reviews Drug Discovery*, *8*(12), 959–968. https://doi.org/10.1038/nrd2961

Myers, S. C. (1977). Determinants of corporate borrowing. *Journal of Financial Economics*, *5*(2), 147–175. https://doi.org/10.1016/0304-405X(77)90015-0

Rothenstein, J. M., Tomlinson, G., Tannock, I. F., & Detsky, A. S. (2011). Company stock prices before and after public announcements related to oncology drugs. *JNCI: Journal of the National Cancer Institute*, *103*(20), 1507–1512. https://doi.org/10.1093/jnci/djr338

Schuhmacher, A., Hinder, M., Brief, E., Gassmann, O., & Hartl, D. (2025). R&D success rates of leading pharmaceutical companies: A benchmarking study. *Drug Discovery Today*, *30*, 104291. https://doi.org/10.1016/j.drudis.2025.104291

Schwartz, E. S. (2004). Patents and R&D as real options. *Economic Notes*, *33*(1), 23–54. https://doi.org/10.1111/j.0391-5026.2004.00124.x

Sharma, A., & Lacey, N. (2004). Linking product development outcomes to market valuation of the firm: The case of the US pharmaceutical industry. *Journal of Product Innovation Management*, *21*(5), 297–308. https://doi.org/10.1111/j.0737-6782.2004.00084.x

Sharpe, W. F. (1964). Capital asset prices: A theory of market equilibrium under condi-

tions of risk. *The Journal of Finance*, *19*(3), 425–442. https://doi.org/10.1111/j.1540-6261.1964.tb02865.x

Singh, M., Rocafort, R., Cai, C., Siah, K. W., & Lo, A. W. (2022). The reaction of sponsor stock prices to clinical trial outcomes: An event study analysis. *PLOS ONE*, *17*(9), e0272851. https://doi.org/10.1371/journal.pone.0272851

Thakor, R. T., Anaya, N., Zhang, Y., Vilanilam, C., Siah, K. W., Wong, C. H., & Lo, A. W. (2017). Just how good an investment is the biopharmaceutical sector? *Nature Biotechnology*, *35*(12), 1149–1157. https://doi.org/10.1038/nbt.4023

Trigeorgis, L. (1993). The nature of option interactions and the valuation of investments with multiple real options. *Journal of Financial and Quantitative Analysis*, *28*(1), 1–20. https://doi.org/10.2307/2331148

Vassolo, R. S., Anand, J., & Folta, T. B. (2004). Non-additivity in portfolios of exploration activities: A real options-based analysis of equity alliances in biotechnology. *Strategic Management Journal*, *25*(11), 1045–1061. https://doi.org/10.1002/smj.414

A. Additional Tables

This appendix provides supplementary tables and robustness checks that support the main empirical analysis.

Table 8. Appendix Table A1: Variable Definitions

Variable	**Definition**
Concurrent trials	Number of active clinical trials linked to a firm in a given month.
Single-trial firm	Firm with one active clinical trial at the time of announcement.
Multi-trial firm	Firm with two or more active clinical trials at the time of announcement.
CAR	Cumulative abnormal return around the clinical trial announcement window.

Table 9. Test of trial outcomes across phases and portfolio depth (Guedj & Scharfstein (2004))

Quartile	**Phase 1**	**Phase 2**	**Phase 3**	**All Phases**
Q1: 1 trial	12/26 (46%)	20/44 (45%)	14/31 (45%)	49/111 (44%)
Q2: 2–3 trials	27/64 (42%)	60/121 (50%)	41/90 (46%)	145/307 (47%)
Q3: 4–6 trials	11/28 (39%)	42/78 (54%)	40/75 (53%)	102/198 (52%)
Q4: 7+ trials	5/9 (56%)	19/47 (40%)	19/63 (30%)	44/123 (36%)

Phase	**Q1 % Neg.**	**Q4 % Neg.**	χ^2	p**-value**
Phase 1	46.2%	55.6%	0.010	0.921
Phase 2	45.5%	40.4%	0.074	0.785
Phase 3	45.2%	30.2%	1.447	0.229
All phases	44.1%	35.8%	1.376	0.241

Notes: Cells report the number of negative announcements over total announcements, with the negative rate in parentheses. A negative announcement serves as a proxy for trial failure. Chi-squared tests compare the proportion of negative announcements between Q1 (single-trial) and Q4 (7+ trials) within each phase. H_0: the negative announcement rate does not differ between Q1 and Q4 (Guedj & Scharfstein (2004)). All p-values are above 0.10; the null hypothesis cannot be rejected at any conventional significance level (n.s. = not significant).

Table 10. Full Sample CAR Test — FF5

		Window $[-1,+1]$				**Window** $[-3,+3]$			
Group	N	**Mean**	t	p**-value**	**Sig.**	**Mean**	t	p**-value**	**Sig.**
Panel A: Signed CAR									
Positive	383	0.2219	7.639	1.78×10^{-13}	***	0.2233	7.587	2.54×10^{-13}	***
Negative	356	−0.1683	−12.199	7.97×10^{-29}	***	−0.1684	−11.425	6.02×10^{-26}	***
Full sample	739	0.0340	1.893	5.88×10^{-2}	*	0.0346	1.893	5.88×10^{-2}	*
Panel B: Absolute $\lvert CAR \rvert$									
Positive	383	0.2689	9.605	1.04×10^{-19}	***	0.2946	10.622	2.95×10^{-23}	***
Negative	356	0.2083	17.133	2.21×10^{-48}	***	0.2236	17.904	1.67×10^{-51}	***
Full sample	739	0.2397	15.291	4.69×10^{-46}	***	0.2604	16.662	3.94×10^{-53}	***

Notes: One-sample t-tests of H_0: mean CAR $= 0$ using Fama–French five-factor abnormal returns. Panel A reports signed CARs; Panel B reports absolute $\lvert$CAR$\rvert$ values. Positive and Negative groups are defined by the sign of the announcement return. p-values are reported in scientific notation. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.10$.

B. Additional Figures

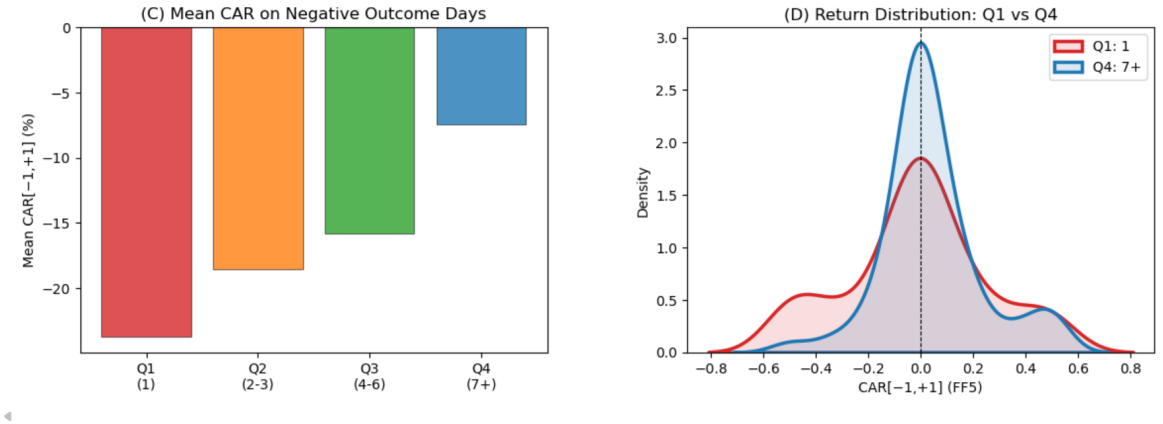

Figure 2

C. AI Disclosure

Generative AI tools were used in a thoughtful and limited manner in the preparation of this thesis. The exhaustive list of tools employed, and their uses: (1) Anthropic's Claude and OpenAI's ChatGPT were used to implement and debug Python code used to query APIs and for Statistical analysis, (2) OpenAI's Prism was used to generate the LaTeX format/template in which the thesis is written, and to debug and implement LaTeX, (3) Anthropic's Claude and OpenAI's ChatGPT

were used to improve grammar and clarity in specific, limited sections of the thesis.

(1) In what ways have these tools contributed to increasing the quality of the thesis?

The use of AI tools has allowed us to iterate our code significantly faster and allowed us to identify and correct bugs in our code very rapidly which allowed us to expand the scope of our research. On reflection, without the use of AI tools we likely would have ended our analysis earlier as the burden of writing additional code would have become a limiting factor. We likely would have written the thesis in a Word document format rather than venturing to use a LaTeX based editor without the use of AI tools, which would have negatively impacted the formatting clarity of our thesis. AI tools did not influence our analysis or methodology.

(2) What potential risks were found using AI and what measures were taken to reduce these risks?

AI tools are inconsistent and do not think for themselves. The code they produce may be incomplete, incorrect, or produce the wrong result. AI tools will confidently claim that they have achieved a task when it is clear that the opposite is true. With this in mind, any and all output from generative AI tools has to be checked manually to ensure they produce the right response and should best be employed iteratively to correct mistakes and errors, rather than to produce entire pieces of code.

(3) What are the insights gained from using AI tools in the thesis writing process?

AI tools are powerful supportive productivity tools when used correctly. Used carelessly AI tools risk incorrect results and may mislead their user.