Non-financial information, financial analysts' industrial expertise, and target price accuracy

Abstract

We investigate whether analysts' industrial expertise improves target price accuracy after the disclosure of non-financial information on the product pipeline, i.e., clinical trial disclosures by pharmaceutical firms. We find that analysts with a scientific education (i.e., PhD in biology, pharmacology, or organic chemistry) produce more accurate target prices for biotechs only, for which there is a greater asymmetry of information. Moreover, the disclosures of clinical trials reduce the accuracy gap between analysts with and without a scientific education who cover biotechs. Finally, scientific education is more important for less experienced analysts who cover biotechs. Overall, we conclude that the disclosures of non-financial information on the product pipeline contribute positively to target price accuracy, especially for less experienced analysts who have less industrial expertise and cover firms with a high asymmetry of information.

Keywords

Clinical trials, Financial analysts, Expertise, Target price, Accuracy.

JEL classification: D82; G17; G24; J24; M41

Non-financial information, financial analysts' industry expertise, and target price accuracy

1. Introduction

As underlined by several authors, the financial statements of companies provide little information about the future payoffs of R&D investments (Barth, Kasznik and McNichols, 2001; Barron, Byard, Kile and Riedl, 2002; Kothari, Laguerre and Leone, 2002; Jones, 2007; Kimbrough, 2007; Palmon and Yezegel, 2012; Lev and Gu, 2016). Indeed, accounting standards require firms to recognize R&D expenses without any specific note. To reduce information asymmetry, financial analysts must therefore consider other sources of information to assess the value of companies investing important resources in R&D.

In the pharmaceutical industry, which is a highly intensive R&D industry,[1] the clinical trial reports of firms are publicly available on the *ClinicalTrials.gov* website. This is key non-financial information about the product pipeline. Lev and Gu (2016, p. 170) posit that such information is the most relevant to investors "*since the product pipeline, in contrast with the historical accounting information, is forward looking, informing about the most important future developments.*" This non-financial information should help analysts better assess the value of firms and, consequently, issue more accurate target prices.[2] However, a relevant interpretation of clinical trial contents requires a good understanding of pharmaceutical techniques and the diseases targeted.

[1] The European Federation of Pharmaceutical Industries and Associations (https://www.efpia.eu/) highlights, for instance, that pharmaceutical firms invest more in R&D than firms from other R&D intensive industries (e.g., software and computer services or technology hardware and equipment).

[2] Anecdotal evidence suggests that analysts use that technical non-financial information to value pharmaceutical firms. A report issued by Barclays (2015/10/09) indicates, for instance: "*A 'minor hit' from the suspended recruitment of AstraZeneca's Phase III trial of durvalumab/AZD9291 trial in non-small-cell lung cancer. An update on clinicaltrials.gov shows recruitment has been suspended in the trial after a signal of increased incident of interstitial lung disease was seen in the Phase Ib trial*."

In this paper, we investigate whether analysts' industrial expertise improves target price accuracy after clinical trial disclosures. *Ex-ante* it is not clear how analysts' industrial expertise moderates the association between clinical trial disclosures and target price accuracy. On the one hand, no reduction in target price errors is to be expected if analysts lack expertise to correctly interpret clinical trial disclosures. In other words, analysts with the appropriate expertise should better interpret this information, and issue more accurate target prices. On the other hand, clinical trial disclosures could also reduce the 'accuracy gap' between experts and non-experts (i.e., target price accuracy is higher for analysts with a greater industrial expertise), because this additional information may compensate, at least partly, for the disadvantage of analysts with less industrial expertise.

Since expertise is defined as a high level of knowledge or skills,[3] we consider that it depends on the analyst's level of education and professional experience. Prior literature has already analyzed those dimensions of analyst expertise. Analysts with more industry expertise (Kadan, Madureira, Wang and Zach, 2012), an advanced degree (e.g., Ph.D., M.D.), and more firm-specific experience, issue more informative stock recommendations on R&D-intensive firms (Palmon and Yezegel, 2012). Analysts with pre-analyst work experience in a related industry also issue more accurate earnings forecasts on firms they follow (Bradley, Goyakka, and Liu, 2017). However, no paper has yet directly investigated the impact of expertise on financial analysts' ability to correctly incorporate non-financial information into target prices.

Prior research has focused on various determinants of target price accuracy (Bilinski, Lyssimachou, and Walker, 2013; Bradshaw, Brown, and Huang, 2013) such as the incentives to disclose optimistic target prices (Chan, Lin, Yu, and Zhao, 2018; Bradshaw, Brown, and Tan, 2019; Lourie, 2019), behavioral biases (Cen, Hilary, and Wei, 2013; Roger, Roger, and Schatt, 2018), and the implementation of improper valuation methods (Gleason, Johnson, and Li, 2013;

[3] https://dictionary.cambridge.org/dictionary/english/expertise.

Green, Hand, and Zhang, 2016). Our paper contributes to this strand of literature by investigating whether industrial expertise influences analysts' ability to interpret clinical trial disclosures.

For our empirical analysis, we focus on two dimensions of industrial expertise. The first is scientific education. Analysts with a PhD related to the pharmaceutical industry should be able to better understand the drug development process. The second is professional experience. Analysts with a pre-analyst work experience in the pharmaceutical industry should better understand the challenges faced by firms developing new drugs. Our sample includes 15,015 target prices available in I/B/E/S, issued on firms (European and U.S.) from the pharmaceutical industry that consists of biotechnology and pharmaceutical companies (respectively Biotechs and Pharmas, here after)[4] over the 2011-2017 period. These firms published 11,407 clinical trial disclosures on the *ClinicalTrials.gov* website during the period. Following Bradley et al. (2017), data on analyst education and professional experience were hand-collected from various websites (e.g., Linkedin).

Our main results are summarized as follows. First, clinical trial disclosures are associated with lower errors, demonstrating that such information helps analysts to issue more accurate target prices. As advocated by Lev and Gu (2016), forcing firms to disclose non-financial information about the product pipeline is beneficial to target price accuracy, because it significantly complements the limited accounting information provided in the financial statements. Second, there is an accuracy gap related to analyst expertise, as target price accuracy is higher for analysts with a scientific education. However, a pre-analyst work experience in the pharmaceutical industry does not significantly affect analysts' ability to issue accurate target prices. Third, the accuracy gap decreases slightly after clinical trial disclosures. In other words,

[4] Biotechnology and pharmaceutical companies produce medicines, but "the medicines made by biotechnology companies are derived from living organisms, while those made by pharmaceutical companies generally have a chemical basis." (https://www.investopedia.com/ask/answers/033115/what-difference-between-biotechnology-company-and-pharmaceutical-company.asp).

the benefits of clinical trial disclosures are greater for analysts without a scientific education, but financial analysts with a greater expertise still issue more accurate target prices. Fourth, analysts' scientific education matters for the valuation of biotechs only, for which there is a greater asymmetry of information. Since those biotechs are not followed by analysts with a specific expertise, we consider that our findings are not driven by reverse causality.

In an additional analysis, we investigate whether the experience as a financial analyst influences our previous results. This analysis is relevant as analyst experience may impact their ability to incorporate new information into target prices. Indeed, it has been documented that analysts with more firm-specific experience are able to better incorporate both prior earnings and stock returns into their current earnings forecasts (Mikhail, Walther and Willis, 1997; 2003). Earnings forecast accuracy is positively associated with general and firm-specific experience (Clement, 1999). However, experience is no longer significant for analyst-firm pairs (Jacob, Lys and Neale, 1999). In other words, differences in target price accuracy for the same firm and analyst are driven by differences in analysts' "innate" ability, and not by experience. Nevertheless, the amount of analysts' task-specific experience also improves target price accuracy (Clement, Koonce and Lopez, 2007). Our findings suggest that financial analysts with less experience who follow biotechs are the ones who benefit the most from clinical trial disclosures. For financial analysts with significant experience who follow biotechs, a scientific education and a pre-analyst work experience are equally important.

Overall, our paper contributes to the literature on the importance of non-financial information for financial analysts when financial statements provide limited information on some key issues for firm valuation. This stream of literature is relatively scarce. Dhaliwal, Radhakrishnan, Tsang, and Yang (2012) investigate the association between disclosure of non-financial information (i.e., corporate social responsibility reports) and analyst forecast accuracy. In a paper similar to ours, Hao et al. (2017) investigate the impact of clinical trial

disclosures on the tasks performed by financial analysts. They show that such technical non-financial information is useful for assessing future payoffs of pharmaceutical companies. However, both papers do not consider analyst expertise, which moderates the association between non-financial information and forecast accuracy. Moreover, they do not analyze target prices, which is a relevant outcome of analysts' reports as it encompasses a larger set of information (i.e., a long-term horizon and the risk of the project, which are not included in short-term annual earnings forecasts).

Our paper is also related to Bradley et al. (2017), who show that a pre-analyst experience in the industry improves annual earnings forecasts accuracy. We find that, even in the same industry, only analysts with a long job tenure following biotechs benefit from their pre-analyst work experience. We therefore also add to the debate on experience as a financial analyst. Mikhail et al. (1997) and Clement (1999) examine whether that experience improves annual earnings forecast. We go a step further by showing that less experienced analysts with a scientific education (PhD related to the pharmaceutical industry) issue more accurate target prices for biotechs only.

The remainder of this paper is organized as follows. Section 2 is dedicated to the literature review, and the hypotheses development. Section 3 describes the research design. We present and discuss the results in section 4. A final section concludes.

2. Prior literature and hypotheses

2.1. The valuation of intangibles-intensive firms by financial analysts

2.1.1. The issuance of biased target prices

To generate target prices, analysts start by collecting information from different sources (e.g., annual reports, macro-economic reports, etc.). All relevant information is then translated into earnings or cash-flows forecasts, which constitute the inputs of the valuation models (Bradshaw, 2002; Asquith, Mikhail, and Au, 2005; Ramnath, Rock, and Shane, 2008; Gleason

et al., 2013; Green et al., 2016). An analyst's report generally contains three key figures: earnings (or/and cash-flow) forecasts, a target price and a recommendation. For investors, these outcomes have different properties and significance. Recommendations are discrete and depend on analysts' specific scales, which raises the possibility that two analysts with identical expectations on a stock could issue different ratings (Bhattacharya and Zhang, 2017; Kadan, Madureira, Wang, and Zach, 2020). Moreover, brokers change their rating scales over time, which limits the consistency of recommendations. Earnings or cash-flow forecasts are usually formulated for a near-term horizon, and do not explicitly account for changes in firm risk. The target price incorporates analysts' long-term assessment of earnings or cash-flows, as well as firm risk, which makes it particularly interesting for investors and for academic research (Brav and Lehavy, 2003; Asquith et al., 2005; Da and Schaumburg, 2011; Gleason et al., 2013; Bilinski et al., 2013; Bradshaw et al., 2013).

It has been documented that analysts tend to issue optimistic target prices.[5] Bradshaw et al. (2013) find, for instance, an average target price error equal to 45%. The literature proposes three main explanations for the issuance of inaccurate target prices. First, analysts may have specific incentives to provide biased numbers, notably when they work for banks that have business relationships with the covered firms (James and Karceski, 2006), hold stocks of these firms (Chan et al., 2018) or are hired in the near future by a firm they cover (Lourie, 2019). However, some mechanisms affect analysts' incentives to produce accurate target prices, especially institutional pressure (Bilinski et al., 2013; Bradshaw et al., 2019). Second, analysts could make questionable judgments or use imperfect valuation models (Demirakos et al., 2010; Gleason et al., 2013; Green et al., 2016). For instance, they may not adjust the inputs for unconditional accounting conservatism, which leads to larger errors (Kim, Nekrasov, Shroff,

[5] For the U.S. market, see Brav and Lehavy (2003), Asquith et al. (2005), Bradshaw et al. (2013), Roger et al. (2018), Kim et al. (2019). For Italy, see Bonini, Zanetti, Bianchini, and Salvi (2010). For the U.K., see Demirakos, Strong, and Walker (2010). For cross-country studies, see Bilinski et al. (2013), Bradshaw et al. (2019).

and Simon, 2019). Third, analysts' cognitive biases may also lead to the issuance of optimistic target prices. Cen, Hilary, and Wei (2013) highlight an anchoring bias, and Roger et al. (2018) observe a small price bias. In this paper, we posit that target price errors may be related to asymmetry of information and uncertainty about future earnings and cash-flows.

2.1.2. Analyst and financial reporting deficiencies

Uncertainty is particularly strong for firms with large intangible assets (Barth et al., 2001; Barron et al., 2002; Amir et al., 2003; Kimbrough, 2007; Palmon and Yezegel, 2012) such as pharmaceutical firms investing large financial and human resources in R&D. Their valuation is particularly difficult because R&D projects are very risky and have a long-term horizon. In fact, it usually takes about ten years to develop new drugs, and only a few projects succeed (DiMasi, Hansen, Grabowski, and Lasagna, 1991; DiMasi and Grabowski, 2007), which makes the future payoffs hard to predict (Kothari, Laguerre, and Leone, 2002; Kimbrough, 2007).

To the extent that great uncertainty is associated with R&D projects, accounting standard-setters consider that the fair value of such internally generated assets cannot be measured with sufficient reliability. Consequently, firms are required to expense R&D investments.[6] This principle adopted by the standard-setters creates therefore a large mismatch of revenues and expenses for intangible-intensive firms (Lev, 2001; Barth et al., 2001; Kimbrough, 2007). In the absence of meaningful information in the financial statements regarding R&D investments, there is a substantial information asymmetry between investors or financial analysts and managers, who have access to private information about the actual status and potential consequences of R&D investments. To summarize, intangible investments and

[6] In countries applying IFRS, the capitalization of some R&D expenses is allowed under very precise conditions. IAS 38 indicates that an intangible asset arising from research & development can be capitalized if an entity can demonstrate the following criteria: (1) Technical feasibility of completing the intangible asset; (2) Intention to complete and use/sell the asset; (3) Ability to use/sell the asset; (4) Existence of a market; (5) Availability of adequate technical, financial, and other resources to complete the asset; (6) Cost of the asset can be measured reliably (https://www.ifrs.org/issued-standards/list-of-standards/ias-38-intangible-assets/). Dinh, Sidhu, and Yu (2019) find that only a small fraction of R&D expenses is capitalized in practice.

accounting standards create serious difficulties to predict a firm's stock price (Aboody and Lev, 2000; Barth et al., 2001; Palmon and Yezegel, 2012; Lev and Gu, 2016).

In the context of potential stock mispricing, financial analysts must increase their effort to reduce information asymmetries by acquiring and processing additional information. The additional effort and costs borne by analysts may be compensated by higher trading fees associated with the disclosure of relevant investment recommendations to investors. This idea is supported by Barth et al. (2001), who find higher analyst coverage for firms with more intangible assets, especially more R&D relative to their industry, and for firms in industries with larger R&D expenses. Furthermore, Barron et al. (2002) show that analysts supplement firms' financial information by placing greater emphasis on their own private information when estimating earnings forecasts, in particular for high-technology manufacturing firms with large R&D expenditures (e.g., electronics, pharmaceuticals, and software). Finally, Palmon and Yezegel (2012) show that analysts' recommendation revisions are more valuable for R&D-intensive firms because the cumulative abnormal returns are significantly higher (lower) for upgrades (downgrades). Overall, these studies suggest that the greater effort made by analysts covering firms with large R&D investments ultimately leads to the production of relevant information in analysts' reports.

Even if analysts make a greater effort, they may nonetheless face severe difficulties to interpret additional information to reduce uncertainty regarding future payoffs. Amir et al. (2003) compare analysts' earnings forecasts for firms with and without R&D, and show that analysts issue more optimistic forecasts for companies with high R&D. Gu and Wang (2005) find a positive association between analysts' earnings forecast errors and firms' intangible intensity that deviates from the industry norm. They also document greater forecast errors for firms with innovative technologies because such technologies are associated with more

uncertain prospects, and smaller errors for biotech/pharma and medical equipment firms that are subject to specific regulations.

2.2. The disclosure of specific non-financial information

2.2.1. The usefulness of non-financial information

Additional information provided voluntarily by managers could help analysts and investors better evaluate the firm. However, it is well known that managers are frequently reluctant to provide additional information for competitive, litigation and reputational reasons (e.g., Guo, Lev, and Zhou, 2004; Graham et al., 2005; Jones, 2007; Simpson, 2010). Furthermore, analysts may face three issues when managers disclose non-financial information about R&D projects. First, relevant information would probably be partially disclosed since managers have incentives to reveal good news, and withhold bad news (Dye, 2001). Second, such non-audited information would not be reliable or credible, as it is not certified by a third party (DeFond and Zhang, 2014). Third, processing non-standardized voluntary information is costlier to analyze (Palmon and Yezegel, 2012), especially when it is non-financial information concerning pioneering innovations whose economic consequences are difficult to estimate (Gu and Wang, 2005). Since analysts optimize their effort and the financial resources invested to perform their task, they prefer searching public information, which is less costly to collect.

In the pharmaceutical industry, the process of drug development is standardized. Pharmaceutical firms start with pre-clinical trials including animal testing. In case of success, they can start clinical trials that consist in testing new drugs on human subjects to assess their effectiveness. There are three main phases of clinical trials, which differ notably in terms of the number of people involved. It usually takes about six to seven years to complete these three steps. These clinical trials are registered in a database developed by the National Library of Medicine for the National Institute of Health, and have been available to the public since 2000

on the *ClinicalTrials.gov* website.[7] If Phase III is successful, the firm demands an approval to the regulator to launch the drug. Finally, a post-development phase (Phase IV) consists of market monitoring (DiMasi et al., 1991; Petrova, 2014).

A new drug advances into the next clinical trial phase only if it has successfully completed the previous phase. Consequently, the probability of launching a drug increases (i.e., uncertainty decreases) as it moves through the different stages of clinical trials. Disclosures about these phases reduce information asymmetry about R&D outcomes, as well as uncertainty regarding the future payoffs. Therefore, clinical trial disclosures should be very useful for analysts and investors (Ely, Simko, and Thomas, 2003; Dedman, Lin, Prakash, and Chang, 2008; Girotra, Terwiesch, and Ulrich, 2007; Hao, Forgione, Guo, and Zhang, 2017; Lev and Gu, 2016).[8]

2.2.2. The usefulness of disclosures about clinical trials for investors and analysts

Prior research has investigated the impact of disclosures about clinical trials on firm market value. Ely et al. (2003) focus on the various stages of product development, and find a significant market response to clinical trial announcements in Phase II. They conclude that Phase II is the initial point at which investors have sufficient confidence that a new drug has reached a minimum potential for success. Girotra et al. (2007) find a strong negative market reaction to failures in Phase III, which is smaller when the firm is developing other projects for

[7] *ClinicalTrials.gov* was created to increase transparency and facilitate public access to clinical trials as a result of the Food and Drug Administration Modernization Act (FDAMA) of 1997. FDAMA required the U.S. Department of Health and Human Services (HHS) to establish a registry of information related to clinical trials for both federally- and privately-funded trials. NIH and FDA worked together to develop the database *ClinicalTrials.gov*, which was made available to the public in February 2000. Registration of clinical trial studies on *ClinicalTrials.gov* is regulated by the Food and Drug Administration Amendments Act (FDAAA), Section 801, which became effective in 2007. FDAAA 801 obligates the responsible party to register the clinical trial information on the *ClinicalTrials.gov* no later than 21 calendar days after enrolling the first human subject in the study. Moreover, the regulation also orders the responsible party to submit the information on clinical trial achievement no later than 12 months after the primary completion date of the clinical trial. FDAAA 801 authorizes civil monetary penalties against responsible parties who fail to comply with registration and/or results submission requirements.

[8] The U.S. market being the most important in the world, big pharmaceutical and innovative firms participate in this procedure to sell their drugs in that country. In Europe, the implementation of a similar system started in 2014, and has been effective since 2022. Before 2014, the authorization to commercialize a drug was subject to national regulations, and required multiple applications.

the same market as the failed project. Dedman et al. (2008) show that drug development announcements have a greater impact on the market value than earnings announcements. They also note that firms announce more good news than bad news, and more news on late-stage developments than on early ones. This pattern of disclosures, and the subsequent market reactions, varies between large firms and their smaller counterparts. Szutowski (2018) finds that the market reaction of European biotechs and pharmas is sensitive to their development stage as stock returns are higher when the level of advancement is low, and smaller when a new drug production is launched. Finally, Bourveau, Capkun, and Wang (2020) document a reduction of the bid-ask spread, a measure of information asymmetries, after the implementation of the Food and Drug Amendments Act (FDAAA), which requires additional disclosures regarding clinical trial results. A reduction of the bid-ask spread is important because it lowers the cost of capital, and subsequently, increases the current stock price.

Overall, prior literature shows that investors revise their expectations about the future cash-flows, suggesting that clinical trial disclosures decrease uncertainty. To the best of our knowledge, only one paper investigates the usefulness of clinical trial disclosures for financial analysts. Hao et al. (2017) analyze the impact of clinical trial disclosures on the tasks performed by financial analysts. They show that such technical non-financial information improves the annual earnings forecasts for the three next years, which suggests that clinical trial disclosures are useful for assessing future payoffs of pharmaceutical companies.

2.2.3. Analysts' education and experience

We ask the following question: Does financial analysts' industrial expertise moderate the association between clinical trial disclosures and target price accuracy? To provide some answers to this question, we consider two dimensions of industrial expertise. The first one is education, i.e., the acquisition of knowledge and skills in schools or universities, and the second

one is professional experience, i.e., the acquisition of knowledge and skills when completing specific professional tasks.

Prior research indicates that investment banks hire analysts who possess specialized training and industry-specific skills (Palmon and Yezegel, 2012). This background allows analysts to understand scientific research in the pharmaceutical field by reading publications and participating in academic conferences. Such expertise helps them to better assess the consequences of an R&D project (i.e., the determination of the probability of success, its horizon, and the expected payoffs). Analysts with advanced degrees (i.e., Ph.D.) provide more informative recommendations for R&D-intensive firms, which suggests that the relevant interpretation of clinical trial reports on innovative drugs requires a previous education in scientific fields such as biology, pharmacology, and organic chemistry.

When interviewing sell-side analysts, Brown, Call, Clement, and Sharp (2015) report that industry knowledge is the most useful input to analysts' earnings forecast and stock recommendations. Moreover, industry knowledge is a significant determinant of sell-side analysts' compensation, suggesting that brokerage houses provide analysts with incentives to satisfy their clients' demand for industry knowledge. Bradley et al. (2017) find that industry expertise acquired from pre-analyst work experience helps analysts to issue more accurate earnings forecasts. Overall, the literature on analyst expertise (i.e., education and experience) shows that such individual characteristics may constitute an important determinant of target price accuracy.

2.3. Hypotheses

In this paper, we emphasize analysts' expertise because the valuation of pharmaceutical firms depends on existing drugs and on drugs under development. While the market size for new drugs can be reasonably approximated, estimating the probability of success (and the final approval from the FDA) requires extensive knowledge of the processes and technologies

involved. This difficulty may explain why target price accuracy is low, especially if analysts with little expertise cover those firms, and expertise is very important when it comes to estimating those probabilities.

In the previous sections, we discussed the fact that clinical trial disclosures should reduce information asymmetries and uncertainty about the future payoffs of R&D projects (Hao et al., 2017; Lev and Gu, 2016), which leads us to formulate the following hypothesis:

H1: Target prices issued after clinical trial disclosures are more accurate.

We also consider that analysts with a scientific education or a pre-analyst work experience in the pharmaceutical industry for many years (i.e., analysts with greater industrial expertise) are more qualified to make accurate forecasts. This idea leads us to formulate the following hypothesis:

H2: Target prices issued by analysts with a greater expertise are more accurate.

Finally, we develop our last hypothesis about the usefulness of clinical trial disclosures for financial analysts with different expertise. In fact, there is no evidence that the benefits of analyzing new clinical trial disclosures are equal across analysts. On the one hand, it is possible that analysts with the appropriate expertise issue more accurate target prices when firms disclose the results of clinical trials, because these analysts know how to interpret new information about drug development, and transform it into accurate forecasts. On the other hand, clinical trial disclosures could also reduce the 'accuracy gap' between experts and non-experts (i.e., target price accuracy is higher for analysts with a greater industrial expertise), because this additional information may compensate, at least partly, the disadvantage of analysts with less industrial expertise. These arguments lead us to formulate our last hypothesis in the nil form:

H3: Clinical trial disclosures benefit all analysts equally as far as target accuracy is concerned.

3. Data and methodology

3.1. Sample

We start by identifying on Datastream all firms in the pharmaceutical industry listed on the U.S. and (major) European markets from 2011 to 2017. We match this set of firms with the I/B/E/S database, which includes target prices for the period of interest. Firms without data in I/B/E/S, target prices without a 12-month horizon, and target price reiterations are excluded.[9] Financial data is extracted from *ThomsonReuters.* We use *ClinicalTrials.gov* to track the disclosure of clinical trials of the selected firms.[10] We collect this information, and keep only the completion of the phases that occurs during the period of interest. Finally, following Bradley et al. (2017), we hand-collect information on analysts' expertise (i.e., education and experience) from publicly available sources such as LinkedIn, Tipranks, and other professional websites.

[INSERT TABLE 1]

The sample selection process, summarized in Table 1, includes 11,407 clinical trial disclosures made by 144 unique firms, followed by 542 financial analysts who issued 15,015 target prices over the sample period. Table 2 reports the annual number of target prices, firms, analysts, and the number of clinical trial disclosures. It shows an increase in the number of target prices and firms, and a decreasing number of clinical trial disclosures over time, in total and for each of the three phases. This negative trend may reflect the increased cost of drug development, and a reduction of the number of products under development (DiMasi et al., 2007).

[INSERT TABLE 2]

3.2. Research design

[9] We find that analysts reiterate their target prices in only 5% of cases, which is in line with prior literature (Bradshaw et al., 2019).

[10] *ClinicalTrials.gov* provides information on the treated disease, the type of interventions, number, age, and gender of participants, phase of the clinical trial, and finally the start and the completion date of the clinical trial. We provide summaries of clinical trial disclosures in Table A1 of the appendices.

3.2.1. Empirical model

Our research design allows us to capture the causal relation between new clinical disclosures and target price errors. To test our hypotheses, we estimate the following baseline model:

$$\begin{aligned} TP\_error_{i,j,t} = {} & \beta_0 + \beta_1\, CTD_{i,t} + \beta_2\, Edu\_Science_{j,t} + \beta_3\, Edu\_Science_{j,t} \times CTD_{i,t} \\ & + \beta_4\, Exp\_Pharma_{j,t} + \beta_5\, Exp\_Pharma_{j,t} \times CTD_{i,t} \\ & + \boldsymbol{\Delta_1\, Job_{i,j,t} + \Delta_2\, Valuation_{i,j,t} + \Delta_3\, Env_{i,t}} \\ & + Firm\_FE + Year\_FE + \varepsilon_{i,j,t} \end{aligned} \qquad \text{(Eq. 1)}$$

where *TP_error* is the target price error, *CTD* is the clinical trial disclosures intensity, *Edu_Science* is the scientific education, *Exp_Phama* is the previous work experience in the pharmaceutical industry, and $\mathbf{Job_{i,j,t}}$, $\mathbf{Valuation_{i,j,t}}$, $\mathbf{Env_{i,t}}$ are three vectors of control variables.

Our first hypothesis states that target prices issued after clinical trial disclosures are more accurate. Thus, we expect a negative coefficient β_1, suggesting lower target price errors when more non-financial information is disclosed. We also posit that target prices issued by analysts with greater expertise are more accurate *(H2).* We therefore expect a negative coefficient β_2, suggesting lower target price errors when analysts have a scientific education, as well as a negative coefficient β_4, suggesting lower errors when analysts have a pre-analyst work experience in the pharmaceutical industry. For our last hypothesis (i.e., clinical trial disclosures benefit all analysts equally as far as target accuracy is concerned), the coefficients β_3 and β_5 of our interaction variables are expected to be nil.

3.2.2. Target price accuracy

Following Bilinski et al. (2013), we use two measures of target price error. The first one is *TPE*, computed as the absolute difference between the target price and the stock price at the end of the 12-month forecast horizon, scaled by the stock price at the target price issue date. The second variable (*TPE_Rev*) considers the first revision of the target price made before the end of the 12-month forecast horizon. It is defined as the absolute difference between the target

price, and the stock price at the target price revision date, scaled by the stock price at the target price issue.[11] Larger values of *TPE* and *TPE_Rev* indicate less accurate target prices.

3.2.3. Clinical trial disclosures

To understand the effect of clinical trial disclosures intensity (*CTD*) on target prices, we define three measures. Ely et al. (2003) consider the number of clinical disclosures at each stage (i.e., Phase I, Phase II, and Phase III). Since our focus is not on the impact of the different phases of clinical trials, and to limit the number of independent variables, *Number_New_CT* is the total number of new clinical trials disclosed between two target prices issued by analyst j on firm i. It includes the three stages of clinical trials, and is potentially subject to a size effect since big pharmas have more lines of future products than small biotechs. Hao et al. (2017) assign different weights to the number of clinical trials based on the probability of success of a new drug. This number being related to firm size, it is deflated by Total Asset. However, Total Asset reflects history as well as the industrial production structure. Given these drawbacks, we choose to define the second proxy as follows. *Drug_Port_1* is the expected number of successful drugs as a percentage of the total pipeline. It is equal to the number of clinical trials times the pre-assigned frequency of success for each phase, deflated by the number of clinical disclosures. This ratio measures the intensity of the clinical trial disclosures between two target prices. A high value of *Drug_Port_1* should generate a strong revision of the target price and, if informative, a more accurate target price. The success rate of the drug is 24% for a clinical trial in Phase I, 32% for Phase II, and 75% for Phase III respectively (DiMasi, 2001). We compute *Drug_Port_1* as follows:

$$Drug\_Port1 = \frac{\#Phase\_I \times 0.24 + \#Phase\_II \times 0.32 + \#Phase\_III \times 0.75}{\#Phase\_I + \#Phase\_II + \#Phase\_III}$$

[11] If an analyst does not revise the initial target price estimate during the 12-month forecast horizon, then *TPE* is equal to *TPE_Rev*.

Finally, the third proxy *Drug_Port_2* uses probabilities of success conditional on the therapeutic group (i.e., oncology, infectious diseases, etc.), and the phase. We use these specific probabilities of success because there is a strong variability among these groups (Wong, Siah, and Lo, 2019).

3.2.4. Analyst expertise

As discussed earlier, we consider two dimensions of analyst expertise, i.e. education and pre-analyst work experience. Based on prior literature, we define *Edu_Science* as the scientific-oriented education of an analyst. Scientific oriented education considers fields where students have a specific and intensive training in experimental research (including statistics) such as pharmacology, biology, and organic chemistry. Medical doctors (MD) are excluded since, in most countries, the curriculum does not include specific training in research. *Edu_Science* is equal to 1 if the analyst has a PhD degree in a scientific field related to the pharmaceutical industry, and 0 otherwise. *Exp_Pharma* measures the pre-analyst work experience (Bradley et al., 2017). It is equal to 1 if she/he worked in the pharmaceutical industry before being a financial analyst, and 0 otherwise.

3.2.5. Control variables

It has been documented that three sets of control variables can explain target price errors. The first set of controls is designed to capture the job characteristics (e.g., Clement, 1999; Harford et al., 2019). *CFA_Holder* is a dummy variable equal to 1 if an analyst has a CFA designation, and 0 otherwise (DeFranco and Zhou, 2009). We measure the potential resources and network available to the analyst by the size of her/his employer (brokerage house). The number of firms in the analyst's portfolio (*Nb_firms_followed*) captures the intensity of the job since following more firms is a more difficult task. Broker size (*Broker_size*) is equal to the (Log) of the number of analysts employed. The specialization of the analyst (*Spec_analyst*) captures the synergies resulting from the concentration of an analyst's portfolio in one or a few industries. The second set of controls is related to key firm characteristics (Roger et al., 2018; Bradshaw et al., 2019):

risk (size, leverage, volatility), growth (R&D, market-to-book, sales growth), and profitability (return on assets, dividend yield). The last set of controls captures potential differences in the environment of the firm. The number of analysts following the firm (*Number_analysts*), and unrelated events that could have affected the stock price (*Price_momentum*), capture the information available on the firm. Global stock market conditions (*Market_return*) is a proxy for the sentiment at the market level, and cross-country institutional differences (regulatory quality, rule of law) is a proxy for differences in market valuation within and across countries (Bradshaw et al., 2019). We include year dummies to control for macroeconomic conditions (*Year_FE*), and firm dummies (*Firm_FE*) to capture non-observable firm characteristics. All continuous variables are winsorized (1% and 99%), and all regressions use cluster standard errors at the analyst level. These variables are defined in the Appendix, Table A1.

4. Results

4.1. Descriptive statistics

Table 3 shows the descriptive statistics. The average target price error, *TPE* is equal to 49.8%, and the median is equal to 27.2% for the full sample. These percentages are in line with the errors usually found in other studies focusing on target price accuracy (e.g., Brav and Lehavy, 2003; Bilinski et al., 2013; Bradley et al., 2017; Roger et al., 2018). The revised measure, *TPE_Rev* shows an average (median) error equal to 36.9% (17.9%). As expected, the error is lower with the second measure because the forecast horizon is shorter. In particular, information released between the current revision and the end of the 12-month horizon is not incorporated into the benchmark price. When analysts revise the target prices, they incorporate six new clinical trial disclosures on average, while the median is equal to 2. These results show that revisions including new clinical trial disclosures are very diverse in terms of information flow incorporated into the target prices.

We also find that almost one-third of the target prices are issued by analysts with a scientific education (PhD related to the pharmaceutical industry), and about 27% are issued by analysts with a pre-analyst work experience in the pharmaceutical industry. The variables capturing the job characteristics like the resources available (*Broker_size*), workload (*Number_firms_followed*), and specialization (*Analyst_specialization*) show an important dispersion. The average broker employs 132 analysts (interquartile range = 195), the average analyst follows 11 firms (interquartile range = 12), and 53% of the firms covered by an analyst are active in the pharmaceutical industry. Finally, we document a large dispersion of the market capitalization (*Size*) and for the R&D intensity, and sales growth. To summarize, the sample contains target prices issued on well-established firms, so-called big pharma, and smaller innovative biotech firms. Therefore, based on the Bureau Van Dijk classification, we split the sample in two sub-samples, and examine separately pharmaceutical firms and biotechnological firms (hereafter biotechs and pharmas),

There are notable differences between pharmas (8,430 obs.) and biotechs (6,585 obs.) in terms of target price errors. The average (median) target price error, *TPE* is equal to 36.7% (21.5%) for the first group, and 66.5% (56.7%) for the second group. The interquartile range is equal to 27.8% for the first group, and 46.2% for the second. The difference in revised target price error (*TPE_Rev*) between the two groups is also very high. The average (median) is 21.5% (12.7%) for the first group, and 56.7% (32.7%) for the second group (the interquartile range is respectively 17.1% and 55%). All these differences (between the first and the second group) are statistically different from zero at the 1% level. This raises the following question: Do analysts following pharmaceutical firms have different expertise? To answer this question, we compare the education and pre-analyst work experience of analysts issuing these forecasts. The proportion of target prices issued by analysts with a scientific education is equal to 32.4% and 32.9% respectively, and not statistically different at the usual level (t-stat = 0.65). Concerning

pre-analyst work experience, the proportions are 24.7% and 29.9% respectively, and this difference is statistically significant at the 1% level. This result indicates that, for biotechs, more target prices are issued by analysts with previous work experience in the pharmaceutical industry before they became financial analysts.[12] Therefore, analysts following biotechs are better equipped in terms of expertise.

We examine the characteristics of the task assigned to analysts following pharmas and biotechs. The first difference comes from the information flow of clinical trial disclosures included when the target price is revised. The average (median) number of new clinical trials is 9.5 (6) for the first group, and 1.8 (2) for the second. The job characteristics are statistically at the 1% level, and economically different. Analysts following pharmas are employed by brokers that are bigger (147.7 vs 114), follow more firms (13 vs 9), and are more specialized since 60% (43%) of the firms in their portfolio are pharmas (biotechs).

Moreover, the analysis of firm characteristics shows that a typical biotech is a small, R&D-intensive, high-growth firm that does not make significant profits, and does not pay dividends, while a pharma is a more mature firm. To summarize, analysts following biotechs have a similar or better expertise than the ones following pharmas. They work for brokers that are (slightly) smaller, follow fewer firms, and are less specialized. In contrast, they follow firms that are at very different stages of development, and are assigned different workloads.

[INSERT TABLE 3]

4.2. Clinical trial disclosures and target price accuracy

We start our multivariate analysis by examining the association between clinical trial disclosures, analysts' expertise and target price errors on the full sample. Table 4 displays the results from estimating the baseline regression (Eq. 1). The 12-month target price error (*TPE*) is in columns 1 to 3, and the revised target price error (*TPE_Rev*) in columns 4 to 6. For both

[12] Note that the proportion of CFA_holder is the same in both sub-samples and equal to 11.2%.

variables, the results are presented with three proxies for the intensity of clinical trial disclosures (*CTD*), i.e., the number of disclosures in columns 1 and 4 (*Number_New_CT*), the first proxy of drug portfolio (*Drug_Portfolio_1*) in columns 2 and 5, and the second proxy of drug portfolio (*Drug_Portfolio_2*) in columns 3 and 6.

In the six columns, the coefficients of *CTD* are negative, and statistically significant at the 1% level, showing that target prices updated after the clinical trial disclosures are more accurate (i.e., lower error). When we consider the average *Number_New_CT*, the improvement is 1.2% for *TPE*, and 3% for *TPE_Rev* on average.[13] The improvement is even higher with the two other proxies, ranging from 5.5% (*TPE* with *Drug_Port_1*) to 8.3% (*TPE_Rev* with *Drug_Port_2*). Everything else equal, the average *TPE_Rev* drops from 36.9% to 28.6% for a revision that follows clinical trial disclosures (with *Drug_Port_2*). This finding is consistent with the idea that CTDs are a useful piece of information for all analysts. It is also consistent with Hao et al. (2017), who show that the estimation of three-year ahead annual earnings forecasts improves after CTDs. Such non-financial information therefore complements the limited information on R&D available in the financial statements, and supports our first hypothesis. Overall, we conclude that systematic disclosure of information on the product pipeline in the pharmaceutical industry is highly informative, which is in line with Lev and Gu (2016).

Concerning scientific education, *Edu_Science* is also negative and statistically significant at the 1% level in the six columns. It is also important from an economic point of view. The average error *TPE* drops by 7.4% (*Number_New_CT*), 9.8% (*Drug_Port_1*), and 9.4% (*Drug_Port_2*) when the analyst has a scientific education. *Edu_Science* generates a similar drop on *TPE_Rev* (from 6.2% with *Drug_Port_1* to 8% with *Number_New_CT*. This finding supports our second hypothesis.

[13] These numbers are obtained by multiplying the corresponding coefficient by the average value of the independent variable.

Finally, when we examine the specific effect of CTDs on analysts with a scientific education (*Edu_science*CTD*), we observe that the corresponding coefficient is positive, and statistically significant at the 1% level. Typically, while *TPE* (*TPE_Rev*) is reduced by 7.4% (8%) when the analyst has a scientific education and the revision does not incorporate any new clinical trials, the error is reduced by 5.6% (6.2%) with *Number_New_CT*, and 3.3% (2.5%) with *Drug_Port_1* and *Drug_Port_2*, after clinical trial disclosures. We interpret this result as follows. All analysts issue more accurate target prices when public information (CTDs) is released. While analysts with a scientific education still issue more accurate target prices than those with no scientific education, their comparative advantage is slightly lower when clinical trials are disclosed (i.e., the accuracy gap is reduced). Therefore, our last hypothesis is rejected.

Previous work experience in the pharmaceutical industry (*Exp_Pharma*), as well as the interaction with clinical trial disclosures (*CTD*), is never statistically significant at the usual levels in the six columns. This is in sharp contrast with Bradley et al. (2017) who show that pre-analyst work experience in a related industry improves annual earnings forecasts. It illustrates the fact that some of the abilities required to issue accurate target prices are industry specific.

Consistent with previous findings, several control variables are statistically significant in these models. In particular, the errors are smaller for large firms (*Size*), which is expected as larger firms have more diversified portfolio of products and clients, and are less exposed to the development of a new drug. In addition, the errors are also smaller for firms that grow faster (*Sales_growth*), have more debt (*Leverage*), and have lower dividend yields. Other variables are statistically significant with *TPE* (*R&D_sales*, *ROA*, *Volatility*), while others are significant with *TPE_Rev* (*Market_return*, *Price_momentum*).[14] The variables related to job characteristics are not significant at the 1% level with *TPE*, but *Nb_firms_followed* and *Broker_size* are

[14] We also run the same regressions with analysts fixed-effects and our results are unchanged. Our variable *CTD* is still significant at the 1% level in the six columns.

statistically significant at the 5% or the 10% level with *TPE_Rev*. To conclude, some key differences between target prices issued for pharmas and biotechs are inherent to the firms themselves.

[INSERT TABLE 4]

4.3. Biotechs *versus* Pharmas

Since it is more difficult to value biotechs than pharmas, we also investigate whether our main results hold for both groups of firms. Biotechs develop a limited number of highly specialized products based on innovative research and technologies. Reducing the idiosyncratic forecasting error requires a strong understanding of cutting-edge applied research. Pharmas hold highly diversified product portfolios, which reduces the potential effect of errors made on individual products as soon as these errors are not fully correlated. Thus, we expect that analysts' expertise matters more for biotechs. Moreover, information asymmetry is greater for biotechs, as they disclose information on a smaller number of clinical trials, and fewer analysts cover them (see descriptive statistics in Table 3).

Table 5 reports the results for the two sub-samples of pharmas and biotechs, with *TPE_Rev*[15]. The disclosures of clinical trials reduce the target price errors for both types of firms. The magnitude is similar to what was found for the full sample or even higher, i.e., 2.9%-12.3% for pharmas and 2.7-4.2% for biotechs. When we examine the coefficients associated with scientific education (*Edu_Science*), the findings are quite different. A scientific education helps analysts reduce target price errors for biotechs only. The error is 8-20% lower, and the corresponding coefficients are statistically significant at the 1% level. The interaction with *CTD* shows a positive sign, but the global effect of scientific education on errors after the disclosures is always negative and statistically significant at the 1% level. When no clinical trial is released, an analyst with scientific education has an error that is 20.4% lower than that of an analyst with

[15] To simplify the presentation, we do not report the results for *TPE* because they do not change our conclusions. These results are available upon request.

no scientific education. The drop is slightly lower, and equal to 17.5% after clinical trial disclosures. Again, CTDs reduce slightly the accuracy gap due to analysts' scientific education.

Pharmas show two coefficients (*Exp_Pharma*) that are statistically significant at the 5% or 10% level. The positive signs in the first two columns suggest that analysts with pre-analyst work experience in the pharmaceutical industry perform worse than analysts without that experience. When cumulated with the coefficient associated with clinical trial disclosures, these coefficients become insignificant at the 10% level. *Exp_Pharma* has the expected sign for biotechs (around 5%), but it is only significant at the 10% level. This effect disappears when clinical trials are disclosed. Overall, we show that scientific education helps analysts issue more accurate target prices for biotechs only. This finding has consequences on the hiring process. Brokers should employ analysts with a scientific education to follow biotechs since they have a competitive advantage for these firms, and only for these firms.

[INSERT TABLE 5]

4.4. Additional analysis: Financial analysts' tenure and target price accuracy

Analysts' tenure in their job helps them better evaluate firms by decreasing earnings and cash-flows forecasts errors (Mikhail et al., 1997, 2003; Clement, 1999). However, this idea is disputed since analysts performing poorly have a higher probability to quit their job, which creates a survival bias. After controlling appropriately, the statistical and economic significance of (general or firm) experience vanishes (Jacob et al., 1999; Hong and Kubik, 2003), and the (residual) forecasting accuracy is attributed to analysts' aptitude (and brokerage house characteristics).

Not accounting for this survival bias may have severe consequences on the results (Jacob, 1999; Clement et al., 2007). To mitigate the bias, we assume that general experience reaches a threshold after a number of years, instead of using the number of years (or a log transformation) that is unbounded. We define a dummy variable, *Exp_analyst* that is equal to 1

if her/his job tenure is above seven years (median of job tenure of the analysts in our sample), and 0 otherwise. This proxy is designed to split both sub-samples of biotechs and pharmas in two groups (long vs. short job tenure). Then, we re-estimate the baseline model on the four groups.

Table 6 reports the results. Starting with pharmas, we see that all *CTD* coefficients remain statistically significant at the 1% level. Economically, clinical trial disclosure coefficients are lower because the average CTD can be higher for long job tenure. *Edu_Science* and *Exp_Pharma* are never significant for long and short job tenure analysts. The conclusion drawn from Table 5 remains unaltered.

For the sub-sample of biotechs, the error decreases by 2.5-3.8% after clinical trial disclosures for short job tenure analysts ("rookies"). This is economically notable, and statistically significant at the 1% level. The coefficient of *Edu_Science* is also statistically significant at the 1% level, and economically important, from 13.2-29.5% before disclosures to 12.2-26% after. As before, *Exp_Pharma* is not statistically significant at the usual levels. After disclosures, the cumulative effect (*Exp_Pharma* + *Exp_Pharma*CTD*) is equal to 1.5-2.6% (not statistically significant). In other words, a scientific education is really important for "rookies", while a pre-analyst work experience is not. The more striking results for "seniors" (long job tenure) are obtained for *Exp_Pharma* and *Edu_Science*. On one hand, an analyst with a pre-analyst work experience in the pharmaceutical industry and a long job tenure makes errors that are 8.8% to 12.6% lower (statistically significant at the 1% level) than those of an analyst with no pre-analyst work experience. On the other hand, scientific education becomes less important. The corresponding coefficients are lower than before (5.2-14.4%), and statistically significant at the 5% level at best. After clinical disclosures, the errors decrease by 7.2% to 11.5%.

To better understand why we observe a surge of the pre-analyst work experience, we compute the drop of errors for senior versus rookies before and after clinical trial disclosures. When we cumulate *Edu_Science* + *Exp_Pharma* before (after) clinical trials, the error drops by 14-27% (11-23.6%) for seniors and 14.7-30% (10.5-26.4%) for rookies. These magnitudes are similar in both cases, and a pre-analyst work experience appears to be a substitute for scientific education. This result can be interpreted as an obsolescence of the scientific education acquired a long time ago in a fast-developing scientific area. An alternative explanation is the re-emergence of the survival bias since seniors survive because they provide (relatively) more accurate forecasts. Therefore, among good forecasters, education becomes less important.

5. Conclusion

The valuation of pharmaceutical firms is challenging because these firms invest important resources in R&D, and provide limited information on these investments in their financial statements. To issue accurate target prices, financial analysts must therefore collect and interpret additional information that reduces information asymmetries and uncertainty. We document that clinical trial disclosures play this role and, therefore, support Lev and Gu (2016) who advocate for the disclosure of systematic information on the product pipeline of pharmaceutical firms. More importantly, we show that scientific education contributes more to the issuance of accurate target prices for biotechs. Pre-analyst work experience is only important for more experienced analysts following biotechs.

Overall, our study contributes to the literature on the relevance of non-financial information disclosure for financial analysts. As the focus of our study is restricted to clinical trial disclosures in the pharmaceutical industry, future research could widen the multiple facets of analysts' expertise in other industries with high levels of intangible investments like software and computer services, or technology hardware and equipment. This would contribute to better understanding what kind of expertise is required in other contexts.

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Table 1. Sample selection

Sample selection criteria	Number of observations
All firms in pharmaceutical industry followed by analysts in I/B/E/S target price database from January 2011 to December 2017	37'576
Less: Target prices without a 12-month forecast horizon	(6'837)
Less: Target prices in a different currency than stock price currency	(2'605)
Less: Observations with missing data from Worldscope	(4'327)
Less: Observations with missing data from *ClinicalTrials.gov*	(2'783)
Number of target price observations	21'024
Less: Observations for which target prices did not change	(866)
Less: Observations without information on analysts' expertise	(5'143)
Final sample of target prices	**15'015**
Number of firms	144
Number of analysts	542
Number of clinical trial disclosures	11'407

Table 2. Sample distribution per year

This table presents sample distribution by year of the number of target price revisions (# TP), the number of unique firms (# Firms), the number of unique analysts (# Analysts), and the number of clinical trial disclosures (# CTD) in total and by phase (# Phase I, # Phase II, # Phase III).

	# TP	# Firms	# Analysts	# CTD			
				TOTAL	# Phase I	# Phase II	# Phase III
2011	1763	92	269	2003	801	674	528
2012	1758	86	240	1784	684	588	512
2013	2296	102	239	1673	613	534	526
2014	2016	117	243	1710	651	540	519
2015	2157	119	267	1458	518	470	470
2016	2433	127	284	1461	526	489	446
2017	2592	128	288	1318	520	422	376

Table 3. Descriptive statistics

This table describes our variables for the full sample, and two sub-samples, i.e., pharmaceutical and biotechnological firms. All the variables are defined in the Appendix, Table A1.

	***Full sample* (15015 obs.)**					***Pharmaceutical firms* (8430 obs.)**					***Biotechnology firms* (6585 obs.)**				
VARIABLES	mean	sd	p25	p50	p75	mean	sd	p25	p50	p75	mean	sd	p25	p50	p75
TPE	0.498	0.627	0.120	0.272	0.591	0.367	0.530	0.0914	0.196	0.369	0.665	0.698	0.204	0.441	0.866
TPE_Rev	0.369	0.599	0.0784	0.179	0.386	0.215	0.385	0.0600	0.127	0.231	0.567	0.747	0.140	0.327	0.695
Number_New_CT	6.138	7.851	1	2	8	9.516	8.965	2	6	18	1.813	2.080	1	2	2
Drug_Portfolio_1	0.248	0.234	0	0.280	0.436	0.342	0.211	0.240	0.397	0.471	0.128	0.205	0	0	0.267
Drug_Portfolio_2	0.332	0.295	0	0.485	0.601	0.443	0.256	0.355	0.557	0.619	0.191	0.281	0	0	0.551
Edu_Science	0.326	0.469				0.324	0.468				0.329	0.470			
Exp_Pharma	0.269	0.444				0.247	0.431				0.299	0.458			
CFA_holder	0.112	0.316				0.112	0.316				0.112	0.316			
Nb_firms_followed	11.42	15.64	2	5	14	13.24	18.26	2	6	16	9.095	11.00	2	5	12
Broker_size	132.7	132.7	22	73	217	147.4	132.8	33	99	241	114.0	130.2	18	45	184
Spec_analyst	0.529	0.308	0.250	0.531	0.783	0.606	0.303	0.389	0.638	0.870	0.430	0.286	0.188	0.407	0.616
Size	9.383	2.229	7.577	9.810	11.40	10.80	1.435	10.46	11.30	11.69	7.567	1.679	6.339	7.517	8.930
Leverage	0.502	0.259	0.336	0.480	0.624	0.524	0.158	0.405	0.513	0.624	0.472	0.346	0.212	0.397	0.624
Volatility (%)	14.25	23.33	2.750	6.597	13.47	14.48	22.55	3.243	6.619	12.48	13.96	24.30	2.257	6.538	15.24
RD_sales	0.381	0.336	0.141	0.198	0.601	0.197	0.143	0.132	0.162	0.214	0.616	0.364	0.208	0.648	1
M_B	6.861	11.59	2.750	4.698	9.213	6.246	7.443	2.685	4.068	8.012	7.648	15.31	2.996	5.885	10.55
Sales_growth (%)	16.43	33.92	0.360	7.580	22.81	10.20	15.59	1.780	5.710	13.05	24.41	46.89	0	16.56	36.65
ROA	0.012	0.280	-0.033	0.077	0.172	0.136	0.120	0.067	0.111	0.190	-0.148	0.340	-0.364	-0.049	0.082
Dividend_yield	1.369	1.753	0	0	2.72	2.283	1.700	0	2.330	3.600	0.198	0.930	0	0	0
Number_analysts	2.724	0.894	2.398	3.091	3.332	3.201	0.362	3.091	3.296	3.401	2.113	0.994	1.609	2.303	2.890
Price_momentum	0.126	0.309	-0.036	0.090	0.235	0.106	0.178	0.002	0.093	0.189	0.151	0.419	-0.128	0.080	0.355
Market_return	0.172	0.122	0.070	0.192	0.266	0.166	0.126	0.064	0.184	0.263	0.179	0.117	0.077	0.195	0.266
Regulatory_quality	1.458	0.226	1.268	1.461	1.628	1.463	0.243	1.268	1.497	1.628	1.453	0.201	1.268	1.461	1.628
Rule_law	1.640	0.177	1.596	1.618	1.645	1.634	0.201	1.596	1.618	1.665	1.647	0.141	1.596	1.618	1.645

Table 4. Target price errors and analyst expertise

This table presents the results for two measures of errors (*TPE* and *TPE_Rev*) and three proxies of clinical trial disclosures. All variables are described the Appendix, Table A1. Firm and year fixed effects are included. Standard errors are clustered at the analyst level. ***, ** and * represent significance at the 1%, 5% and 10% respectively.

	TPE			TPE_Rev		
	Number_ New_CT	Drug_ Port1	Drug_ Port2	Number_ New_CT	Drug_ Port1	Drug_ Port2
CTD	-0.002***	-0.224***	-0.193***	-0.005***	-0.311***	-0.250***
	(0.001)	(0.040)	(0.035)	(0.001)	(0.051)	(0.038)
Edu_Science	-0.074***	-0.098***	-0.094***	-0.080***	-0.062***	-0.063***
	(0.020)	(0.019)	(0.021)	(0.018)	(0.017)	(0.018)
Edu_Science*CTD	0.003***	0.262***	0.184***	0.003***	0.148***	0.114***
	(0.001)	(0.052)	(0.041)	(0.001)	(0.048)	(0.038)
Exp_Pharma	0.017	0.013	0.017	-0.001	-0.022	-0.025
	(0.028)	(0.026)	(0.026)	(0.025)	(0.021)	(0.022)
Exp_Pharma*CTD	-0.000	0.003	-0.010	0.000	0.081	0.067
	(0.001)	(0.056)	(0.042)	(0.001)	(0.053)	(0.042)
CFA_holder	-0.000	-0.001	-0.001	0.010	0.007	0.008
	(0.016)	(0.016)	(0.016)	(0.017)	(0.016)	(0.016)
Nb_firms_followed	0.008	0.008	0.008	0.010**	0.011**	0.011**
	(0.006)	(0.006)	(0.006)	(0.005)	(0.005)	(0.005)
Broker_size	-0.002	-0.002	-0.002	-0.010**	-0.009*	-0.009*
	(0.004)	(0.004)	(0.004)	(0.005)	(0.005)	(0.005)
Spec_analyst	0.033	0.027	0.029	0.029	0.030	0.031
	(0.030)	(0.029)	(0.029)	(0.024)	(0.023)	(0.023)
Size	-0.194***	-0.197***	-0.195***	-0.220***	-0.225***	-0.223***
	(0.020)	(0.019)	(0.019)	(0.023)	(0.022)	(0.022)
Leverage	-0.285***	-0.296***	-0.292***	-0.101*	-0.117**	-0.110**
	(0.073)	(0.072)	(0.072)	(0.052)	(0.052)	(0.051)
Volatility	-0.002***	-0.002***	-0.002***	0.000	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)
RD_sales	-0.271***	-0.257***	-0.254***	-0.059	-0.040	-0.038
	(0.081)	(0.080)	(0.080)	(0.068)	(0.067)	(0.067)
M_B	-0.001	-0.001*	-0.001*	0.000	0.000	0.000
	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)
Sales_growth	-0.001***	-0.001***	-0.001***	-0.001**	-0.001**	-0.001**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
ROA	-0.477***	-0.482***	-0.475***	-0.034	-0.041	-0.031
	(0.093)	(0.092)	(0.091)	(0.072)	(0.071)	(0.071)
Dividend_yield	-0.018**	-0.016**	-0.018**	0.030***	0.033***	0.029***
	(0.008)	(0.008)	(0.008)	(0.007)	(0.007)	(0.007)
Number_analysts	-0.032	-0.024	-0.023	0.036	0.052	0.053
	(0.047)	(0.046)	(0.046)	(0.040)	(0.039)	(0.039)
Price_momentum	-0.017	-0.017	-0.020	-0.074***	-0.074***	-0.076***
	(0.020)	(0.019)	(0.020)	(0.020)	(0.020)	(0.020)
Market_return	0.097*	0.114**	0.118**	-0.271***	-0.251***	-0.250***
	(0.058)	(0.057)	(0.057)	(0.056)	(0.056)	(0.056)
Regulatory_quality	0.432**	0.416**	0.410**	0.216**	0.197**	0.191**
	(0.179)	(0.176)	(0.176)	(0.088)	(0.085)	(0.086)
Rule_law	-0.694**	-0.675**	-0.672**	0.059	0.090	0.093
	(0.333)	(0.327)	(0.327)	(0.168)	(0.161)	(0.163)
Constant	2.884***	2.905***	2.890***	1.948***	1.919***	1.902***
	(0.375)	(0.372)	(0.373)	(0.304)	(0.291)	(0.293)
YEAR FE	YES	YES	YES	YES	YES	YES
FIRM FE	YES	YES	YES	YES	YES	YES
Observations	15,015	15,015	15,015	15,015	15,015	15,015
Adjusted R-squared	0.499	0.502	0.502	0.413	0.415	0.415

Table 5. Pharmaceutical vs biotechnology firms

This table presents the results for the two subsamples of large pharmaceutical firms and biotechs with the revised measure of errors (*TPE_Rev*) and three proxies of clinical trial disclosures intensity. All variables are described in the Appendix, Table A1. Standard errors are clustered at the analyst level. ***, ** and * represent significance at the 1%, 5% and 10% respectively.

	Pharmaceutical firms			Biotechnology firms		
	Number_ New_CT	Drug_ Port1	Drug_ Port2	Number_ New_CT	Drug_ Port1	Drug_ Port2
CTD	-0.003***	-0.245***	-0.277***	-0.015***	-0.324***	-0.163***
	(0.001)	(0.032)	(0.036)	(0.004)	(0.105)	(0.054)
Edu_Science	-0.011	-0.006	-0.016	-0.204***	-0.086***	-0.080***
	(0.019)	(0.023)	(0.028)	(0.045)	(0.023)	(0.023)
Edu_Science*CTD	0.001	0.039	0.049	0.016***	0.160*	0.083
	(0.001)	(0.058)	(0.056)	(0.004)	(0.093)	(0.052)
Exp_Pharma	0.060*	0.058**	0.036	-0.054	-0.055*	-0.044
	(0.031)	(0.028)	(0.032)	(0.059)	(0.028)	(0.029)
Exp_Pharma*CTD	-0.002	-0.115*	-0.040	0.004	0.242**	0.105*
	(0.001)	(0.064)	(0.057)	(0.005)	(0.102)	(0.062)
Constant	1.169***	1.093***	1.010***	2.081***	1.869***	1.890***
	(0.372)	(0.353)	(0.348)	(0.513)	(0.490)	(0.491)
CONTROL	YES	YES	YES	YES	YES	YES
YEAR FE	YES	YES	YES	YES	YES	YES
FIRM FE	YES	YES	YES	YES	YES	YES
Observations	8,430	8,430	8,430	6,585	6,585	6,585
Adjusted R-squared	0.197	0.207	0.216	0.427	0.424	0.422

Table 6. High and low analyst experience

This table presents the results for the four subsamples of pharmaceutical firms and biotechs for high and low analyst experience with the revised measure of errors (*TPE_Rev.*) and three proxies of clinical trial disclosures intensity. All variables are described in the Appendix, Table A1. Standard errors are clustered at the analyst level. ***, **, and * represent significance at the 1%, 5% and 10% respectively.

	Pharmaceutical firms						Biotechnology firms					
	Long job tenure			Short job tenure			Long job tenure			Short job tenure		
	Number_ New_CT	Drug_ Port1	Drug_ Port2	Number_ New_CT	Drug_ Port1	Drug_ Port2	Number_ New_CT	Drug_ Port1	Drug_ Port2	Number_ New_CT	Drug_ Port1	Drug_ Port2
CTD	-0.002***	-0.186***	-0.234***	-0.005***	-0.334***	-0.339***	-0.011***	-0.259*	-0.154**	-0.020***	-0.320**	-0.135*
	(0.001)	(0.037)	(0.042)	(0.002)	(0.055)	(0.059)	(0.004)	(0.131)	(0.068)	(0.007)	(0.141)	(0.069)
Edu_Science	0.013	0.014	-0.000	-0.045	-0.042	-0.043	-0.144**	-0.058*	-0.052	-0.295***	-0.132***	-0.132***
	(0.023)	(0.028)	(0.035)	(0.041)	(0.042)	(0.047)	(0.055)	(0.034)	(0.032)	(0.078)	(0.044)	(0.049)
Edu_Science*CTD	-0.000	-0.000	0.027	0.002	0.124	0.105	0.012**	0.142	0.068	0.020***	0.094	0.054
	(0.001)	(0.073)	(0.070)	(0.002)	(0.097)	(0.092)	(0.005)	(0.110)	(0.070)	(0.007)	(0.156)	(0.087)
Exp_Pharma	0.059	0.047	0.029	0.063	0.080*	0.059	-0.126***	-0.097***	-0.088***	-0.006	-0.029	-0.015
	(0.041)	(0.037)	(0.039)	(0.056)	(0.047)	(0.056)	(0.048)	(0.033)	(0.032)	(0.092)	(0.047)	(0.048)
Exp_Pharma*CTD	-0.002	-0.119	-0.050	-0.001	-0.124	-0.046	0.006	0.183	0.083	0.002	0.373**	0.164*
	(0.002)	(0.084)	(0.071)	(0.002)	(0.101)	(0.098)	(0.004)	(0.114)	(0.067)	(0.008)	(0.157)	(0.094)
Constant	0.434	0.384	0.335	3.076***	2.911***	2.788***	1.836**	1.742**	1.763**	2.648***	2.192***	2.207***
	(0.427)	(0.414)	(0.409)	(0.667)	(0.650)	(0.654)	(0.733)	(0.743)	(0.743)	(0.747)	(0.708)	(0.723)
CONTROL	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
YEAR FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
FIRM FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	5,668	5,668	5,668	2,762	2,762	2,762	3,462	3,462	3,462	3,123	3,123	3,123
Adjusted R-squared	0.172	0.180	0.189	0.245	0.255	0.261	0.467	0.466	0.465	0.430	0.424	0.421

Appendix

Table A1. Variable definitions

Variable	Definition
TPE	The absolute difference between the target price, and the stock price at the end of the 12-month forecast horizon, scaled by the stock price at the target price issue date.
TPE_Rev	The absolute difference between the target price, and the stock price on the subsequent TP revision date, scaled by the stock price at the TP issue date.
Number_New_CT	The number of new clinical trial information disclosed between reports t0 and t+1 of analyst j that follows firm i.
Drug_Port_1	The sum of the clinical trial announcements between reports t0 and t+1 of analyst j, where each clinical trial is weighted according to its potential for success deflated by the number of clinical trial announcements. DiMasi (2001).
Drug_Port_2	The sum of the clinical trial announcements between reports t0 and t+1 of analyst j, where each clinical trial is attributed to its' specific therapeutic group, and is weighted according to its probability of success deflated by the number of clinical trial announcements. Wong et al. (2019).
Edu_Science	Dummy variable equal to 1 if an analyst has a PhD degree in pharmacy, biology, and organic chemistry, 0 otherwise.
Exp_Pharma	Dummy variable equal to 1 if an analyst has worked in the pharmaceutical industry before being a financial analyst, 0 otherwise.
CFA_holder	Dummy variable equal to 1 if the analyst is a CFA charterholder, and 0 otherwise.
Exp_analyst	Dummy variable equal to 1 if the analyst experience is higher than 7 years (median for the 542 analysts in our sample), and 0 otherwise.
Nb_firms_followed	The logarithm of the number of firms followed by an analyst during the last 12 months.
Broker_size	The logarithm of the number of analysts employed by the broker house during last 12 months.
Spec_analyst	The ratio of the number of TP issued by an analyst in the pharmaceutical industry divided by the total TP issued during the last 12 months.
Size	The logarithm of the firm market capitalization measured at the TP issue date.
Leverage	The ratio of total debt to total assets.
Volatility	The standard deviation of closing prices over the 12 months ending three trading days before the target price release date.
RD_sales	R&D expenditures scaled by sales.
M_B	Market-to-book ratio, measured as the ratio of market capitalization to total common equity.
Sales_growth	The annual growth of total revenues over the past five years.
ROA	The ratio of operating income to total equity.
Dividend_yield	The ratio of dividend per share to share price.
Price_momentum	The six-month buy-and-hold raw return ending three trading days before the target price release date.
Number_analysts	The logarithm of the number of analysts following the firm in the previous year.
Price_momentum	The six-month buy-and-hold raw return ending three trading days before the target price release date.
Market_return	The return on the leading market index for the primary exchange where the firm’s stock lists over 12 months after the TP issue date.
Regulatory_quality	Captures perceptions of the ability of the government to formulate and implement sound policies and regulations that permit and promote private sector development.
Rule_law	Captures perceptions of the extent to which agents have confidence in and abide by the rules of society, and in particular, the quality of contract enforcement, property rights, the police, and the courts, as well as the likelihood of crime and violence.

Appendix

Table A2. Summaries of clinical trial disclosures available on *ClinicalTrials.gov*

Firm	Title of the study	Treated condition	Drug intervention	Outcome Measures	Age	Phase	# of Patients	Start Date	Completion Date
AstraZeneca	A Single Dose PD & PK Study With Two Formulations of Abediterol in Patients With Asthma	Asthma	Drug: Abediterol 0.156 µg|Drug: Abediterol 2.5 µg|Drug: Abediterol 0.05 µg|Other: Placebo	Change From Baseline in Trough Forced Expiratory Volume in 1 Second (FEV1)	18 Years to 75 Years (Adult, Older Adult)	Phase 1	30	June 21, 2016	Nov. 29, 2016
Bayer	Phase II Copanlisib in Relapsed/Refractory Diffuse Large B-cell Lymphoma (DLBCL)	Diffuse, Large B-Cell, Lymphoma	Drug: Copanlisib (Aliqopa, BAY80-6946)	Objective Response Rate (ORR) in Total Population Based on Investigator Assessment|ORR by CD79b Status Based on Investigator Assessment	18 Years and older (Adult, Older Adult)	Phase 2	67	May 8, 2015	Jan. 19, 2018
Guerbet	Safety and Efficacy Evaluation of DOTAREM® in MRI of Central Nervous System (CNS) Lesions	Diagnostic Self Evaluation|Central Nervous System Diseases	Drug: Dotarem (gadoterate meglumine)|Drug: Magnevist (gadopentetate dimeglumine)	MRI Lesion Visualization (Border Delineation, Internal Morphology and Contrast Enhancement) at Patient Level for Both "Pre" and "Paired" Evaluation	2 Years and older (Child, Adult, Older Adult)	Phase 3	416	September 21, 2010	Nov. 14, 2011
Ipsen	Dysport® Pediatric Lower Limb Spasticity Study	Cerebral Palsy|Muscle Spasticity|Children	Drug: Botulinum type A toxin (Dysport®)|Drug: Placebo	Change in MAS Score in the Gastrocnemius-soleus Complex (GSC) at the Ankle Joint of the (Most) Affected Lower Limb	2 Years to 17 Years (Child)	Phase 3	241	July 12, 2011	June 3, 2014
MorphoSys	Study of Fc-Optimized Anti-CD19 Antibody (MOR00208) to Treat B-cell Acute Lymphoblastic Leukemia(B-ALL)	Acute Lymphoblastic Leukemia	Drug: MOR00208 (formerly Xmab5574)	Overall Response Rate (ORR)|Patients Response Duration Evaluation by Hematology, Bone Marrow Aspirates or Biopsy, CT	16 Years and older (Child, Adult, Older Adult)	Phase 2	22	April 17, 2013	March 28, 2015
Novartis	Efficacy and Safety of SPA100 (Fixed-dose Combination of Aliskiren/Amlodipine) in Patients With Essential Hypertension	Essential Hypertension	Drug: Aliskiren/Amlodipine 150/2.5 mg|Drug: Aliskiren/amlodipine 150/5 mg	Change From Baseline in Mean Sitting Diastolic Blood Pressure (msDBP) to End of Study (Week 8)	20 Years and older (Adult, Older Adult)	Phase 3	1342	October 11, 2010	May 18, 2011
Sanofi	Comparison of a New Formulation of Insulin Glargine With Lantus in Patients With Type 1 Diabetes Mellitus on Basal Plus Mealtime Insulin	Type 1 Diabetes Mellitus	Drug: HOE901-U300 (new formulation of insulin glargine)|Drug: Lantus (insulin glargine)	Percentage of Time in Target Plasma Glucose Range (4.4-7.8 mmol/L [80-140 mg/dL])	18 Years to 70 Years (Adult, Older Adult)	Phase 2	59	August 19, 2012	May 2, 2013