Market Reactions to Innovative Firms' Earnings News

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Abstract

We examine beauty contest effects in disruptive technology firms. Based on beauty contest theory, we predict that uncertain business and valuation models of disruptive technology firms result in stronger market reactions to public information than non-disruptive firms. Consistent with this prediction, we find that price reactions and trading volume around earnings announcements are greater for disruptive technology firms. Our results indicate that more sophisticated market participants, such as financial analysts, are also subject to the beauty contest effect. We find that analysts' target price forecast revisions, but not their earnings forecast revisions, are more sensitive to earnings news for disruptive technology firms. This is consistent with a stronger presence of beauty contest effects when analysts forecast more subjective metrics, such as target prices. Moreover, the dispersion of stock recommendations relative to that of profitability forecasts is smaller for disruptive technology firms, consistent with overweighting public information.

Keywords: Innovative companies, earnings news, stock returns

1. Introduction

One of the defining aspects of the post-Great Recession economy has been the rise of new technology companies that have disrupted traditional business models in a variety of industries through technological innovation.[1] Although these companies have had a profound effect on society, surprisingly little research has been done on disruptive companies in the accounting and finance literature. Our goal in this paper is to (1) identify a sample of disruptive firms and explore their attributes on a variety of dimensions, and (2) test whether properties of disruptive firms are consistent with the so-called beauty contest effect.

The beauty contest effect was popularized by John Maynard Keynes in the 1930's. A defining feature of beauty contests is that the selection criteria of the winner of a contest are subjective. Spectators who wish to guess the winner will focus on guessing other spectators' guesses, rather than picking the person who, they personally believe, should be the winner. Keynes discusses the similarity of a stock market to a beauty contest. ''… professional investment may be likened to those newspaper competitions in which the competitors have to pick out the six prettiest faces from a hundred photographs, the prize being awarded to the competitor whose choice most nearly corresponds to the average preferences of the competitors as a whole; so that each competitor has to pick, not those faces which he himself finds prettiest, but those which he thinks likeliest to catch the fancy of the other competitors, all of whom are looking at the problem from the same point of view. It is not a case of choosing those which, to the best of one's judgement, are really the prettiest, nor even those which average opinion genuinely thinks the prettiest." (Keynes, 1936, p. 156).

[1] The term of "Disruptive Technology" was introduced and first defined by Bower and Christensen (1995).

Analytical models have shown that the beauty contest effect leads to over-reliance on public information relative to private information (Morris and Shin, 2002; Allen, Morris, and Shin, 2006). As winners of a beauty contest are chosen based on the average opinion rather than the fundamentals, participants in a beauty contest are more likely to anchor on public information. While his prediction has been tested in experimental studies (Cornand and Heinemann, 2014; Baeriswyl and Cornand, 2016), evidence using archival data is rather scarce (with the exception of Cremers, Kapeek, and Sautner, 2021). Our study attempts to fill the gap by testing predictions of beauty contest theories using disruptive technology (hereafter DT) firms' price patterns and market participants' behavior.

The main feature of disruptive technology is not just that the technology itself is new, but that markets for the technology are new. As products of disruptive technologies take a long time to be adopted by consumers, some of them fail and are never adopted. This uncertainty about market demand for disruptive technology makes the fundamentals of DT firms ambiguous. Hence, investing in DT firms is analogous to participating in beauty contests as spectators. The lack of clear and objective fundamentals of DT firms induces investors to guess other investors' beliefs, which is a common beauty contest incentive as described in Morris and Shin (2002).

Beauty contest effects can manifest in the properties of stock price and analyst forecasts. Based on theoretical predictions of beauty contest theory, we make three empirical predictions for DT firms. First, beauty contest effects lead to overreaction to public information (Morris and Shin, 2002; Allen, Morris, and Shin, 2006). The direction of future stock price changes is more likely to be based on easily identifiable public signals, such as earnings announcements. Hence, we predict that the market reaction around the earnings announcement (i.e., the earnings response coefficient) is greater for DT firms than non-DT firms. Second, high order beliefs in beauty contests can lead to different interpretations for the same public announcements, and this increased disagreement can lead to higher trading volume (Kondor, 2012). Therefore, we predict that trading volume changes around earnings announcements are greater for DT firms than non-DT firms. Third, beauty contest effects can manifest among more sophisticated market participants, such as analysts. We expect beauty contest effects when analysts forecast a relatively subjective metrics of DT firms, such as stock price, but not when they forecast an objective target such as earnings. Because beauty contest effects cause greater reactions to public information, we predict that the revisions of analyst target price forecasts are more sensitive to earnings news for DT firms than non-DT firms. In contrast, beauty contest effects are likely to be weaker for earnings forecasts. Therefore, we predict that the revisions of analysts' earnings per share (hereafter EPS) forecasts to earnings news is similar for DT firms and non-DT firms. Finally, beauty contest effects can also manifest in analysts' forecasts at the group level. We predict that analysts who follow DT firms are more likely to herd, in that their forecasts are closer to each other, compared to analysts following non-DT firms.

To construct the sample of DT firms, we collect a list of companies from the CNBC Disruptor 50 list, ARK Innovation ETF (ARKK) and the Indxx USD Disruptive Technologies Index. Our sample of 130 DT firms are predominantly from the IT (72 firms) and healthcare (27 firms) industries. We then construct the sample of control firms which is comprised of 8,050 non-DT firms covered by both Compustat and CRSP between 2000 and 2021. Descriptive statistics indicate that DT firms are slightly larger and have lower book to market ratios, lower accounting performance, lower leverage, and higher stock volatility than non-DT firms. In addition, DT firms are younger and followed by more analysts than non-DT firms. DT firms also have lower stock turnover, grow faster, and have more positive earnings surprises than non-DT firms.

Our test results provide support for our predictions. First, market reactions to earnings announcements are significantly greater for DT firms. In the three-day window around earnings announcements, the abnormal returns of DT firms based on either market adjustment or the Fama-French three-factor model adjustment are higher than those of non-DT firms. More specifically, the market reaction for DT firms around earnings announcements is on average 32.4% greater than the market reaction for non-DT firms. Second, the trading volume is significantly greater for DT firms around earnings announcements. Scaling trading volume around earnings announcements by those of non-earnings announcement periods, we find that the relative trade volume during an earnings announcement is greater for DT firms than for non-DT firms. Third, the revisions of analysts' target price forecasts in response to earnings news are more sensitive for DT firms than non-DT firms, while there is no significant difference in revisions of analysts' EPS forecasts in response to earnings news between DT firms and non-DT firms. Fourth, the relative dispersion of stock recommendations to that of profitability forecasts is significantly smaller for DT firms than non-DT firms. Our results are robust to matching DT firms and non-DT firms based on entropy balancing of the first, second, and third moments of key firm characteristics, which alleviates concerns on potential correlated omitted variable problems.

Prior studies document that the presence of short-term institutional investors may induce beauty contest effects. That is, the stock price of firms with a high proportion of short-term traders tend to overreact to news by overweighting (underweighting) public (private) signals. The price effect of short-term investors is predicted to be accompanied by future price reversals (Cremers, Kapeek, and Sautner, 2021). We check whether the beauty contest effect of DT firms is distinct from that of short-term institutions (STI) by examining whether DT firms exhibit a price reversal subsequent to earnings announcements, similar to STI. Our results indicate no significant price reversal for DT firms in the 6 to 35 days window after earnings announcements. Similar results are obtained for the 5 to 60 days window after earnings announcements.

We contribute to the literature by identifying a sample of DT firms and examining their key attributes. Furthermore, we contribute to the literature on beauty contests. The concept of beauty contests has drawn the attention of many analytical or experimental researchers (e.g., Morris and Shin, 2002; Allen, Morris, and Shin, 2006; Cornand and Heinemann, 2014; Baeriswyl and Cornand, 2016). These studies predict that the reaction to public information is much stronger when beauty contest incentives are present (e.g., Morris and Shin, 2002). However, this prediction has not been empirically tested for DT firms, where beauty contest effects are likely to be stronger because of their ambiguous fundamentals and future cash flow. Our study fills this gap by testing whether DT firms display stronger beauty contest effects, relative to non-DT firms, using stock price patterns and market participants' behavior. Our results show that all market participants, including sophisticated ones, are subject to beauty contest effects when valuation is ambiguous, while forecasts of metrics (e.g., EPS) that do not involve valuation do not display beauty contest effects.

Overall, our study adds new evidence to the literature on beauty contest effect that is driven by firm fundamentals rather than the investment horizon of traders. Our study complements the beauty contest effect among short-term institutional investors, documented in Cremers, Kapeek and Sautner (2021), by demonstrating that beauty contest effects can exist for all market participants in the absence of clear business or valuation models as in DT firms.

2. Literature

This section describes the definition of disruptive technology, the literature of beauty contests, and the potential beauty contest effects among DT firms.

2.1 Disruptive technology

The main feature of disruptive technology is not just that the technology itself is new, but also markets for the technology are new. “Disruptive technologies introduce a very different package of attributes from the one mainstream customers historically value, and they often perform far worse along one or two dimensions that are particularly important to those customers. As a rule, mainstream customers are unwilling to use a disruptive product in applications they know and understand. At first, then, disruptive technologies tend to be used and valued only in new markets or new applications; in fact, they generally make possible the emergence of new markets” (Bower and Christensen, 1995, p. 45). In contrast, other technology changes that are new but where markets are not new is defined as sustaining technology. “Sustaining technologies tend to maintain a rate of improvement; that is, they give customers something more or better in the attributes they already value.” (Bower and Christensen, 1995, p. 45).

Startups rather than established companies are often adopters of disruptive technologies as mainstream customers usually direct the investment of established companies (Christensen, 2013). A startup is often aimed at creating a new way of getting something done. Established companies tend to focus on their mainstream customers and pursue incremental improvements that tailor to their existing customers. Recent disruptive technology examples include Blockchains, ride-sharing apps, and Artificial Intelligence. [2]

Recently, the media and investment funds have begun to define and cover DT firms. For example, CNBC publishes a list of 50 DT firms each year using their proprietary Disruptor 50 methodology. “While technologies including AI, 5G, cloud computing and the Internet of Things are key to many companies making the 2021 Disruptor 50 list, the sectors they are upending are

[2] Note that disruptive technology is defined relative to the time. In the past, things like the automobile and television were disruptive technologies.

widespread, from financial services to health care, biotech, education, food, media, agriculture and transportation."[3]

The investment focus of some ETFs or mutual funds is DT firms. One of the well-known ETFs that invests primarily in DT firms is ARK Innovation ETF (ARKK). ARKK defines ‘‘disruptive innovation’’ as the introduction of a technologically enabled new product or service that potentially changes the way the world works. Companies within ARKK include those relating to the areas of DNA Technologies and the "Genomic Revolution", Automation, Robotics, and Energy Storage, Artificial Intelligence and the "Next Generation Internet" and Fintech Innovation.[4] Indxx USD Disruptive Technologies Index, a well-known index that tracks the performance of DT firms, has defined disruptive technologies as being comprised of the following themes: 3D printing, Clean Energy and Smart Grid, Cloud Computing, Cybersecurity, Data and Analytics, Fintech, Robotics and Artificial Intelligence, Internet of Things, Mobile Payment, and Healthcare Innovation.[5]

Disruptive technology has greater uncertainty than other technology changes because the market for the technology is new and risky. Many products of disruptive technologies take a long period to be adopted by consumers. Some of them are never adopted and disappear. Thus, the market for disruptive technology is highly uncertain compared with other technological changes. This uncertainty about the market itself for the disruptive technology makes investing in DT firms more like beauty contests.

2.2 Beauty contests

[3] https://www.cnbc.com/2021/05/25/these-are-the-2021-cnbc-disruptor-50-companies.html, accessed Aug 22, 2022
[4] https://ark-funds.com/funds/arkk/, accessed Aug 22, 2022
[5] https://www.indxx.com/indices/thematic/indxx-usd-disruptive-technologies-index-ntr, accessed July 27, 2022

The idea that stock markets have the element of beauty contests was first raised by Keynes (1936). The driver of the beauty contest effect is the lack of an objective measure for the outcome of the contest. Since there is no exogenous anchor for the outcome, contest participants have the “herding” incentive to predict the action of others. In order to predict what others will do, they will try to predict what others think. It is not about who I think is the prettiest, but rather guessing who others think is the prettiest, and this guessing goes on infinitely. Others try to guess my guess on their thought, and so on. These higher order beliefs are the key economic force in beauty contests (Morris and Shin, 2002).

A key driver of a beauty contest is the subjectiveness of the selection criteria for the winner. If there is a clear fundamental that everyone agrees upon, beauty contest effects are unlikely to be present. Typical beauty contests lack consensus in the intrinsic value for the subject of prediction in a contest. For instance, when spectators are asked to pick the most beautiful face in a beauty contest, each spectator is likely to have his/her own unique perspective on standards of beauty. When there is a lack of unanimous agreement on what should be the objective criteria for selecting the winner, picking the face that others think is most beautiful instead of the true subjective personal beliefs will be an optimal winning strategy. Such behavior of guessing others’ beliefs instead of adhering to your own beliefs is one of the defining features of the beauty contest effect.

Therefore, an increased level of difficulty in measuring the intrinsic value of an object of prediction in a contest leads to stronger beauty contest effects. In the absence of an anchor to the objective value, contesters are more likely to guess others’ opinions instead. The intrinsic value of DT firms is difficult to measure because the valuation of these firms involves understanding and predicting the future of the disruptive technologies. Hence, the valuation that all market participants can agree upon is often impossible as the market for DT firms is new and demand for its products is unknown. In contrast, for firms with mature technologies and long histories of operation, the demand for their products is more predictable and firm values can be tied more closely to fundamentals driven by product demand. We expect that beauty contest effects are stronger for DT firms than firms that are more established.

Beauty contest effects have been studied in a few analytical studies. Morris and Shin (2002) analyze the beauty contest effect in a simplified game in which economic agents have incentives to choose actions that are not only closer to the fundamental but also to be closer to the average action of others. The weight on the latter is a measure of the strength of beauty contest incentives. The main theoretical insight of their model is that beauty contest incentives cause agents to overreact to public information and underreact to private information. This is because public information is available to everyone; everyone knows that everyone observes the public information. As public information becomes the anchor for everyone in forming the high order beliefs, the reaction to public information is expected to be much stronger in the presence of beauty contest incentives.

Allen. Morris and Shin (2006) show that an endogenous “beauty-contest-like effect” may arise when traders have short trading horizons. The short horizon traders speculate and trade around the short-term price movements rather than long-run fundamentals. Hence, these traders primarily focus on guessing other traders’ beliefs and trading behavior by overweighting public signals, making their motivation to predict short-term price akin to a beauty contest incentive. Allen. Morris and Shin (2006) analyze the high order beliefs on asset pricing in a dynamic overlapping generation trading model with rational expectations. They assume that traders have heterogeneous private information and show that beauty contest incentives lead to inefficient aggregation of private information in price due to traders overreacting to public information.

Cornand and Heinemann (2014) conduct experiments based on Morris and Shin (2002) and find that overreaction to public information exists, but it is weaker than theoretical predictions. They propose that participants may have limited order beliefs as opposed to the infinite order beliefs in the original theory. The bounded rationality in forming an infinite level of high order beliefs reduces the overreaction to public information.

Recent archival papers have examined the role of high order beliefs of short horizon trading based on Allen, Morris and Shin's (2006) and find evidence supporting their prediction (Cremers, Kapeek, and Sautner, 2021). Specifically, they study market reactions to the release of analysts' consensus stock recommendations, a public information event that attracts short-term traders' attention. They find that optimistic (pessimistic) analyst recommendations are preceded by positive (negative) stock returns and followed by negative (positive) return reversals in the presence of more short-term traders (proxied by short-term institutional holdings). They argue that this evidence is consistent with short-term traders' overreaction to public information (i.e., analysts' consensus recommendations), which reverses in the future as the overreaction is corrected.

Our study is distinct from prior short-term trader studies in two ways. First, we examine the price patterns and market participants' behavior of DT firms, the fundamental values of which are inherently difficult to estimate. The beauty-contest-like effect of short-term traders is driven by their trading incentives and strategies, not by the innate difficulty in estimating the values of the stocks they are holding. That is, we study beauty contest effects driven by fundamentals rather than certain traders, which is more consistent with the lack-of-objective-value settings originally described in the beauty contest theory. [6] Second, because the beauty contest effects of DT firms are driven by the lack of means to estimate their fundamental values due to the innovative nature

[6] In the short-term traders setting, market participants may have means to value a stock to some extent, whereas in the DT firms setting, the objective value of a stock is difficult to measure for all market participants.

of their business models and uncertainty in market demand, the effect is likely to be present among all traders including both short and long horizon traders as well as sophisticated and unsophisticated market participants. Thus, we perform tests of whether the forecasts issued by sophisticated market participants (analysts) are also consistent with beauty contest effects.

Moreover, since everyone is under the influence of the beauty contest effect, the stock price reaction caused by the beauty contest effect is unlikely to reverse in the near future. That is, price reactions associated with DT firms are not considered overreaction, hence no immediate reversal is expected.[7]

3. Hypotheses

In our first hypothesis, we examine market reactions to public disclosure. Allen, Morris and Shin (2006) suggest that "any model where higher-order beliefs play a role in pricing assets will deliver the conclusion that there is an excess reliance on public information" (p. 721). The earnings announcement is a major event of public disclosure. Because investors with uncertain valuations are more likely to rely on public signals such as earnings announcements, they are likely to react more strongly to earnings announcements when beauty contest incentives are stronger. Because the beauty contest incentives are likely to be stronger for DT firms than non-DT firms, we predict that the stock price response to earnings news is greater for DT firms than non-DT firms, controlling for other factors that may affect stock price responses around earnings announcements.

We note that our earnings response coefficient (ERC) test results can be affected by countervailing forces. For instance, DT firms are likely to have greater uncertainty regarding

[7] The beauty contest effects will eventually fade away, in the long run, as DT firms become more mature because the valuation of their fundamentals will become more objective.

fundamentals, which may reduce ERC (Imhoff and Lobo, 1992; Stein and Wang, 2016). Imhoff and Lobo (1992) use the variance in analysts' earnings forecasts prior to a firm's annual earnings announcement to proxy for ex ante uncertainty. They find that market reaction to earnings news is greater for firms with lower uncertainty. However, this countervailing effect is likely to bias our tests against finding results that are consistent with the beauty contest effect. We control for various firm characteristics in our tests to isolate the beauty contest effect of DT firms. Furthermore, in section 6 we use entropy-balance matching of DT firms and non-DT firms to more directly control for any systematic differences in firm characteristics.

H1: The market response to an earnings announcement is greater for DT firms than non-DT firms.

The beauty contest effects also have implications for trading volume. Kondor (2012) shows that public announcements trigger updates in beliefs about others' beliefs when traders possess differential private information. Even though public information reduces disagreement about fundamentals, it can increase disagreement in high order beliefs when the correlation among traders' private information is low. This increase in disagreement in high order beliefs manifests itself in increased trading volume around public announcements. Kondor (2012) applies the assumption of short horizon trading to incorporate high order beliefs in his model, which play an important role when beauty contest effects are present. Because DT firms are likely subject to greater beauty contest effects compared to non-DT firms, we predict that the trading volume around earnings announcements is greater for DT firms than non-DT firms.

H2: Trading volume around earnings announcements is greater for DT firms than non-DT firms.

In the first two hypotheses, we used stock prices to capture the beauty contest effects. Stock prices are affected by the behavior of all market participants. Next, we examine whether beauty contest effects are present among a subgroup of market participants, financial analysts, who are relatively more sophisticated.

When forecasting stock prices of DT firms, even sophisticated financial analysts are likely to be influenced by beauty contest effects. Analysts are likely to react more strongly to public information such as earnings news when beauty contest effects are present. As the stock prices of DT firms are more subjective than those of non-DT firms, we predict that analysts' target price forecasts are more sensitive to earnings news for DT firms than non-DT firms, which is analogous to our prediction in H1 based on stock prices.

On the other hand, earnings are more objective metrics than stock prices. Hence, beauty contests effects are likely to be weaker when analysts predict earnings. We predict that analysts' EPS forecast revisions in response to earnings news will be similar for DT firms and non-DT firms. We summarize our hypotheses regarding analysts' target price and EPS forecasts in H3.

H3: The revisions of analyst target price forecasts in response to earnings news are greater for DT firms than non-DT firms.

H3': The revisions of analyst earnings forecasts in response to earnings news are not different between DT firms and non-DT firms.

Our last hypothesis captures the manifestation of beauty contest effects in the dispersion of analysts' forecasts. H3 predicts that analysts tend to overweight public information when they are following DT firms. This suggests that analysts' forecasts are likely to be less dispersed due to their common use of the same public information. To measure analysts' herding we use stock recommendations following prior research that has shown herding in recommendations (e.g., Welch, 2000; Jegadeesh and Kim, 2010). Stock recommendations represent a subjective estimate of value similar to target price forecasts but without the sparseness of target price forecast data. Thus, we expect analysts are more likely to issue similar stock recommendations for DT firms, resulting in a smaller dispersion. However, as the difference in the dispersion of stock recommendations between DT firms and non-DT firms can be affected by the difference in the difficulty in predicting firm fundamentals, we scale the dispersion of stock recommendations by the dispersion of analysts' earnings forecasts. This leads to the following hypothesis.

H4: The dispersion in analysts' forecast recommendations relative to dispersion in earnings is smaller for DT firms than non-DT firms.

4. Research Design and Measurement of Variables

We identify DT firms from three public sources. Our first source of DT firms is CNBC Disruptor 50 list. CNBC has been publishing the 50 most disruptive companies annually since 2013. Most of these companies were private startups with innovative technology when they first appeared on the list. The list also provides the outcomes of these firms since their first appearance in this list. For instance, firms may end up closing their business, be acquired by other companies, or go public via IPO (e.g., Twitter, Snapchat, and Uber).

Our second source of DT firms is ARK Innovation ETF, the inception date of which is October 30, 2014. ARK Innovation ETF is a publicly traded fund (Ticker symbol: ARKK) that primarily invests in innovative companies and has drawn much attention from the investor community due to its superior performance right after the COVID 19 market crash. We obtain the quarterly holdings data of ARK Innovation ETF from the mutual fund holdings data of Thomson/Refinitiv, which is compiled from its SEC filings. The current largest holdings of ARK

Innovation ETF as of June 30, 2022 include Tesla, Zoom, Roku, Crispr Therapeutics, and Teladoc Health among many disruptive firms.

Our last source of DT firms is the Indxx USD Disruptive Technologies Index. According to the index's website, Indxx is a "Net Total Return Index which is based around companies that enter traditional markets with new digital forms of production and distribution, are likely to disrupt an existing market and value network, displace established market leading firms, products and alliances and increasingly gain market share".[8] We obtain the list of 74 firms included in this index as of December 2021. Because this is a market-based index, all included firms are public firms.

Our list of DT firms combines all firms from the three lists above, which includes all firms listed in CNBC Disruptor list between 2013 and 2022, all stocks held by ARK Innovation ETF between the inception date and 2021, and all stocks covered by Indxx as of December 31, 2021.[9]

We test H1, the differential stock price reaction to earnings news, by running the following two models.

$$ABRET\,[-1, 1] = \beta_0 + \beta_1\, ES + \beta_2\, DT + \beta_3\, ES * DT + B_4\, Controls + B_5\, ES * Controls + B_6\, IndDummies + B_7\, ES * IndDummies + B_8\, YearDummies + B_9\, ES * YearDummies + e \qquad (1)$$

$$|ABRET\,[-1, 1]| = \beta_0 + \beta_1\, |ES| + \beta_2\, DT + \beta_3\, |ES| * DT + B_4\, Controls + B_5\, |ES| * Controls + B_6\, IndDummies + B_7\, |ES| * IndDummies + B_8\, YearDummies + B_9\, |ES| * YearDummies + e \qquad (2)$$

In model (1), *ABRET [-1, 1]* is either market-adjusted or Fama-French three-factor-adjusted return from one day before to one day after the quarterly earnings announcement date. *ES* is earnings surprise, measured as the difference between actual EPS and the median value of the last consensus analyst EPS forecast before earnings announcement. *DT* is an indicator variable that

[8] https://www.indxx.com/indices/thematic/indxx-usd-disruptive-technologies-index-ntr, accessed July 27, 2022
[9] The historical holdings of Indxx were not available, so we use the holdings of the most recent filing.

equals one for DT firms, and zero for non-DT firms. Our variable of interest is the interaction between *ES* and *DT*. A positive β_3 will be consistent with H1 as it means that the stock price reaction to earnings news is greater for DT firms compared to non-DT firms.

Controls include the following variables: *Size, ROA, BTM, Leverage, Loss, Volatility, SaleGrowth, LogFirmAge, LogNumAna,* and *FundTurnover.* We also include the interactions between *ES* and each control variable as explanatory variables (*ES* * *Controls*). Firm characteristics are included because they can affect the market's reaction to earnings announcements. For instance, Size, ROA, BTM, Leverage, Loss, Volatility, SaleGrowth, and *LogFirmAge* may capture firm risk or growth potential and hence affect stock price reaction (Collins and Kothari, 1989; Fama and French, 1992, 1993; Hayn, 1995). *LogNumAna,* is the logarithm of the number of analysts following the firm, which captures the firm's information environment (Dempsey, 1989; Christensen, Smith, and Stuerke, 2004). We also control for investor turnover as prior studies document that short-term investors may induce a beauty contest effect in firm stock price due to their short-term investment horizons (Cremers, Pareek, and Sautener, 2021). *FundTurnover* captures the presence of short-term investors, measured by fund turnover as of the beginning of the quarter. *FundTurnover* is calculated as the weighted average quarterly portfolio turnover of a firm's institutional investors, weighted by the amount the institutions have invested in the stock (Gaspar, Massa, and Matos, 2005; Cremers, Pareek, and Sautener, 2021). Finally, we control for industry and year fixed effects and their interactions with *ES*. Industry fixed effects is based on Fama-French 12 industry classification. Detailed definitions of all variables are provided in the Appendix.

In model (2), we examine the magnitude of market reaction to unsigned earnings surprise. The dependent variable in this regression is |*AbRet [-1, 1]*|, the absolute value of abnormal return from one day before to one day after the quarterly earnings announcement date. As our focus in this test is the magnitude of market reaction, we replace *ES* in model (1) with its absolute value.

We test H2, the abnormal trading volume between DT firms and non-DT firms, using the following regression model.

$$Log\ (Volume\ [-1,1]\ /\ Volume\ [-50,-10]) = \beta_0 + \beta_1\ |ES| + \beta_2\ DT + \beta_3\ |ES| * DT + B_4\ Controls + B_5\ |ES| * Controls + B_6\ IndDummies + B_7\ |ES| * IndDummies + B_8\ YearDummies + B_9\ |ES| * YearDummies + e \quad (3)$$

The dependent variable is the logarithm of trading volume in the earnings announcement window scaled by the trading volume in the [-50 days, -10 days] reference window. Because stock trading occurs when the market has new information, regardless of good news or bad news, we again replace *ES* in model (1) with its absolute value.

We test H3, the differential sensitivity of the revisions of analyst target price (EPS) forecasts between DT firms and non-DT firms, using the following regression model.

$$Analysts\ Forecast\ Revision = \beta_0 + \beta_1\ ES + \beta_2\ DT + \beta_3\ ES * DT + B_4\ Controls + B_5\ ES * Controls + B_6\ IndDummies + B_7\ ES * IndDummies + B_8\ YearDummies + B_9\ ES * YearDummies + e \quad (4)$$

We try two alternative dependent variables in model (4). First, *PriceTargetRev* is the revision of analyst stock price target around earnings announcement. *PriceTargetRev* is defined as the difference between the median value of the most recent analyst target price forecasts after earnings announcement and the median value of the last analyst target price forecasts before earnings announcement, scaled by the firm’s stock price at the end of the quarter. Second, *EPSRev* is defined as the difference between the median value of the most recent analyst EPS forecasts for the next quarter, issued after earnings announcement, and the median value of the last analyst EPS forecasts for the next quarter, issued before earnings announcement. We align the timing of analyst target price forecasts and EPS forecasts to compare beauty contest effects in these two measures. We predict that analysts will overreact to earnings news in their target price forecasts but not for EPS forecasts, so we expect β_3 to be positive only when *PriceTargetRev* is the dependent variable.

Finally, we test H4, the differential dispersion in analyst stock recommendations between DT firms and non-DT firms, using the following regression.

$$Log\ (RecDisp/\ MarginDisp) = \beta_0 + \beta_1\ DT + \beta_2\ Size + \beta_3\ ROA + \beta_4\ BTM + \beta_5\ Leverage + \beta_6\ Loss + \beta_7\ Volatility + \beta_8\ SaleGrowth + \beta_9\ LogFirmAge + \beta_{10}\ LogNumAna + \beta_{11}\ FundTurnover + B_{12}\ IndDummies + B_{13}\ YearDummies + e \quad (5)$$

The dependent variable is *Log (RecDisp/ MarginDisp)*, which is measured by dividing analysts' recommendation dispersion (*RecDisp*) by analysts' EPS forecast dispersion (*MarginDisp*). This measure captures analysts' recommendation dispersion relative to the dispersion of their forecast regarding profitability as the dependent variable. *RecDisp*, which is the standard deviation of last analyst stock recommendations before the earnings announcement. IBES codes stock recommendation in a 5-point scale: strong sell=1, sell =2, hold=3, buy=4, strong buy=5. *MarginDisp* is the dispersion of analysts' forecast regarding the firm's profitability. Our goal in testing H4 is to compare the dispersion of stock recommendation against the dispersion of earnings forecast. Because the most common earnings forecasts, EPS forecasts, are mechanically inversely related to the number of firm shares, we instead use profit margin ratio as the measure of profitability that can be derived from EPS (Margin = EPS * Number of Shares / Revenue). That is, *MarginDisp* is calculated as the standard deviation of analyst EPS forecasts before earnings announcement, multiplied by the firm's total outstanding shares and divided by total revenue. Firm characteristics, industry fixed effects, and year fixed effects are controlled for as in earlier models.

5. Results

5.1 Sample selection and summary statistics

Table 1 summarizes our sample selection process. In Panel A, we start with 63 firms in the CNBC Disruptor 50 list, 136 firms from the ARKK ETF, and 74 firms from the Indxx USD Disruptive Technologies Index to construct our sample of DT firms. We drop 17 firms that are missing in Compustat, 37 repeated firms that are listed in more than one source, 34 firms that are missing in CRSP, and 24 firms that are missing in IBES, which results in 161 unique DT firms. Limiting the sample years to be after 2000 results in 3,869 firm-quarters.[10] Requiring non-missing values for variable(s) used in our regression analyses further deletes 31 DT firms and 770 firm-quarter observations. Our final sample of DT firms is comprised of 130 firms with 3,099 firm-quarters.

Panel B shows that most of our sample DT firms are from the IT industry (72 firms) and healthcare industry (27 firms). In Panel C, we construct the non-DT firms sample starting from the 12,377 firms covered by both Compustat and CRSP between 2000 and 2021. Requiring non-missing IBES data and excluding DT firms drops 2,485 firms and 130 firms, respectively, which results in 9,762 non-DT firms with 239,090 firm-quarters. Further requiring non-missing values for variable(s) used in our regression analyses deletes 1,712 firms and 43,466 firm-quarters. Our final sample of non-DT firms is comprised of 8,050 firms with 195,624 firm-quarters.

Table 2 provides summary statistics for the DT firms (Panel A) and non-DT firms (Panel B) of our sample. Firm characteristics of DT firms are often different from those of non-DT firms. DT firms tend to have slightly larger firm size measured by total assets, lower book to market ratio,

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[10] Most of our sample DT firms have an initial public offering date after 2000. 19 firms started to be traded publicly before 2000.

lower accounting performance, lower leverage, and higher stock volatility, compared to non-DT firms. DT firms are also younger than non-DT firms and followed by more analysts. They have lower stock turnover, higher sales growth, and more positive earnings surprises. All of these characteristics of DT firms are consistent with disruptive firms that have low earnings but high growth and valuation and went public recently. DT firms' market-adjusted and three-factor abnormal returns in the three-day earnings announcement window are generally higher than non-DT firms.

The market trades more actively on DT firms during earnings announcements (mean trade volume = 0.032 versus 0.014, median = 0.022 versus 0.009). Although trade volume is also higher for DT firms in the reference window of [-50 days, -10 days], the difference is smaller (mean = 0.014 versus 0.008, median = 0.011 versus 0.006) and Log (Volume [-1,1] / Volume [-50,-10]) that measures the relative trade volume during earnings announcement is greater for DT firms than for non-DT firms (mean = 0.675 versus 0.359, median = 0.687 versus 0.369). This provides initial support for our H2. Regarding analysts, we find greater dispersion among their stock recommendations and profit margin forecasts for DT firms than for non-DT firms (for example, mean recommendation standard deviation = 0.820 versus 0.762, mean profit margin forecast standard deviation = 0.101 versus 0.065). This is consistent with greater uncertainty regarding DT firms' profitability and stock price. However, consistent with H4, the increase in analysts' dispersion on stock recommendation for DT firms is relatively lower than that for earnings forecasts based on the lower value of Log (Rec. Std. Dev. / Margin Std. Dev.) (mean = 4.25 versus 4.70, median = 4.58 versus 5.04).

5.2 Market reaction to earnings announcement (H1 and H2)

Table 3 provides regression results for abnormal stock return during the three-day earnings announcement window using model (1). We use two different measures of abnormal returns based on value-weighted market adjustment and the adjustment of expected return calculated from the Fama-French three-factor model (Fama and French, 1993). Consistent with the stock market reacting to news embedded in announced earnings, *ES* is positive and statistically significant in all model specifications in Table 3. *DT* is also significantly positive in all columns, suggesting that the stock return in this event window is generally more positive for DT firms. Our variable of interest, the interaction between *ES* and *DT*, has a positive and statistically significant coefficient in all columns. For example, in Column (2) where abnormal return is measured with the market-adjusted model and all control variables are included, the coefficient for *DT* * *ES* is 0.6702 and the p-value is 0.001. Based on the coefficient of *ES* in the same column, this suggests that market reaction to earnings news for DT firms is on average 32.4% (0.6702/2.0675=32.4%) greater than that for non-DT firms. Thus, our results are consistent with H1 that the stock market reacts more strongly to new information in earnings for DT firms because the beauty contest effect is stronger. In Table 4, we examine the magnitude of market reaction to unsigned earnings surprise using model (2). The coefficient of *DT* * | *ES* | is positive and statistically significant in three out of four models, again consistent with the market reacting stronger to DT firms' earnings announcements.

In Table 5, we test H2 with model (3) where the dependent variable is the relative trade volume in the earnings announcement window. We find the coefficient of *DT* * | *ES* | is significantly positive (for example, coefficient = 3.3915, p-value = 0.037 in column (2) where all control variables are used). Thus, consistent with H2, the market trades more actively on DT firms' new information during the earnings announcement period.

Overall, our results in Tables 3-5 suggest that stock market participants react more strongly to earnings news regarding DT firms. More specifically, our results indicate that the market reaction to earnings announcements as well as trading volume around earnings announcements are greater for DT firms. This is consistent with our argument that beauty contest incentives are stronger for DT firms than for non-DT firms.

5.3 Analysts' forecast revision and dispersion (H3, H3' and H4)

The results of testing H3 and H3' using model (4) are presented in Table 6. Columns (1) and (2) (columns (3) and (4)) show the results of testing the differential sensitivity of the revisions of analyst target price (EPS) forecasts around earnings announcements, using different sets of control variables. The coefficient of *DT * ES* is significantly positive in both columns (1) and (2), indicating that analysts' target price forecast revisions are more sensitive to earnings news. This is consistent with H3 that analysts following DT firms display stronger beauty contest effects in their target price forecasts even though they are sophisticated market participants. In contrast, the coefficient of *DT * ES* is not significant in columns (3) and (4) where we examine analyst EPS forecast revisions around earnings announcements, which is consistent with H3'.[11]

Results of our test of H4 using model (5) are provided in Table 7. Our summary statistics in Table 2 suggest that analysts have greater dispersion over both stock recommendation and profitability forecasts for DT firms, likely due to these firms' greater uncertainty regarding profitability and stock price. Thus, we examine the relative dispersion of stock recommendations versus profitability forecasts using *Log (RecDisp / MarginDisp)* as the dependent variable. In both columns of Table 7, *DT* has a negative and statistically significant coefficient. This is consistent with H4, that analysts herd more on their stock recommendations for DT firms.

[11] In untabulated analysis, we measure analysts' forecast revision based on mean forecast values and find similar results.

Overall, our results in Tables 6 and 7 are consistent with analysts responding to public information about DT firm in the same fashion as stock market participants. Our results show that beauty contest effects are present when it involves valuation of DT firms (i.e., target price forecasts and stock recommendations), but not when it involves forecasting of a relatively objective metric (i.e., EPS). This is because EPS forecasts involve less subjective estimation as they are likely to be based on objective metrics such as sales growth, management guidance, etc.

6. Additional Tests

The descriptive statistics in Table 2 suggest that firm characteristics of DT firms and non-DT firms can be quite different. Although we control for various firm characteristics in our regressions, it is still possible that the intrinsically different firm characteristics of DT and non-DT firms could drive our results in Tables 3-7. To mitigate this potential correlated omitted variable problem, we employ entropy balancing matching of DT firms and non-DT firms in terms of the first, second, and third moments of key firm characteristics. Entropy balance matching puts different weights on different observations such that post-weighting distributional properties of DT firms and non-DT firms are virtually identical and ensures covariate balance (Hainmueller, 2012; McMullin and Schonberger, 2015). This quasi-matching technique is known to be better than propensity score matching and has been used in many prior studies (Wilde, 2017; Chapman, Miller, Neilson, and White, 2022). In our context, it allows for the comparison of the beauty contest effect between DT firms and non-DT firms while holding constant various firm characteristics.

To implement entropy balancing, we first find the proper weights of observations by matching DT firms and non-DT firms with respect to the first, second, and third moments of all control variables (*Size, ROA, BTM, Leverage, Loss, Volatility, SaleGrowth, LogFirmAge,* *LogNumAna,* and *FundTurnover*). We then apply the weights in our regressions in models (1) to (4). Table 8 shows that the results with entropy balance matching are qualitatively similar to our previous results in Tables 3 to 7.

Our next additional test involves examining future stock returns after earnings announcements. According to Cremers, Kapeek, and Sautner (2021), short-term institutional investors can exhibit beauty contest effects of stock price overreaction to news by overweighting public signals and underweighting private signals. As this overreaction is driven by investment horizons of short-term institutional investors, it will be accompanied by future price reversal (Cremers, Kapeek, and Sautner, 2021). Although we control for the presence of short-term institutional investors in all of our models by including *FundTurnover* variable, we try to further distinguish the price effect of DT firms from that of short-term investors by examining future stock returns. If the price effect of DT firms is not driven by short-term investors, we will not see a reversal in subsequent stock price.

In order to test whether there is a reversal in the stock market reaction after earnings announcements, we replace the dependent variables in model (2) with abnormal returns from 6 to 35 days following the earnings announcement. The results of this test are presented in Table 9. In both the regular regressions as well as the regressions with entropy balancing, the coefficient for *DT * ES* is not different from zero at conventional statistical levels. Thus, unlike in the case of short-term investors in Cremers, Kapeek, and Sautner (2021), we do not find evidence that there is a stock price reversal after earnings announcements for DT firms.[12]

7. Conclusions and Discussion

[12] In an additional untabulated test, we examine a longer subsequent event window from 5 to 60 days following an earnings announcement. We continue to find no evidence of a reversal.

In this study, we examine beauty contest effects in DT firms. Our descriptive analysis of DT firms indicates that DT firms are slightly larger, and have lower book to market ratio, lower accounting performance, lower leverage, and higher stock volatility than non-DT firms. DT firms are also younger than non-DT firms and followed by more analysts than non-DT firms. In addition, DT firms have lower stock turnover, higher sales growth, and more positive earnings surprises than non-DT firms.

We predict the reaction to public information for DT firms to be much stronger according to beauty contest theory and test this prediction using the price patterns and market participants' behavior of DT firms. Our results provide support for this prediction. In particular, we show that market reactions to earnings announcements are significantly greater for DT firms, and trading volume is significantly greater for DT firms around an earnings announcement. We find a similar effect for more sophisticated market participants, financial analysts. More specifically, we show that analysts' target price forecast revisions are more sensitive to earnings news for DT firms than non-DT firms, while there is no significant difference between analysts' EPS forecast revisions to earnings news between DT firms and non-DT firms. We also show that the dispersion of stock recommendations relative to that of profitability forecasts is significantly smaller for DT firms than non-DT firms. Our results are robust to entropy balance matching, which alleviates concerns regarding a potential correlated omitted variable problem.

The beauty contest effect among DT firms is distinct from the effect of short-term institutional investors (Cremers, Kapeek, and Sautner, 2021) who tend to overreact to news by overweighting (underweighting) public (private) signals. Unlike short-term institutions, DT firm effects are not accompanied by future price reversals. Our study provides novel evidence on the stock price and sophisticated market participants of disruptive technology firms exhibiting beauty contests effects.

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Appendix. Variable Definitions

<u>Dependent variables</u>	
Market-adjusted ABRET	Abnormal stock return in specified event window obtained from *WRDS Event Study* tool using the following additional parameters: estimation window = 100 days, minimum number of valid returns = 70, Gap = 50 days, model = market-adjusted model.
Three-factor ABRET	Abnormal stock return in specified event window obtained from *WRDS Event Study* tool using the following additional parameters: estimation window = 100 days, minimum number of valid returns = 70, Gap = 50 days, model = Fama-French Three Factor Model.
Log (Volume [-1,1] / Volume [-50,-10])	= Log (the average value of stock trade volume in the [-1,1] window around earnings announcement date / the average value of stock trade volume in the [-50, -10] window around earnings announcement date).
PriceTargetRev	The median value of the most recent analyst price target forecasts after earnings announcement minus the median value of the last analyst price target forecasts before earnings announcement, scaled by the firm's stock price at the end of the quarter.
EPSRev	The median value of the most recent analyst EPS forecasts for the next quarter, issued after earnings announcement minus the median value of the last analyst EPS forecasts for the next quarter, issued before earnings announcement, scaled by the firm's stock price at the end of the quarter.
Log (RecDisp / MarginDisp)	= Log (*RecDisp / (0.002 + MarginDisp))*. 0.002 is added to avoid missing value caused by observations with a 0 denominator. *RecDisp* is the standard deviation of last analyst stock recommendations for the firm before earnings announcement. *MarginDisp* the standard deviation of analyst EPS forecasts before earnings announcement, multiplied by the firm's total outstanding shares and divided by actual total revenue for the quarter.
<u>Independent variables</u>	
DT	= 1 for DT firms, and 0 for non-DT firms. DT-firms and non-DT firms are selected based on steps in Panel A and Panel C of Table 1, respectively.
ES	= Actual EPS – Median consensus analyst EPS forecast before earnings announcement.
Size	Firm size, measured as the natural log of the firm's total assets.
ROA	= Income after depreciation divided by average total assets.
BTM	Book value of equity divided by market value of equity.
Leverage	Leverage of the firm, calculated as long-term debt divided by total assets.
Loss	= 1 if Income after depreciation < 0, =0 otherwise.
Volatility	Stock volatility, measured as the standard deviation of the firm's monthly stock returns over the past 60 months, then converted to annual volatility.
SaleGrowth	Current sales minus sales four quarters before, scaled by the current sales
LogFirmAge	= Log (firm age). Firm age is calculated as current fiscal year – the firm's first available fiscal year in CompuStat + 1
LogNumAna	= Log (number of analysts providing the current quarter EPS forecast before earnings announcement)
FundTurnover	The weighted average quarterly portfolio turnover of a firm's institutional investors, weighted by the amount the institutions have invested in the stock (Gaspar, Massa, and Matos, 2005; Cremers, Pareek, and Sautener, 2021).

Table 1. Sample Selection

Panel A breaks down the DT firm observations in our sample. Panel B shows the distribution of DT firms by Fama-French 12 industries. Panel C describes the sample selection procedure of non-DT firms.

Panel A. Selection of DT firms sample

	Observations
Start from: DT firms identified in CNBC list, ARKK, and Indxx	63, 136, 74
Less:	
Firms not found in CompuStat	(17)
Repeated firms found in more than one source	(37)
Firms not found in CRSP	(34)
Firms not found in IBES	(24)
Initial DT firms sample	161
Corresponding DT firm-quarters post 2000	3,869
Less: firm-quarters missing variable(s)	(770)
Final sample of DT firm-quarters	3,099
Final sample of DT firms	130

Panel B. Distribution of DT firms by Fama-French 12 industries

Industry	Num. Firms
Consumer Nondurables	2
Consumer Durables	5
Manufacturing	4
Oil, Gas, and Coal Extraction and Products	0
Chemicals and Allied Products	1
Business Equipment - Computers, Software, and Electronic Equipment	72
Telephone and Television Transmission	2
Utilities	0
Wholesale, Retail, and Some Services	1
Healthcare, Medical Equipment, and Drugs	27
Finance	9
Other	7

Panel C. Selection of non-DT firms sample

	Observations
All CompuStat-CRSP firms between 2000 and 2021	12,377
Less:	
Firms not found in IBES	(2,485)
Sample DT firms	(130)
Initial non-DT firms sample	9,762
Corresponding non-DT firm-quarters	239,090
Less: firm-quarters missing variable(s)	(43,466)

Final sample non-DT firm-quarters	195,624
Final sample of non-DT firms	8,050

Table 2. Summary Statistics

Panels A and B report the descriptive statistics of DT and non-DT firm observations in our sample, respectively. All variables are defined in Appendix. ***, **, * correspond to statistically significant difference between DT firms and non-DT firms at 1%, 5%, and 10%, respectively, for two-tailed tests.

Panel A. Summary statistics - DT firms

Variable	Mean	Median	Q1	Q3	Min	Max	Std Dev
Size	7.17**	7.12***	5.83	8.39	3.18	11.89	1.75
BTM	0.223***	0.161***	0.084	0.284	-0.468	2.955	0.259
ROA	-0.014***	0.004***	-0.037	0.022	-0.250	0.086	0.059
Leverage	0.181***	0.105***	0.000	0.311	0.000	0.938	0.200
Loss	0.452***	0	0	1	0	1	0.498
Stock Volatility	0.518***	0.479***	0.346	0.638	0.098	1.664	0.249
Number of Analysts	15.17***	13***	7	21	1	45	9.67
Sale Growth	0.359***	0.239***	0.095	0.441	-0.802	3.614	0.612
Firm Age	9.77***	9***	6	13	3	25	4.99
Stock Turnover	0.193***	0.182***	0.146	0.228	0.054	0.600	0.066
Earnings Surprise	0.001***	0.001***	0.000	0.002	-0.090	0.058	0.007
Market-adjusted Abnormal Return [-1,1]	0.010***	0.008***	-0.051	0.068	-0.268	0.285	0.106
Three-Factor Abnormal Return [-1,1]	0.008***	0.005***	-0.054	0.067	-0.270	0.284	0.105
Trade Volume [-1,1]	0.032***	0.022***	0.012	0.042	0.000	0.110	0.027
Trade Volume [-50,-10]	0.014***	0.011***	0.007	0.018	0.000	0.055	0.011
Log (Volume [-1,1] / Volume [-50,-10])	0.675***	0.687***	0.345	1.012	-1.959	2.254	0.526
Analysts Recommendation Std. Dev.	0.820***	0.820***	0.710	0.930	0.000	1.340	0.201
Profit Margin Forecast Std. Dev.	0.101***	0.011***	0.005	0.028	0.000	2.837	0.368
Log (Rec. Std. Dev. / Margin Std. Dev.)	4.25***	4.58***	3.76	5.20	-1.07	6.63	1.46

Panel B. Summary statistics - Non-DT firms

Variable	Mean	Median	Q1	Q3	Min	Max	Std Dev
Size	7.09	7.04	5.70	8.36	2.84	12.24	1.96
BTM	0.571	0.469	0.262	0.755	-0.468	2.955	0.494
ROA	-0.001	0.006	-0.001	0.019	-0.250	0.086	0.046
Leverage	0.226	0.182	0.041	0.350	0.000	0.938	0.213
Loss	0.267	0	0	1	0	1	0.442
Stock Volatitliy	0.472	0.400	0.279	0.589	0.030	1.664	0.272
NumAnalysts	7.68	6	3	11	1	51	6.53
SaleGrowth	0.155	0.069	-0.035	0.208	-0.802	3.614	0.519
FirmAge	21.90	17	9	29	2	72	16.47
Stock Turnover	0.201	0.186	0.147	0.236	0.054	0.600	0.079
Earnings Surprise	0.000	0.000	-0.001	0.002	-0.090	0.058	0.015
Market-adjusted Abnormal Return [-1,1]	0.001	0.001	-0.038	0.042	-0.268	0.285	0.085
Three-Factor Abnormal Return [-1,1]	0.000	0.000	-0.039	0.041	-0.270	0.284	0.085
Trade Volume [-1,1]	0.014	0.009	0.004	0.018	0.000	0.110	0.017
Trade Volume [-50,-10]	0.008	0.006	0.003	0.010	0.000	0.055	0.008

Log (Volume [-1,1] / Volume [-50,-10])	0.359	0.369	-0.007	0.743	-2.247	2.254	0.637
Analysts Recommendation Std. Dev.	0.762	0.800	0.580	0.950	0.000	1.340	0.295
Profit Margin Forecast Std. Dev.	0.065	0.006	0.002	0.016	0.000	2.837	0.319
Log (Rec. Std. Dev. / Margin Std. Dev.)	4.70	5.04	4.17	5.62	-1.68	6.67	1.37

Table 3. Response to Earnings Announcement

This table compares the three-day abnormal stock returns around earnings announcements between DT firms and non-DT firms using regression model (1). All variables are defined in Appendix. ***, **, * correspond to statistical significance at 1%, 5%, and 10%, respectively, for two-tailed tests.

	Market-adjusted ABRET [-1,1]		Three-Factor ABRET [-1,1]	
	(1)	(2)	(3)	(4)
ES	2.2957***	2.0675***	2.1822***	1.9580***
	(0.000)	(0.000)	(0.000)	(0.000)
DT	0.0122***	0.0109***	0.0109***	0.0097***
	(0.000)	(0.000)	(0.000)	(0.000)
DT * ES	0.6076***	0.6702***	0.7208***	0.7862***
	(0.003)	(0.001)	(0.001)	(0.000)
Size	-0.0011***	-0.0010***	-0.0014***	-0.0014***
	(0.000)	(0.000)	(0.000)	(0.000)
ROA	0.0974***	0.0974***	0.0792***	0.0796***
	(0.000)	(0.000)	(0.000)	(0.000)
BTM	0.0093***	0.0098***	0.0125***	0.0130***
	(0.000)	(0.000)	(0.000)	(0.000)
Leverage	0.0061***	0.0063***	0.0070***	0.0072***
	(0.000)	(0.000)	(0.000)	(0.000)
Loss	-0.0101***	-0.0099***	-0.0086***	-0.0085***
	(0.000)	(0.000)	(0.000)	(0.000)
Volatility	-0.0032***	-0.0041***	-0.0085***	-0.0090***
	(0.001)	(0.000)	(0.000)	(0.000)
LogNumAna	0.0006**	0.0005	0.0012***	0.0012***
	(0.050)	(0.111)	(0.000)	(0.000)
SaleGrowth		0.0054***		0.0047***
		(0.000)		(0.000)
LogFirmAge		-0.0007**		-0.0006**
		(0.015)		(0.040)
FundTurnover		-0.0146***		-0.0165***
		(0.000)		(0.000)
Size * ES	-0.0831***	-0.1017***	-0.0755***	-0.0949***
	(0.000)	(0.000)	(0.000)	(0.000)
ROA * ES	5.1540***	5.0559***	4.8492***	4.7646***
	(0.000)	(0.000)	(0.000)	(0.000)
BTM * ES	-0.1096***	-0.1027***	-0.1064***	-0.1001***
	(0.000)	(0.000)	(0.000)	(0.000)
Leverage * ES	-0.6490***	-0.6176***	-0.6617***	-0.6326***
	(0.000)	(0.000)	(0.000)	(0.000)
Loss * ES	-0.9074***	-0.9147***	-0.8960***	-0.9035***
	(0.000)	(0.000)	(0.000)	(0.000)
Volatility * ES	-0.0610	-0.0130	-0.0659	-0.0171
	(0.207)	(0.790)	(0.173)	(0.727)
LogNumAna * ES	0.4407***	0.4470***	0.4289***	0.4366***
	(0.000)	(0.000)	(0.000)	(0.000)
SaleGrowth * ES		-0.0323*		-0.0330*
		(0.059)		(0.054)
LogFirmAge * ES		0.1372***		0.1399***
		(0.000)		(0.000)
FundTurnover * ES		-0.2020		-0.2067
		(0.142)		(0.134)

Constant	0.0100***	0.0133***	0.0060***	0.0098***
	(0.000)	(0.000)	(0.000)	(0.000)
Industry fixed effect	Y	Y	Y	Y
Year fixed effect	Y	Y	Y	Y
ES * Industry fixed effect	Y	Y	Y	Y
ES * Year fixed effect	Y	Y	Y	Y
Observations	198,723	198,723	198,723	198,723
R-squared	0.068	0.069	0.064	0.065

Table 4. Response to Earnings Announcement – Magnitude of Response

This table compares the absolute value of three-day abnormal stock returns around earnings announcements between DT firms and non-DT firms using regression model (2). All variables are defined in Appendix. ***, **, * correspond to statistical significance at 1%, 5%, and 10%, respectively, for two-tailed tests.

	|Market-adjusted ABRET [-1,1]|		|Three-Factor ABRET [-1,1]|	
	(1)	(2)	(3)	(4)
| ES |	0.3484***	0.1373	0.3638***	0.1858**
	(0.000)	(0.114)	(0.000)	(0.032)
DT	0.0094***	0.0081***	0.0092***	0.0079***
	(0.000)	(0.000)	(0.000)	(0.000)
DT * | ES |	0.2229	0.3093**	0.2558*	0.3335**
	(0.139)	(0.041)	(0.089)	(0.027)
Size	-0.0041***	-0.0036***	-0.0042***	-0.0038***
	(0.000)	(0.000)	(0.000)	(0.000)
ROA	0.0651***	0.0636***	0.0667***	0.0652***
	(0.000)	(0.000)	(0.000)	(0.000)
BTM	0.0047***	0.0048***	0.0047***	0.0048***
	(0.000)	(0.000)	(0.000)	(0.000)
Leverage	0.0024***	0.0017**	0.0027***	0.0019**
	(0.001)	(0.023)	(0.000)	(0.011)
Loss	0.0047***	0.0046***	0.0047***	0.0045***
	(0.000)	(0.000)	(0.000)	(0.000)
Volatility	0.0542***	0.0518***	0.0552***	0.0529***
	(0.000)	(0.000)	(0.000)	(0.000)
LogNumAna	0.0060***	0.0057***	0.0060***	0.0057***
	(0.000)	(0.000)	(0.000)	(0.000)
SaleGrowth		0.0023***		0.0020***
		(0.000)		(0.000)
LogFirmAge		-0.0016***		-0.0015***
		(0.000)		(0.000)
FundTurnover		0.0116***		0.0123***
		(0.000)		(0.000)
Size * | ES |	0.0445***	0.0203**	0.0420***	0.0198**
	(0.000)	(0.016)	(0.000)	(0.019)
ROA * | ES |	-0.0065	0.0099	-0.1331	-0.1138
	(0.967)	(0.951)	(0.401)	(0.475)
BTM * | ES |	-0.0159	-0.0150	-0.0199	-0.0189
	(0.204)	(0.233)	(0.112)	(0.133)
Leverage * | ES |	0.0903**	0.1161***	0.0993**	0.1241***
	(0.033)	(0.006)	(0.019)	(0.004)

Loss * | ES |	-0.2873***	-0.2902***	-0.2805***	-0.2824***
	(0.000)	(0.000)	(0.000)	(0.000)
Volatility * | ES |	-0.3827***	-0.3148***	-0.3578***	-0.2945***
	(0.000)	(0.000)	(0.000)	(0.000)
LogNumAna * | ES |	0.0874***	0.1033***	0.0677***	0.0822***
	(0.000)	(0.000)	(0.000)	(0.000)
SaleGrowth * | ES |		-0.0517***		-0.0453***
		(0.000)		(0.001)
LogFirmAge * | ES |		0.1404***		0.1244***
		(0.000)		(0.000)
FundTurnover * | ES |		-0.0476		-0.0728
		(0.656)		(0.495)
Constant	0.0513***	0.0500***	0.0506***	0.0492***
	(0.000)	(0.000)	(0.000)	(0.000)
Industry fixed effect	Y	Y	Y	Y
Year fixed effect	Y	Y	Y	Y
| ES | * Industry fixed effect	Y	Y	Y	Y
| ES | * Year fixed effect	Y	Y	Y	Y
Observations	198,723	198,723	198,723	198,723
R-squared	0.159	0.160	0.164	0.165

Table 5. Trading volume

This table compares the trading volume over three days around earnings announcements between DT firms and non-DT firms using regression model (3). All variables are defined in Appendix. ***, **, * correspond to statistical significance at 1%, 5%, and 10%, respectively, for two-tailed tests.

	Log (Volume [-1,1] / Volume [-50,-10])	
	(1)	(2)
| ES |	5.1522***	3.8655***
	(0.000)	(0.000)
DT	0.1115***	0.1270***
	(0.000)	(0.000)
DT * | ES |	3.1520*	3.3915**
	(0.052)	(0.037)
Size	-0.0082***	-0.0109***
	(0.000)	(0.000)
ROA	1.8206***	1.7885***
	(0.000)	(0.000)
BTM	-0.0619***	-0.0578***
	(0.000)	(0.000)
Leverage	0.0010	0.0050
	(0.904)	(0.531)
Loss	-0.0253***	-0.0242***
	(0.000)	(0.000)
Volatility	0.1780***	0.1656***
	(0.000)	(0.000)
LogNumAna	0.1467***	0.1486***
	(0.000)	(0.000)
SaleGrowth		0.0137***
		(0.000)
LogFirmAge		0.0261***
		(0.000)
FundTurnover		0.2562***
		(0.000)
Size * | ES |	0.1737**	0.0842
	(0.045)	(0.351)
ROA * | ES |	-5.4455***	-5.6681***
	(0.001)	(0.001)
BTM * | ES |	0.5767***	0.5786***
	(0.000)	(0.000)
Leverage * | ES |	-1.6922***	-1.6256***
	(0.000)	(0.000)
Loss * | ES |	-3.3291***	-3.3436***

	(0.000)	(0.000)
Volatility * | ES |	-3.0860***	-2.6949***
	(0.000)	(0.000)
LogNumAna * | ES |	-0.2945*	-0.2381
	(0.050)	(0.116)
SaleGrowth * | ES |		-0.0301
		(0.838)
LogFirmAge * | ES |		0.8239***
		(0.000)
FundTurnover * | ES |		-1.0676
		(0.353)
Constant	-0.1843***	-0.3021***
	(0.000)	(0.000)
Industry fixed effect	Y	Y
Year fixed effect	Y	Y
| ES | * Industry fixed effect	Y	Y
| ES | * Year fixed effect	Y	Y
Observations	197,000	197,000
R-squared	0.151	0.152

Table 6. Analysts' Forecast Revision

This table compares analysts' forecast revision around earnings announcements between DT firms and non-DT firms using regression model (4). All variables are defined in Appendix. ***, **, * correspond to statistical significance at 1%, 5%, and 10%, respectively, for two-tailed tests.

	PriceTargetRev		EPSRev	
	(1)	(2)	(3)	(4)
ES	4.0169***	3.4934***	0.2197***	0.2123***
	(0.000)	(0.000)	(0.000)	(0.000)
DT	0.0377***	0.0383***	-0.0006***	-0.0004**
	(0.000)	(0.000)	(0.000)	(0.046)
DT * ES	1.0093**	1.1387***	0.0191	0.0277
	(0.011)	(0.004)	(0.428)	(0.250)
Size	0.0017***	0.0016***	0.0001***	0.0000
	(0.000)	(0.000)	(0.000)	(0.407)
ROA	0.2262***	0.2266***	-0.0411***	-0.0409***
	(0.000)	(0.000)	(0.000)	(0.000)
BTM	-0.0334***	-0.0332***	0.0005***	0.0004***
	(0.000)	(0.000)	(0.000)	(0.000)
Leverage	-0.0096***	-0.0093***	0.0015***	0.0016***
	(0.000)	(0.000)	(0.000)	(0.000)
Loss	-0.0215***	-0.0213***	-0.0005***	-0.0005***
	(0.000)	(0.000)	(0.000)	(0.000)
Volatility	-0.0047**	-0.0049**	0.0022***	0.0024***
	(0.019)	(0.017)	(0.000)	(0.000)
LogNumAna	-0.0079***	-0.0078***	-0.0005***	-0.0005***
	(0.000)	(0.000)	(0.000)	(0.000)
SaleGrowth		0.0012		-0.0005***
		(0.118)		(0.000)
LogFirmAge		0.0012**		0.0003***
		(0.047)		(0.000)
FundTurnover		0.0081		0.0006*
		(0.175)		(0.094)
Size * ES	-0.1839***	-0.2201***	-0.0150***	-0.0177***
	(0.000)	(0.000)	(0.000)	(0.000)
ROA * ES	7.1849***	7.3543***	0.3141***	0.3320***
	(0.000)	(0.000)	(0.000)	(0.000)
BTM * ES	-0.3429***	-0.3432***	0.0051**	0.0046**
	(0.000)	(0.000)	(0.016)	(0.029)
Leverage * ES	-0.9946***	-0.9912***	-0.0064	-0.0066
	(0.000)	(0.000)	(0.384)	(0.369)
Loss * ES	-1.6931***	-1.7233***	-0.0193***	-0.0207***
	(0.000)	(0.000)	(0.000)	(0.000)
Volatility * ES	-0.6037***	-0.5627***	0.0031	0.0082
	(0.000)	(0.000)	(0.633)	(0.216)
LogNumAna * ES	0.7374***	0.7598***	0.0288***	0.0307***
	(0.000)	(0.000)	(0.000)	(0.000)
SaleGrowth * ES		-0.1771***		-0.0075***
		(0.000)		(0.001)
LogFirmAge * ES		0.2364***		0.0127***
		(0.000)		(0.000)
FundTurnover * ES		0.7174**		-0.0249
		(0.022)		(0.186)

Constant	0.0289***	0.0241***	0.0004**	-0.0001
	(0.000)	(0.000)	(0.024)	(0.682)
Industry fixed effect	Y	Y	Y	Y
Year fixed effect	Y	Y	Y	Y
ES * Industry fixed effect	Y	Y	Y	Y
ES * Year fixed effect	Y	Y	Y	Y
Observations	183,469	183,469	183,469	183,469
R-squared	0.099	0.100	0.080	0.082

Table 7. Analysts' Forecast Dispersion

This table compares the log value of the ratio of the dispersion of analyst stock recommendations dispersion (RecDisp) to the dispersion of analyst profitability forecasts (MarginDisp), between DT firms and non-DT firms using regression model (5). All variables are defined in Appendix. ***, **, * correspond to statistical significance at 1%, 5%, and 10%, respectively, for two-tailed tests.

	Log (RecDisp / MarginDisp)	
	(1)	(2)
DT	-0.1181***	-0.0403**
	(0.000)	(0.031)
Size	0.1047***	0.0789***
	(0.000)	(0.000)
ROA	8.7494***	8.8058***
	(0.000)	(0.000)
BTM	0.0334***	0.0277***
	(0.000)	(0.000)
Leverage	-0.0353***	-0.0007
	(0.007)	(0.956)
Loss	-0.3482***	-0.3405***
	(0.000)	(0.000)
Volatility	-0.8907***	-0.7826***
	(0.000)	(0.000)
LogNumAna	0.0449***	0.0643***
	(0.000)	(0.000)
SaleGrowth		-0.0921***
		(0.000)
LogFirmAge		0.1040***
		(0.000)
FundTurnover		-0.3071***
		(0.000)
Constant	4.6715***	4.6087***
	(0.000)	(0.000)
Ind. fixed effect	Y	Y
Year fixed effect	Y	Y
Observations	157,064	157,064
R-squared	0.465	0.470

Table 8. Entropy Balancing

Panel A (Panel B) repeats Tables 3-5 (Tables 6-7) using entropy balance matching of DT firms and non-DT firms, based on the first, second, and third moments of control variables. All regressions use the full set of control variables and correspond to the even-numbered columns of Tables 3-7. All variables are defined in Appendix. ***, **, * correspond to statistical significance at 1%, 5%, and 10%, respectively, for two-tailed tests.

Panel A. Stock market reaction to earnings announcement

	Market-Adj. ABRET [-1,1]	Three-Factor ABRET [-1,1]	| Market-Adj. ABRET [-1,1]|	| Three-Factor ABRET [-1,1]|	Log (Volume [-1,1] / Volume [-50,-10])
DT	0.0078***	0.0080***	0.0040**	0.0036**	0.0778***
	(0.001)	(0.001)	(0.013)	(0.026)	(0.000)
ES	4.7932***	4.7147***			
	(0.000)	(0.000)			
DT	0.0078***	0.0080***	0.0040**	0.0036**	0.0778***
	(0.001)	(0.001)	(0.013)	(0.026)	(0.000)
DT * ES	0.5532*	0.5766*			
	(0.095)	(0.089)			
| ES |			1.1785	1.2416	5.1840
			(0.112)	(0.101)	(0.376)
DT * | ES |			0.4149*	0.3974	5.3009**
			(0.093)	(0.116)	(0.013)
Control variables	Y	Y	Y	Y	Y
Fixed effects	Y	Y	Y	Y	Y
Observations	198,723	198,723	198,723	198,723	197,000
R-squared	0.051	0.051	0.121	0.122	0.215

Panel B. Analysts' forecast revision and dispersion

	PriceTargetRev	EPSRev	Log (RecDisp / MarginDisp)
ES	7.7224**	0.1990	-0.1117***
	(0.034)	(0.285)	(0.000)
DT	0.0187***	-0.0002	
	(0.000)	(0.109)	
DT * ES	1.6041**	0.0348	
	(0.028)	(0.441)	
Control variables	Y	Y	Y
Fixed effects	Y	Y	Y
Observations	183,469	183,469	157,064
R-squared	0.135	0.128	0.555

Table 9. Subsequent stock price movement

This table compares the stock returns subsequent to earnings announcements between DT firms and non-DT firms using regression model (5) with a modified [6,35] event window. All variables are defined in Appendix. ***, **, * correspond to statistical significance at 1%, 5%, and 10%, respectively, for two-tailed tests.

	Regular		Entropy balancing	
	Market-Adj. ABRET [6,35]	Three-Factor ABRET [6,35]	Market-Adj. ABRET [6,35]	Three-Factor ABRET [6,35]
DT	0.0296***	0.0109***	0.0211***	0.0148***
	(0.000)	(0.001)	(0.000)	(0.000)
ES	0.5068**	0.2206	-0.0089	-2.5537
	(0.021)	(0.377)	(0.996)	(0.312)
DT * ES	0.2326	0.2271	0.0629	-0.2291
	(0.548)	(0.605)	(0.915)	(0.754)
Control variables	Y	Y	Y	Y
Fixed effects	Y	Y	Y	Y
Observations	198,970	198,970	198,970	198,970
R-squared	0.016	0.027	0.041	0.037