

Do you believe in second chances?

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ABSTRACT

We study the feedback effect in disruptive technology (DT) firms. DT firms are typically young, high-growth companies. Since these firms often lack established product markets and customer bases, we predict that DT firm managers are more likely to adjust their investment decisions in response to negative market feedback to sustain high growth and survive the early stages of their firm's lifecycle. Consequently, the negative performance of DT firms is less likely to persist. We also predict that sophisticated market participants, such as financial analysts, will react less strongly to negative news from DT firms compared to traditional firms because they expect DT firm managers to take corrective action. Consistent with these predictions, we find that the capital expenditures of DT firms are more sensitive to negative information reflected in stock prices, and their negative earnings are less persistent than those of traditional firms. Additionally, we find that analysts' forecast revisions for DT firms are less responsive to negative earnings news than those for traditional firms. Our findings demonstrate that managers of DT firms exhibit stronger feedback effects, indicating that they learn more from the negative information embedded in stock prices. Furthermore, analysts are more forgiving of DT firms' negative news, anticipating that managers are likely to adjust their investment and operational decisions to address and reverse their negative situation.

Keywords: Innovative companies, Analyst forecasts, Ambiguity aversion, Earnings persistence

1. Introduction

Disruptive technology (hereafter DT) companies bring technological innovations that disrupt traditional business models. A unique feature of DT firms is that their technology is novel, and the market for these innovations is also new. Compared to traditional companies, DT firms often exhibit higher growth potential but face greater uncertainty. DT firms can be likened to a new species with infinite upside potential in terms of future performance but heightened uncertainty regarding survival.

Given this uncertainty and the constant need to sustain high growth, DT firm managers are more likely to be responsive to negative market feedback than managers of traditional firms. Furthermore, top executives of DT firms often exhibit greater flexibility in adapting to changing environments, as they are frequently the founders of these companies, possessing deep insights and innovative ideas. For instance, Jensen Huang recognized the potential of Graphic Processing Units (GPUs) for training artificial intelligence (AI) long before competitors and shifted Nvidia's R&D focus to developing chips and a software environment (Compute Unified Device Architecture, CUDA) tailored to AI training. In this study, we examine whether managers of DT firms are more inclined to learn from negative stock market feedback compared to traditional firms and whether market participants understand these efforts.

The feedback effect literature predicts that decision-makers, such as managers, can learn valuable information from financial markets, which aggregate private information held by market participants. Accordingly, managers adjust their investment and operational decisions based on this feedback (Goldstein, 2023). Managers are generally more responsive to negative information than positive information because negative signals often indicate potential problems that could jeopardize the firm's operations, reputation, or financial health. Managers are compelled to act

swiftly to prevent further deterioration and safeguard the firm's value. In contrast, positive information typically signals that the firm is performing well, reducing the urgency to intervene or adjust strategies. This behavior aligns with loss aversion in behavioral economics theories (Kahneman and Tversky, 1979), which suggests that individuals weigh potential losses more heavily than equivalent gains. Moreover, the consequences of inaction in the face of negative information are often more severe than inaction in response to positive information. Failing to address negative signals can lead to further declines in performance, investor trust, and firm value, while neglecting positive signals may simply represent a missed opportunity without immediate harm.

DT firms provide a unique setting to study the feedback effect because top executives of DT firms often have deep insights and strong incentives to sense market trends and adapt to changing environments more effectively than managers of traditional firms. The uncertainty surrounding DT firms, stemming from unestablished markets, limited customer bases, and constrained resources in the early stages of their lifecycle—combined with the need for high growth and competition with established firms, necessitates that DT firm managers pay close attention to negative feedback from investors.

Because DT firm managers are required to be more flexible in responding to negative market feedback, they are more likely to reduce current investments in response to a negative market reaction. Hence, we predict that the sensitivity of investment decisions to negative information embedded in stock prices will be greater for DT firms than for non-DT firms. This stronger feedback effect also suggests that the negative earnings performance of DT firms will be less persistent than that of traditional firms because DT managers are more likely to cut investments with a low chance of success, thereby reversing negative earnings in the near future.

Given that DT firm managers are more responsive to negative market feedback, rational market participants are likely to anticipate that bad performance will not persist and will improve soon. As a result, sophisticated investors are expected to react less pessimistically to negative news about DT firms than to similar news about non-DT firms. Specifically, financial analysts are less likely to revise their forecasts downward in response to bad news from DT firms, making them appear more forgiving of such firms.

Our empirical findings are consistent with these predictions. We find that the capital expenditures of DT firms are more sensitive to negative stock returns than those of non-DT firms, suggesting that DT managers are more attuned to and adaptive to negative market feedback. Additionally, we observe that negative changes in the return on assets (ROA) of DT firms are less persistent than those of non-DT firms. Furthermore, analysts issue more optimistic forecasts for DT firms than for non-DT firms following negative earnings news. These results suggest that market participants are more forgiving of DT firms' bad news, anticipating that managers will adjust their investment and operational strategies to address their situation.

Additional analyses reveal that the reduced persistence of negative ROA changes in DT firms, compared to traditional firms, is primarily driven by young, high-growth DT firms. More mature or low-growth DT firms exhibit similar ROA persistence to traditional firms, suggesting that the need to sustain high growth and survive early stages motivates DT managers to heed market feedback.

Our study contributes to the feedback effect literature by providing evidence consistent with theoretical predictions. Edmans, Goldstein, and Jiang (2015) suggest that investors may refrain from trading on negative information because they anticipate that managers will take

corrective action based on the private information revealed through trading, thereby reducing the profitability of such trades.

We demonstrate that DT firm managers' investment decisions and analysts' forecast revisions are aligned with DT managers' tendency to respond to negative market feedback. We also highlight the consequences of these managerial actions by showing reduced persistence in negative earnings.

On the other hand, our findings contrast with predictions from ambiguity theories. Ambiguity theories suggest that when market participants are uncertain about the underlying state, they assume a worst-case scenario, resulting in greater sensitivity to bad news than good news (Gilboa and Schmeidler, 1989; Camerer and Weber, 1992; Hansen and Sargent, 2001; Epstein and Schneider, 2008). Since DT firms operate in new and ambiguous markets without historical data, aversion of ambiguity would predict that analysts would react more pessimistically to bad news. Our finding that analysts issue more optimistic forecasts for DT firms after bad news supports feedback effect theories, rather than ambiguity theories.

We also contribute to the understanding of DT firms by examining the feedback effects in DT firms. Caylor et al. (2023) apply beauty contest theory to DT firm valuations, arguing that public signals serve as an anchor for higher order beliefs when the participants are forecasting an ambiguous target. That is, the forecasts of an ambiguous target will be largely determined by the average beliefs of investors. Consistent with this, they find that analysts' price forecasts are more responsive to earnings news for DT firms than for non-DT firms, as the future stock price of DT firms is a fundamentally ambiguous target. We expand the understanding of DT firms by examining how feedback effects can influence investment decisions of DT firms in response to information in the stock price. Our results demonstrate that the uncertain nature of DT firms'

business may have an impact on investors' reaction to the news of DT firms as well as the managers' decision making.

2. Theories and Hypothesis Development

In this section, we define disruptive technology companies, review the literature on feedback effects and competing theories, and develop our hypotheses.

2.1. Disruptive technology companies

One defining aspect of the post-Great Recession economy is the rise of disruptive technology (DT) companies introducing innovations that transform traditional business models across various industries. The distinguishing feature of DT firms is not only that their technologies are new but also that the markets for these technologies are nascent. As products of disruptive technologies take a long time to be adopted by consumers, some of them fail and are never adopted.

DT firms are typically associated with higher growth and greater upside potential than traditional companies. However, these firms face constrained resources and must continually raise capital to sustain high growth. Consequently, DT firm managers must carefully monitor market trends and heed feedback from market participants. Without doing so, DT firms may struggle to survive the early stages of their lifecycle. Moreover, many DT firms are founded by individuals with deep insights and innovative ideas, many of whom remain as top executives or directors post-IPO (e.g., Sergey Brin of Google, Jensen Huang of Nvidia, and Mark Zuckerberg of Meta). These executives recognize the importance of understanding customer needs and incorporating market reactions into their decisions. As a result, they are often willing to adjust their operational and investment decisions, as well as their long-term strategies, in response to market feedback.

For example, Meta began investing heavily in metaverse technology and rebranded the company from Facebook to Meta in 2021, driven by Mark Zuckerberg's belief in the metaverse's

high growth potential. This strategic move aimed to expand the markets for its social networking applications, such as Facebook and Instagram. Similarly, Jensen Huang recognized the significance of Graphic Processing Units (GPUs) for training Artificial Intelligence (AI) long before competitors and redirected Nvidia's R&D focus to develop chips and software (e.g., CUDA) tailored for AI training.

In another example, Apple recently announced the discontinuation of its electric car development to refocus on AI products. This decision followed investor reactions that were increasingly positive toward AI stocks and negative toward the electric car industry, reflecting shifts in demand for these technologies. These swift decisions and adjustments by top executives in response to market feedback have been instrumental in the success of their companies.

2.2. Feedback effects

The feedback effect literature suggests that financial markets aggregate diverse information from participants, reflecting it in asset prices. These prices serve as signals that guide decisions in the real economy, such as investments and resource allocation. As such, decision-makers can learn from market prices and adjust their actions accordingly (Goldstein, 2023). This feedback loop implies that market prices not only reflect fundamentals but can also influence them.

According to feedback effect studies, managers tend to respond more to negative information than positive information for several reasons (Edmans, Goldstein, and Jiang, 2015). First, negative information often signals potential problems that could threaten the firm's operations, reputation, or financial health. Managers are compelled to act to prevent further deterioration and safeguard the firm's value. In contrast, positive information typically indicates that the firm is already performing well, so managers may see less urgency to intervene or alter strategies. This aligns with behavioral economics predictions, namely loss aversion, which posits

that individuals, including managers, tend to weigh potential losses more heavily than equivalent gains (Kahneman and Tversky, 1979). Second, the consequences of inaction in the face of negative information are often more severe than inaction in response to positive information. Failing to address negative information can lead to further declines in performance, investor trust, and firm value, whereas failing to act on positive information, while a missed opportunity, is less likely to cause immediate harm.

Hence, certain managers may use the information embedded in stock prices to adjust their current actions. For instance, when the stock price reflects bad news, managers may revise their investment decisions to improve performance, such as reducing overinvestment or discontinuing unprofitable projects. These adjustments can turn around firm performance relatively quickly, making bad news less likely to persist. As a result, market participants may be more forgiving of bad news, anticipating a swift turnaround in the situation.

Consistent with this reasoning, Edmans, Goldstein, and Jiang (2015) demonstrate that stock price feedback influences managerial actions in response to negative information. Managers interpret declining prices as signals that investors perceive weaknesses or inefficiencies, prompting corrective measures. Similarly, Ovtchinnikov and McConnell (2009) show that managers of firms having financial constraints are more responsive to stock price movements, which suggests that these managers are more likely to curtail investments in response to negative stock returns to avoid downside risks.

On the other hand, when stock prices reflect good news, managers learn that their current investment decisions are expected to be profitable and may simply maintain their existing investments. Consequently, the market feedback effect on the persistence of good performance

may not be as strong as its effect on the persistence of bad performance, assuming that managers are prone to listening to market feedback.

Prior research on the feedback effect has provided valuable insights (for a review of the feedback literature, see Goldstein, 2023). Analytically, Edmans, Goldstein, and Jiang (2015) incorporate feedback effects into a trading model and predict that bad news is likely to flow more slowly into prices than good news. This occurs because investors may refrain from trading on negative information, expecting managers to take corrective actions based on private information revealed through their trading, thereby reducing the profitability of trading on such information.

Empirically, several studies provide evidence consistent with the feedback effect. For instance, Luo (2005) shows that acquisitions are more likely to be canceled when stock prices react negatively to their announcements. Foucault and Fresard (2014) find that firms' investments are more sensitive to their peers' stock prices when those prices are more informative and when their own stock prices are less informative. Zuo (2016) demonstrates that firms revise their earnings forecasts in response to price movements after the original forecast, particularly when the price contains more information. Jayaraman and Wu (2020) document how firms use voluntary disclosures on capital expenditures as a tool to elicit information from the market. Additionally, Goldstein, Liu, and Yang (2022) survey Chinese firms and find that 75.2% of respondents indicate that stock prices contain information relevant for investment decisions.

As DT firms often have constrained resources and need to continuously raise additional capital for growth, their managers are more likely to seek and act on negative market feedback regarding capital expenditure and product development decisions. Moreover, DT firm managers, as innovative entrepreneurs with deep insights, tend to better interpret changing environments and

market conditions. Hence, they are more likely to exhibit greater flexibility in adapting their investment decisions based on market feedback.

Consequently, we predict that the sensitivity of investment decisions to negative price information is greater for DT firms than for traditional firms. We also predict that the negative performance of DT firms is less persistent than that of non-DT firms. Our hypotheses, based on these predictions, are described in the following.

H1: Capital expenditure is more responsive to negative stock price information for DT firms than non-DT firms.

H2: Negative performance persists less for DT firms than non-DT firms.

Furthermore, as theorized by Edmans, Goldstein, and Jiang (2015), market participants' reactions to the bad news of DT firms are likely to be dampened. This is because rational and sophisticated market participants expect DT firm managers to take corrective actions to address and reverse the negative situation. We use analyst forecast revisions as a proxy for sophisticated market participants' reactions to firms' bad news. Our third hypothesis pertains to analyst forecast revisions.

H3: Analyst forecast revisions in response to a negative earnings surprise is less pessimistic for DT firms than non-DT firms.

2.3. Competing theory regarding ambiguity effects

In H3, we hypothesize that the reactions of sophisticated market participants, such as financial analysts, to negative news about DT firms will be dampened relative to their reactions to similar news about traditional firms. However, an alternative prediction can be derived from ambiguity theories. Ambiguity theories suggest that when market participants are agnostic about the underlying distribution of the current state, they tend to assume the worst-case scenario among

the set of all possible distributions. This conservative approach may lead to asymmetric investor behavior, with greater weight placed on bad news than on good news (Gilboa and Schmeidler, 1989; Camerer and Weber, 1992; Hansen and Sargent, 2001; Epstein and Schneider, 2008). Williams (2015) provides consistent evidence, showing that after an economic shock that increases macro-uncertainty, investors tend to react asymmetrically to earnings news, placing greater emphasis on bad news than on good news. In contrast, investors respond symmetrically to both good and bad news in the absence of such a shock.

Ambiguity is distinct from known uncertainty (i.e., risk). Risk refers to uncertainty about the current state corresponding to an unfavorable point in a known distribution, whereas ambiguity arises in situations where the distribution of the current state itself is unknown. In other words, ambiguity describes a scenario where subjects lack knowledge about the underlying probability distribution.

Since DT firms rely on new technologies, little historical data is available for investors to evaluate their future cash flows. This suggests that the fundamentals of DT firms are intrinsically ambiguous, making it challenging for market participants to estimate the distribution of these firms' future performance. In contrast, firms with more mature technologies have historical data available, allowing market participants to better evaluate their future outcome distributions. Ambiguity aversion theories predict that market reactions to bad news are likely to outweigh reactions to good news under ambiguity (Epstein and Schneider, 2008). Therefore, greater asymmetrical reactions to bad news compared to good news are expected for DT firms relative to traditional firms.

As the predictions from feedback effects and ambiguity theories contradict each other, our tests of H3 aim to provide insights into the behavior of market participants, such as financial

analysts, in response to news about DT firms. If feedback effects dominate, we expect to find dampened reactions to bad news compared to good news for DT firms, relative to traditional firms. In this case, analysts, serving as a proxy for sophisticated market participants, will appear more forgiving of DT firms' bad news. Conversely, if ambiguity effects dominate, analysts will exhibit more punitive reactions to DT firms' bad news.

3. Data and Methodology

3.1. Sample

Following Caylor, Hong, Park, and Qu (2023), we identify DT firms using three public sources. The first source is the CNBC Disruptor 50 List, which publishes an annual list of the 50 most disruptive companies. Examples of DT firms identified from this list include Twitter, Snapchat, and Uber.

The second source is the ARK Innovation ETF (Ticker symbol: ARKK), a publicly traded fund that primarily invests in innovative companies. We obtain the quarterly holdings data of ARK Innovation ETF from its SEC filings. Examples of DT firms identified through ARKK include Tesla, Zoom, Roku, Crispr Therapeutics, and Teladoc Health.

The final source is the Indxx USD Disruptive Technologies Index. Indxx is a "Net Total Return Index based around companies that enter traditional markets with new digital forms of production and distribution, are likely to disrupt existing markets and value networks, displace established market-leading firms, products, and alliances, and increasingly gain market share."¹ We obtain data on the 74 firms included in this index as of December 2021.

¹ <https://www.indxx.com/indices/thematic/indxx-usd-disruptive-technologies-index-ntr>, accessed July 27, 2022

Our list of DT firms combines all firms from these three sources, including all companies listed on the CNBC Disruptor 50 List between 2013 and 2022, all stocks held by ARK Innovation ETF from its inception through 2021, and all stocks included in the Indxx USD Disruptive Technologies Index as of December 31, 2021.²

3.2. Methodology

We test H1 using the following regression model.

$$\Delta INVESTMENT = \beta_0 + \beta_1 RETURN_DT + \beta_2 RETURN_NONDT + \beta_3 NEGRET \times RETURN_DT + \beta_4 NEGRET \times RETURN_NONDT + \beta_5 \Delta \frac{1}{LAGASSET} + \beta_6 \Delta FUTURERETURN + \beta_7 \Delta CASHFLOW + YEARFE \quad (1)$$

In model (1), we use the change of three different investment measures from the previous fiscal year to the current fiscal year as the dependent variable: $\Delta CAPX$, the change in capital expenditure; ΔRD , the change in R&D expenditure; and ΔDAT , the change in the growth of total assets. DT ($NONDT$) is an indicator variable for DT firms (non-DT firms). $RETURN$ represents the annual stock return, measured over the previous fiscal year. We separately define $RETURN_DT$ and $RETURN_NONDT$ as stock return for DT and Non-DT firms. $RETURN_DT$ ($RETURN_NONDT$) equals $RETURN$ for DT (Non-DT) firms and zero for Non-DT (DT) firms. $NEGRET$ is an indicator variable for negative annual stock returns (i.e., $RETURN$). The coefficients of interest are β_3 and β_4 . Because H1 predicts that investment is more responsive to negative stock price information for DT firms than non-DT firms, we expect β_3 to be greater than β_4 . Following Chen, Goldstein, and Jiang (2006), we also include the following control variables of changes from the previous year to the current year: $\Delta(1/LAGASSET)$, $\Delta(FUTURERETURN)$, and $\Delta(CASHFLOW)$ ³. $1/LAGASSET$ controls for the scale effect of the dependent variables and is

² The historical holdings of Indxx were not available, so we use the holdings of the most recent filing.

³ Chen, Goldstein, and Jiang (2006) use a levels model where investment is the dependent variable, and the levels of these variables are used as control variables. Since our model uses the change in investment as the dependent variable, our control variables are also changes.

measured as 1 divided by the previous year's total assets, *FUTURERETURN* is the firm's three-year ahead annual stock return and *CASHFLOW* is operating cash flow.

To examine H2, we use the following regression models.

$$\begin{aligned} AROA_{t+1} = & \beta_0 + \beta_1 AROA_DT_t + \beta_2 AROA_NONDT_t + \beta_3 INCROA * AROA_DT_t + \\ & \beta_4 INCROA * AROA_NONDT_t + \beta_5 DECROA * AROA_DT_t + \beta_6 DECROA * \\ & AROA_NONDT_t + \beta_7 SIZE + \beta_8 MTB + \beta_9 LEV + \beta_{10} VOLITILITY + \\ & \beta_{11} SALEGROWTH + INDUSTRY FIXED EFFECTS + YEAR FIXED EFFECTS \end{aligned} \quad (2)$$

and

$$\begin{aligned} \Delta AROA_{t+1} = & \beta_0 + \beta_1 \Delta AROA_DT_t + \beta_2 \Delta AROA_NONDT_t + \beta_3 INCROA * \Delta AROA_DT_t + \\ & \beta_4 INCROA * \Delta AROA_NONDT_t + \beta_5 DECROA * \Delta AROA_DT_t + \beta_6 DECROA * \\ & \Delta AROA_NONDT_t + \beta_7 SIZE + \beta_8 MTB + \beta_9 LEV + \beta_{10} VOLITILITY + \\ & \beta_{11} SALEGROWTH + INDUSTRY FIXED EFFECTS + YEAR FIXED EFFECTS \end{aligned} \quad (3)$$

In model (2), the dependent variable is $AROA_{t+1}$, the next year's industry-adjusted ROA, measured as the firm's ROA adjusted by the median ROA of the firm's industry in the same year. We define industry by the Farmer-French 48 industry classification (Fama and French, 1997). $AROA_DT_t$ ($AROA_NONDT_t$) equals current period industry-adjusted ROA for DT (Non-DT) firms and zero for Non-DT (DT) firms. $INCROA$ ($DECROA$) is an indicator variable for the increase (decrease) of $AROA$ relative to the previous year. We include controls for firm size ($SIZE$), market-to-book value of equity (MTB), leverage (LEV), stock volatility ($VOLITILITY$) and sales growth ($SALEGROWTH$). Additionally, we control for industry and year fixed effects, where industry fixed effects are based on the Fama-French 12 industry classification. Detailed definitions of all variables are provided in the Appendix. The coefficients of interest are β_5 and β_6 . Because H2 predicts that negative performance persists less for DT firms than non-DT firms, we expect β_5 to be less positive than β_6 .

In model (3), we examine the reversal of the current period's performance change. The dependent variable, $\Delta AROA_{t+1}$, is the firm's change in industry-adjusted ROA from the current

year to the next year. $\Delta AROA_DT_i$ ($\Delta AROA_NONDT_i$), current period performance change, equals the change in AROA from the previous year to the current year for DT (Non-DT) firms and zero for Non-DT (DT) firms. We define $INCROA$ and $DECROA$ the same way as in model (2). The coefficients of interest are β_5 and β_6 . Based on H2, we expect negative AROA change from the last period to the current period to reverse more in the next period for DT firms than for non-DT firms and predict that β_5 will be more negative than β_6 .

To examine H3, we use the following regression model.

$$\begin{aligned} \Delta PTGFORECAST (\Delta EPSFORECAST) = & \beta_0 + \beta_1 \Delta ROA + \beta_2 DT + \beta_3 DT * \Delta ROA + \\ & \beta_4 DECROA * \Delta ROA + \beta_5 DECROA * DT * \Delta ROA + \beta_6 QSIZE + \beta_7 QBM + \beta_8 QLEV + \\ & \beta_9 QSALEGROWTH + \beta_{10} QLOSS + \beta_{11} VOLITILITY + \beta_{12} QSIZE * \Delta ROA + \beta_{13} QBM * \\ & \Delta ROA + \beta_{14} QLEV * \Delta ROA + \beta_{15} QSALEGROWTH * \Delta ROA + \beta_{16} QLOSS * \Delta ROA + \\ & \beta_{17} VOLITILITY * \Delta ROA + INDUSTRY DUMMIES * \Delta ROA + YEAR DUMMIES * \Delta ROA + \\ & INDUSTRY FIXED EFFECTS + YEAR FIXED EFFECTS \end{aligned} \quad (4)$$

In model (4), the dependent variables are target price forecast revision ($\Delta PTGFORECAST$) and EPS forecast revision ($\Delta EPSFORECAST$) around quarterly earnings announcement. $\Delta PTGFORECAST$ ($\Delta EPSFORECAST$) is defined as the difference between the median value of the most recent analyst target price forecasts (next quarter EPS forecasts) 30 days after current quarter's earnings announcement and the median value of the last analyst target price forecasts (next quarter EPS forecasts) the day before current quarter earnings announcement, scaled by the firm's stock price at the end of the current quarter. ΔROA is the change in ROA from the last year to the current year for the same quarter. $DECROA$ is an indicator variable that equals one if ΔROA is negative and zero otherwise. We include controls for firm size ($QSIZE$), book-to-market value of equity (QBM), leverage ($QLEV$), loss firms ($QLOSS$), Stock volatility ($VOLITILITY$) and sales growth ($QSALEGROWTH$), along with the interactions of these variables with ΔROA . Additionally, we control for industry and year fixed effects and their interactions with ΔROA . Industry fixed effects are based on the Fama-French 12 industry classification. Detailed definitions

of all variables are provided in the Appendix. The coefficient of interest is β_5 , which is expected to be negative.

4. Results

4.1. Sample selection and summary statistics

Table 1 summarizes our sample selection process. The sample in our study is the intersection of Compustat, CRSP, and IBES. Starting from 220,424 firm-year observations covered in Compustat, we delete 87,501 observations missing annual return information and 47,278 observations missing industry-adjusted ROA. We then delete 35,052 observations not covered by IBES and 18,822 observations missing control variables. Our final sample firm-years for testing H1 and H2 include 31,771 observations. These observations correspond to 127,084 firm-quarters. In the tests of H3, we lose additional observations due to missing variables, resulting in samples ranging from 121,023 to 121,789 observations.

Table 2 provides summary statistics of variables in our tests of H1 and H2 for the DT firms (Panel A) and non-DT firms (Panel B). Firm characteristics of DT firms are often different from those of non-DT firms. DT firms tend to have greater investment as measured by *RD* and *AT*. Their investment also has more negative changes from the previous year, based on the three changes in investment variables. Further, DT firms on average have greater *AROA*, $\Delta AROA$, *INCROA*, and *RETURN*, suggesting stronger accounting and stock market performance. DT firms also are younger, have larger firm size measured by total assets, higher cash flows, higher market to book ratio, lower leverage, and higher stock volatility, compared to non-DT firms. These characteristics of DT firms are consistent with disruptive firms that have high growth and valuation and went public recently.

4.2. Investment sensitivity to stock price (H1)

Table 3 presents the regression results for the sensitivity of changes in investment to stock returns using model (1). We use three alternative measures of changes in investment: changes in capital expenditure, changes in R&D expenditure, and changes in total assets. Consistent with the predictions of the feedback effect, we find that the coefficient of $NEGRET * RETURN_DT$ (β_3) is significantly positive and greater than the coefficient of $NEGRET * RETURN_NONDT$ (β_4). For instance, in column (1), where the dependent variable is changes in capital expenditure, the coefficient for $NEGRET * RETURN_DT$ (β_3) is 0.038, which is significantly positive ($p=0.000$) and greater than the coefficient of $NEGRET * RETURN_NONDT$ (β_4). F-test for the difference between these two coefficients has a p-value of 0.075. Similar results are observed in other columns using alternative measures of investment.

Interestingly, the changes in investment for DT firms do not appear to be sensitive to positive stock returns, as the coefficient of $RETURN_DT$ (β_1) is not significant. In contrast, the changes in investment for non-DT firms are sensitive to positive stock returns, as the coefficient of $RETURN_NONDT$ (β_2) is consistently significant. These results suggest that managers of DT firms are particularly responsive to negative market feedback when making investment decisions, while managers of non-DT firms exhibit less asymmetric sensitivity to positive vs. negative market feedback in their investment decisions.

The asymmetrically larger sensitivity of DT firms' investment decisions to negative market feedback is consistent with our predictions that managers of young, high-growth firms like DT firms are more sensitive to negative market feedback because each decision is critical for the firm's survival and for establishing markets for their innovative technologies. Delayed

reactions to negative market feedback may result in losing access to capital and, ultimately, failure to survive the early stages of their lifecycle.

In contrast, managers of non-DT firms have less incentive to respond to market feedback and display little urgency to react to negative market signals. Non-DT firms typically have established product markets, customer bases, and abundant resources. Consequently, the reactions of non-DT firm managers to market feedback are more likely to be symmetric yet muted.

Our results in Table 3 are consistent with our first hypothesis, indicating that DT firm managers are more likely to adjust their investment decisions in response to negative market feedback.

4.3. Earnings persistence (H2)

Next, we examine the persistence of earnings using model (2). Since DT firm managers are more likely to take corrective actions in response to negative market feedback, the persistence of poor earnings performance is expected to be reduced. Therefore, H2 predicts that ROA will be less persistent for DT firms when it is negative.

Table 4 presents the result of testing H2. In Columns (1) and (2), we use equation (2) to examine the persistence of industry-adjusted ROA (*AROA*). In Column (1), DT firms generally display less persistence in earnings, as the coefficient of *AROA_DT* ($\beta_1=0.377$) is significantly smaller than that of *AROA_NONDT* ($\beta_2=0.480$), with the p-value of F-test less than 0.001. In Column (2), when we break down *AROA* into the increased versus decreased *AROA*, we find that DT firms' performance show less persistence than non-DT firms when *AROA* decreases from the previous year. Specifically, the coefficient of *DECROA*AROA_DT* ($\beta_5=0.281$) is significantly smaller than the coefficient of *DECROA*AROA_NONDT* ($\beta_6=0.406$), with an F-test p-

vale<0.001. This is consistent with H2 that negative performance is less likely to persistent for DT than non-DT firms. Similar patterns are not observed when *AROA* increases from the previous period. The coefficient of *INCROA*AROA_DT* ($\beta_3=0.696$) is smaller than the coefficient of *INCROA*AROA_NONDT* ($\beta_4=0.734$) but the difference is not significant with an F-test p-vale=0.489.

Columns (3) and (4) use model in equation (3) to examine the reversal of current performance change in the next period. Our results in Column (3) indicate that the overall reversal of *AROA* change is similar for DT and non-DT firms. The coefficient of $\Delta AROA_DT$ (β_1) is not statistically different from that of $\Delta AROA_NONDT$ (β_2). However, when we separate the change in *AROA* into positive and negative changes in Column (4), we find that the persistence of negative earnings changes is smaller for DT firms than for non-DT firms. The coefficient of *DECROA*ΔAROA_DT* ($\beta_5=-0.806$) is significantly more negative than the coefficient of *DECROA*ΔAROA_NONDT* ($\beta_6=-0.617$), with an F-test p-value<0.001. This suggests that negative earnings changes reverse more (80.6% on average) for DT firms than for non-DT firms (61.7% on average) and is consistent with our H2 prediction. When current performance change is positive, we find that DT firms have more persistent earnings change in the next period than non-DT firms ($\beta_3=0.215$ versus $\beta_4=-0.037$).

4.4. Analysts' forecast revision (H3)

H3 predicts that analyst forecast revisions in response to a negative earnings change, relative to a positive earnings change, will be more optimistic (or less pessimistic) for DT firms than for non-DT firms. This is because sophisticated market participants, such as analysts, expect DT firm managers to take corrective action in adverse situations (e.g., a negative earnings change). As a result, analysts revise their forecasts less pessimistically.

We test this hypothesis using revisions of analysts' target price forecasts and earnings forecasts in model (4). Table 5 presents summary statistics for variables used in this model. We find that analysts' make more positive revisions on their price target (*APTGFORECAST*) and EPS (*AEPSFORECAST*) forecasts for DT firms. Similar to the patterns we observe in Table 2 for the annual control variables, we find differences in firm characteristics among the quarterly control variables used in model (4).

Table 6 presents the results of these tests of H3 based on model (4). Column (1) shows the sensitivity of analysts' target price forecast revisions to changes in ROA, without splitting the sample into positive and negative changes in ROA. Column (2) presents the corresponding sensitivity for earnings forecast revisions. In column (1), we observe that changes in target price forecasts are positively related to changes in ROA ($\beta_1=0.944$, $p=0.007$), but the sensitivity of these changes is not statistically different between DT firms and non-DT firms ($\beta_3=0.041$, $p=0.461$). On the other hand, column (2) shows that changes in earnings forecasts are not significantly related to changes in ROA ($\beta_1=-0.014$, $p=0.341$), and the sensitivity of these changes to ROA is also not statistically different between DT firms and non-DT firms ($\beta_3=-0.003$, $p=0.169$). It is possible that the effect of DT firm managers' corrective action on earnings (EPS) takes multiple periods to materialize. Consequently, analysts might revise their EPS forecasts more conservatively while revising their target price forecasts more aggressively, anticipating that the effective corrective actions taken by DT firm managers will become evident in future periods.

In columns (3) and (4), we further examine whether analyst forecast revisions for negative changes in ROA are asymmetrically more optimistic (or less pessimistic) than those for positive changes in ROA for DT firms. We find that the coefficient of *DECROA* Δ ROA*DT* is

significantly negative for both target price forecast revisions and earnings forecast revisions. For instance, in column (3), the coefficient for $DECROA * \Delta ROA * DT$ for target price forecast revisions is -0.366, significant at the 1% level. Similarly, in column (4), the coefficient for $DECROA * \Delta ROA * DT$ for earnings forecast revisions is -0.011, significant at the 10% level. Overall, these results support our third hypothesis based on feedback effects, which predicts that analysts are more forgiving of bad news for DT firms. In contrast, the results are inconsistent with the predictions of ambiguity effects.

4.5. Cross-sectional analysis

If the flexibility to adapt is the main driver of our results, we expect stronger effects in DT firms that are younger and have faster sales growth. For DT firms that have survived the initial stage of growth, quickly adapting to the market might not be the first priority, and hence, weaker results are expected.

In Table 7, we separate the full samples into young (10 years old or younger) versus mature (more than 10 years old) firms and rerun regressions in models (1) to (4). In Panel A that repeats Table 3 analysis regarding firms' investment decisions for the two subsamples, we find that the response to negative returns for DT firms (β_3) continues to be stronger than that for non-DT firms (β_4) only for young firms (Columns (1) to (3)). However, we note that the F-test p values for $\beta_3 = \beta_4$ are not below conventional statistical levels. In Panel B that repeats Table 4 analysis regarding firms' future performance for the two subsamples, we find that the decreasing earnings levels continue to be less persistent for DT firms than for non-DT firms (β_6 being more positive than β_5) only among young firms (Column (2), F-test p value < 0.001) but not among mature firms (Column (6)). Similarly, previous period's decrease in earnings is more likely to reverse for DT firms than for non-DT firms (β_5 being more negative than β_6) only among young firms (Column (4), F-test p

value <0.001) but not among mature firms (Column (8)). In Panel C that repeats Table 6 analysis regarding analysts' earnings and price target revision for the two subsamples, we find that analysts revise price target forecasts less in response to decreased earnings for DT than for non-DT firms (significantly negative β_5) only among younger firms (Column (1)) but not among mature firms (Column (3)). However, we do not observe a similar pattern for EPS revisions in Columns (2) and (4). This may be due to a potential delay in the effect of management actions on EPS. Overall, in Table 7, we find some evidence that our main results and Tables 3, 4, and 6 are stronger for younger DT firms.

In Table 8, we divide our full samples based on high (above median) versus low (at or below median) sales growth and perform analysis similar to Table 7. As expected, we find evidence of stronger results for DT firms having a higher sales growth rate. For example, in Panel A, DT firms adjust down R&D more than non-DT firms in response to negative stock return ($\beta_3 > \beta_4$) when sales growth is high (Column (2)) but not when sales growth is low (Column (5)). In Panel B, decreased earnings are less persistent ($\beta_5 < \beta_6$) for DT than for non-DT firms when sales growth is high (Column (2)) but not when sales growth is low (Column (6)). In Panel C, analysts revise price target forecasts less in response to decreased earnings for DT than for non-DT firms (significantly negative β_5) only among firms with higher sales growth (Column (1)) but not among firms with lower sales growth (Column (3)).

Overall, our results in Tables 7 and 8 suggest that managers of DT firms adjust their investment decisions in response to negative market feedback to help their firms survive the early life cycle and sustain high growth until they establish a product market and customer base.

5. Conclusion

In this study, we examine the feedback effect in disruptive technology (DT) firms. We predict that DT firms will exhibit greater flexibility in adjusting their investments in response to negative market feedback. Our results support this prediction using three different measures of investment. Additionally, we predict that the negative performance of DT firms will be less persistent due to the adjustments managers make to their investments, and our findings are consistent with this prediction.

Finally, we analyze financial analysts' forecast revisions in response to negative news reported by DT firms. Based on the feedback effect, we expect financial analysts to be more forgiving of bad news. On the other hand, a competing theory, ambiguity aversion, offers a contradictory prediction. Our results align with the feedback effect, suggesting that analysts do not anticipate poor performance to persist, which reflecting a rational expectation that managers will adjust their investments to address their situation.

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Appendix. Variable Definitions

<u>Dependent variables</u>	
<i>ΔCAPX</i>	Change in the firm's capital expenditure from the previous year to the current year, capital expenditure is scaled by total asset at the beginning of the year.
<i>ARD</i>	Change in the firm's R&D from the previous year to the current year, R&D is scaled by total asset at the beginning of the year.
<i>ADAT</i>	Change from the previous year to the current year on the change of total assets. Change of total assets in a year is calculated as the difference between current year's ending total assets and last year's ending total assets, divided by last year's ending total assets.
<i>AROA</i>	Firm's ROA (income before extraordinary items divided by average total assets) minus industry median ROA. Industry is defined by the Farmer-French 48 industry classification (Fama and French, 1997)
<i>PriceTargetRev</i>	The median value of analysts' price target forecasts 30 days after earnings announcement minus the median value of analysts' price target forecasts the day before earnings announcement, scaled by the firm's stock price at the end of the quarter.
<i>EPSRev</i>	The median value of analysts' EPS forecasts for the next quarter 30 days after earnings announcement minus the median value of analysts' EPS forecasts for the next quarter on the day before earnings announcement, scaled by the firm's stock price at the end of the quarter.
<u>Independent variables</u>	
<i>RETURN_DT</i>	Annual stock return for DT firms and zero for non-DT firms.
<i>RETURN_NONDT</i>	Annual stock return for non-DT firms and zero for DT firms.
<i>NEGRET</i>	Equal to 1 if annual stock return is negative, zero otherwise.
<i>FUTURERETURN</i>	Three-year ahead annual stock return.
<i>CASHFLOW</i>	Net income before extraordinary item + depreciation and amortization expenses + R&D expenses, scaled by lagged assets.
<i>AROA_DT</i>	AROA for DT firms and zero for non-DT firms.
<i>AROA_NONDT</i>	AROA for non-DT firms and zero for DT firms.
<i>INCROA</i>	Equal to 1 if AROA increased from the previous year, zero otherwise.
<i>DECROA</i>	Equal to 1 if AROA decreased from the previous year, zero otherwise.
<i>Size</i>	Firm size, measured as the natural log of the firm's total assets.
<i>MTB</i>	Market value of equity divided by book value of equity.
<i>Leverage</i>	Leverage of the firm, calculated as long-term debt divided by total assets.
<i>Volatility</i>	Stock volatility, measured as the standard deviation of the firm's monthly stock returns over the past 60 months, then converted to annual volatility.
<i>SaleGrowth</i>	Current sales minus sales four quarters before, scaled by the current sales

Table 1. Sample selection

This table reports the sample selection process for our study. Starting from 220,424 firm-year observations in Compustat between 2000 and 2020, we select 31,771 observations for testing H1 and H2. These observations correspond to 127,084 firm-quarters. Additional deletions result in the final samples used in H3.

Compustat firm-years between 2000 and 2020	220,424
Less:	
Firm-years missing annual return	(87,501)
Firm-years missing industry-adjusted ROA	(47,278)
Firm-years not covered by IBES	(35,052)
Firm-years missing control variables	(18,822)
Final sample firm-years for testing H1 and H2	31,771
Corresponding firm-quarters	127,084

Table 2. Descriptive statistics (H1&H2)

Panels A and B report the descriptive statistics of DT and non-DT firm observations, respectively, in our sample in testing H1 and H2. 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 for annual variables - DT firms (546 obs)

Variable	Mean	Median	Q1	Q3	Min	Max	Std Dev
<i>CAPX</i>	0.063	0.037	0.020	0.074	0.000	0.364	0.074
<i>RD</i>	0.142***	0.104***	0.036	0.204	0.000	0.724	0.140
<i>DAT</i>	0.370***	0.194***	0.049	0.400	-0.491	2.388	0.594
<i>ΔCAPX</i>	-0.008*	-0.001	-0.016	0.008	-0.173	0.112	0.044
<i>ΔRD</i>	-0.011***	0.000	-0.013	0.010	-0.248	0.154	0.065
<i>ΔDAT</i>	-0.101***	-0.010	-0.197	0.151	-2.187	1.471	0.632
<i>AROA</i>	0.021*	0.030	-0.010	0.084	-11.414	3.350	0.239
<i>ΔAROA</i>	0.018**	0.005***	-0.027	0.039	-4.728	4.225	0.309
<i>INCROA</i>	0.568***	1.000***	0.000	1.000	0.000	1.000	0.496
<i>RETURN</i>	0.259***	0.131***	-0.126	0.492	-0.849	2.733	0.665
<i>NEGRET</i>	0.359***	0.000***	0.000	1.000	0.000	1.000	0.480
<i>FUTURERET</i>	0.309***	0.196***	-0.049	0.504	-0.794	5.220	0.632
<i>CASHFLOW</i>	0.150***	0.169***	0.051	0.272	-2.455	2.031	0.295
<i>AGE</i>	8.756***	8.000***	5.000	12.000	3.000	21.000	4.384
<i>SALEGROWTH</i>	0.449***	0.247***	0.111	0.461	-0.923	7.534	0.942
<i>SIZE</i>	7.892***	8.009***	6.686	9.096	3.126	10.814	1.632
<i>MTB</i>	7.212***	5.068***	3.014	8.954	-34.352	45.728	10.120
<i>LEVERAGE</i>	0.203***	0.110***	0.029	0.310	0.000	1.532	0.234
<i>VOLATILITY</i>	0.546***	0.500***	0.352	0.670	0.149	1.692	0.267

Panel B. Summary statistics for annual variables – Non-DT firms (31,225 obs)

Variable	Mean	Median	Q1	Q3	Min	Max	Std Dev
<i>CAPX</i>	0.060	0.037	0.019	0.072	0.000	0.364	0.067
<i>RD</i>	0.058	0.004	0.000	0.069	0.000	0.745	0.115
<i>DAT</i>	0.150	0.062	-0.022	0.184	-0.491	2.388	0.401
<i>ΔCAPX</i>	-0.005	-0.001	-0.012	0.008	-0.173	0.112	0.038
<i>ΔRD</i>	-0.003	0.000	0.000	0.000	-0.248	0.154	0.044
<i>ΔDAT</i>	-0.043	-0.005	-0.131	0.106	-2.187	1.471	0.454
<i>AROA</i>	0.002	0.044	-0.051	0.106	-5.535	0.663	0.315
<i>ΔAROA</i>	-0.002	0.000	-0.028	0.024	-4.728	4.225	0.228
<i>INCROA</i>	0.501	1.000	0.000	1.000	0.000	1.000	0.500
<i>RETURN</i>	0.154	0.084	-0.189	0.364	-0.849	2.733	0.576
<i>NEGRET</i>	0.418	0.000	0.000	1.000	0.000	1.000	0.493
<i>FUTURERET</i>	0.173	0.091	-0.158	0.351	-0.993	32.000	0.736
<i>CASHFLOW</i>	0.113	0.114	0.062	0.184	-11.852	3.446	0.250
<i>AGE</i>	22.631	17.000	9.000	32.000	2.000	68.000	17.000
<i>SALEGROWTH</i>	0.179	0.079	-0.014	0.211	-1.000	7.534	0.649
<i>SIZE</i>	6.923	6.830	5.689	8.078	0.103	10.814	1.758
<i>MTB</i>	3.141	2.258	1.415	3.777	-34.352	45.728	6.028
<i>LEVERAGE</i>	0.279	0.247	0.069	0.429	0.000	1.787	0.238
<i>VOLATILITY</i>	0.503	0.437	0.310	0.623	0.055	1.692	0.273

Table 3. Investment decision

This table reports the results for our tests of H1. All variables are defined in Appendix. Numbers in parentheses are p-values. ***, **, * correspond to statistically significant difference between DT firms and non-DT firms at 1%, 5%, and 10%, respectively, for two-tailed tests.

VARIABLES	(1) <i>ΔCAPX</i>	(2) <i>ΔRD</i>	(3) <i>ΔDAT</i>
<i>RETURN_DT</i> (β_1)	0.003 (0.217)	0.002 (0.503)	-0.024 (0.328)
<i>RETURN_NONDT</i> (β_2)	0.007*** (0.000)	0.002*** (0.003)	0.037*** (0.000)
<i>NEGRET*RETURN_DT</i> (β_3)	0.038*** (0.000)	0.028*** (0.000)	0.306*** (0.000)
<i>NEGRET * RETURN_NONDT</i> (β_4)	0.025*** (0.000)	0.010*** (0.000)	0.116*** (0.000)
<i>Δ(1/LAGASSET)</i>	2.051*** (0.000)	5.799*** (0.000)	61.107*** (0.000)
<i>Δ(FUTURERETURN)</i>	0.000 (0.310)	0.001*** (0.000)	0.013*** (0.000)
<i>Δ(CASHFLOW)</i>	0.042*** (0.000)	0.045*** (0.000)	0.875*** (0.000)
Constant	-0.013*** (0.000)	-0.005*** (0.000)	-0.104*** (0.000)
Year FE	Y	Y	Y
Observations	31,771	31,771	31,771
R-squared	0.126	0.239	0.311
F-test p value: $\beta_3 = \beta_4$	0.075	0.020	0.013

Table 4. Earnings persistence

This table reports the results for our tests of H2. All variables are defined in Appendix. Numbers in parentheses are p-values. ***, **, * correspond to statistically significant difference between DT firms and non-DT firms at 1%, 5%, and 10%, respectively, for two-tailed tests.

VARIABLES	$AROA_{t+1}$		$\Delta AROA_{t+1}$	
	(1)	(2)	(3)	(4)
$(\Delta)AROA_DT_t (\beta_1)$	0.377*** (0.000)		-0.358*** (0.000)	
$(\Delta)AROA_NONDT_t (\beta_2)$	0.480*** (0.000)		-0.373*** (0.000)	
$(\Delta) INCROA * AROA_DT_t (\beta_3)$		0.696*** (0.000)		0.215*** (0.000)
$(\Delta) INCROA * AROA_NONDT_t (\beta_4)$		0.734*** (0.000)		-0.037*** (0.000)
$(\Delta) DECROA * AROA_DT_t (\beta_5)$		0.281*** (0.000)		-0.806*** (0.000)
$(\Delta) DECROA * AROA_NonDT_t (\beta_6)$		0.406*** (0.000)		-0.617*** (0.000)
SIZE	0.011*** (0.000)	0.009*** (0.000)	-0.002*** (0.002)	0.001 (0.399)
MTB	0.002*** (0.000)	0.001*** (0.000)	0.001*** (0.000)	0.001*** (0.000)
LEVERAGE	0.008 (0.141)	0.015*** (0.003)	0.076*** (0.000)	0.061*** (0.000)
VOLATILITY	-0.086*** (0.000)	-0.084*** (0.000)	0.008 (0.183)	-0.057*** (0.000)
SALEGROWTH	-0.034*** (0.000)	-0.036*** (0.000)	-0.013*** (0.000)	-0.021*** (0.000)
Constant	-0.023*** (0.008)	-0.028*** (0.001)	-0.046*** (0.000)	-0.039*** (0.000)
Industry fixed effect	Y	Y	Y	Y
Year fixed effect	Y	Y	Y	Y
Observations	31,771	31,771	31,771	31,771
R-squared	0.321	0.340	0.148	0.248
F-test p value: $\beta_1 = \beta_2$	<0.001		0.626	
F-test p value: $\beta_3 = \beta_4$	0.489		<0.001	
F-test p value: $\beta_5 = \beta_6$	<0.001		<0.001	

Table 5. Descriptive statistics (H3)

Panels A and B report the descriptive statistics of DT and non-DT firm observations, respectively, in our sample in testing H3. 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 for quarterly variable - DT firms

Variable	Mean	Median	Q1	Q3	Min	Max	Std Dev
<i>ΔPTGFORECAST</i>	0.034***	0.008***	0.000	0.080	-0.333	0.364	0.112
<i>ΔEPSFORECAST</i>	0.000***	0.000***	-0.001	0.000	-0.022	0.013	0.003
<i>ΔROA</i>	0.002***	0.001***	-0.009	0.012	-0.136	0.132	0.034
<i>QSIZE</i>	7.105***	7.062***	5.785	8.315	3.182	11.894	1.712
<i>QBTM</i>	0.219***	0.161***	0.084	0.283	-0.468	2.955	0.240
<i>QLEV</i>	0.176***	0.101***	0.000	0.304	0.000	0.938	0.198
<i>QSALEGROWTH</i>	0.370***	0.248***	0.099	0.449	-0.802	3.614	0.624
<i>QLOSS</i>	0.464***	0.000***	0.000	1.000	0.000	1.000	0.499

Panel B. Summary statistics for quarterly variable – Non-DT firms

Variable	Mean	Median	Q1	Q3	Min	Max	Std Dev
<i>ΔPTGFORECAST</i>	0.008	0.000	0.000	0.032	-0.333	0.364	0.095
<i>ΔEPSFORECAST</i>	-0.001	0.000	-0.001	0.000	-0.022	0.013	0.004
<i>ΔROA</i>	-0.001	0.000	-0.008	0.007	-0.136	0.132	0.032
<i>QSIZE</i>	6.769	6.665	5.411	7.993	2.845	12.236	1.881
<i>QBTM</i>	0.520	0.409	0.227	0.685	-0.468	2.955	0.487
<i>QLEV</i>	0.236	0.199	0.025	0.368	0.000	0.938	0.222
<i>QSALEGROWTH</i>	0.166	0.071	-0.038	0.218	-0.802	3.614	0.554
<i>QLOSS</i>	0.312	0.000	0.000	1.000	0.000	1.000	0.463

Table 6. Analysts' price forecast revision

This table reports the results for our tests of H3. All variables are defined in Appendix. Numbers in parentheses are p-values. ***, **, * correspond to statistically significant difference between DT firms and non-DT firms at 1%, 5%, and 10%, respectively, for two-tailed tests.

VARIABLES	(1) <i>ΔPTGFORECAST</i>	(2) <i>ΔEPSFORECAST</i>	(3) <i>ΔPTGFORECAST</i>	(4) <i>ΔEPSFORECAST</i>
<i>ΔROA</i> (β_1)	0.944*** (0.007)	-0.014 (0.341)	0.859** (0.014)	-0.018 (0.228)
<i>DT</i> (β_2)	0.022*** (0.000)	0.000*** (0.006)	0.018*** (0.000)	0.000 (0.269)
<i>ΔROA</i> * <i>DT</i> (β_3)	0.041 (0.461)	-0.003 (0.169)	0.215** (0.011)	0.002 (0.626)
<i>DECROA</i> * <i>ΔROA</i> (β_4)			0.225*** (0.000)	0.010*** (0.000)
<i>DECROA</i> * <i>ΔROA</i> * <i>DT</i> (β_5)			-0.366*** (0.008)	-0.011* (0.072)
<i>QSIZE</i>	-0.000 (0.843)	0.000*** (0.000)	-0.000 (0.421)	0.000*** (0.000)
<i>QBTM</i>	-0.013*** (0.000)	-0.001*** (0.000)	-0.013*** (0.000)	-0.001*** (0.000)
<i>QLEV</i>	-0.007*** (0.000)	-0.001*** (0.000)	-0.007*** (0.000)	-0.001*** (0.000)
<i>QSALEGROWTH</i>	0.003*** (0.000)	0.000*** (0.000)	0.003*** (0.000)	0.000*** (0.000)
<i>QLOSS</i>	-0.021*** (0.000)	-0.001*** (0.000)	-0.019*** (0.000)	-0.001*** (0.000)
<i>VOLATILITY</i>	-0.001 (0.375)	-0.000** (0.024)	0.001 (0.454)	-0.000 (0.587)
<i>QSIZE</i> * <i>ΔROA</i>	-0.032*** (0.000)	0.000 (0.732)	-0.033*** (0.000)	0.000 (0.855)
<i>QBTM</i> * <i>ΔROA</i>	0.047*** (0.006)	0.009*** (0.000)	0.040** (0.020)	0.009*** (0.000)
<i>QLEV</i> * <i>ΔROA</i>	0.038 (0.312)	0.011*** (0.000)	0.039 (0.303)	0.011*** (0.000)
<i>QSALEGROWTH</i> * <i>ΔROA</i>	-0.045*** (0.000)	-0.003*** (0.000)	-0.023** (0.024)	-0.002*** (0.000)
<i>QLOSS</i> * <i>ΔROA</i>	-0.201*** (0.000)	0.000 (0.973)	-0.249*** (0.000)	-0.002** (0.019)
<i>VOLATILITY</i> * <i>ΔROA</i>	-0.132*** (0.000)	-0.002 (0.108)	-0.111*** (0.002)	-0.001 (0.328)
Constant	0.043*** (0.000)	0.002*** (0.000)	0.044*** (0.000)	0.002*** (0.000)
Industry fixed effect	Y	Y	Y	Y
Year fixed effect	Y	Y	Y	Y
Industry Dummies * <i>ΔROA</i>	Y	Y	Y	Y
Year Dummies * <i>ΔROA</i>	Y	Y	Y	Y
Observations	121,789	121,023	121,789	121,023
R-squared	0.080	0.082	0.081	0.082

Table 7. Young versus mature firms

This table reports cross-sectional analysis based on firm age. Our full samples are divided to young (10 years old or younger) and mature (more than 10 years old) subsamples. Panel A repeats the analysis in Table 3 for each subsample. Panel B repeats the analysis in Table 4 for each subsample. Panel C repeats the analysis in Table 6 for each subsample. All variables are defined in Appendix. Numbers in parentheses are p-values. ***, **, * correspond to statistically significant difference between DT firms and non-DT firms at 1%, 5%, and 10%, respectively, for two-tailed tests.

Panel A. Investment decision

	Young			Mature		
	(1) $\Delta CAPX$	(2) ΔRD	(3) ΔDAT	(4) $\Delta CAPX$	(5) ΔRD	(6) ΔDAT
$RETURN_DT (\beta_1)$	0.003 (0.458)	0.001 (0.712)	-0.052 (0.140)	0.007* (0.071)	0.006 (0.134)	0.070* (0.098)
$RETURN_NONDT (\beta_2)$	0.007*** (0.000)	0.003** (0.011)	0.041*** (0.000)	0.006*** (0.000)	-0.000 (0.982)	0.027*** (0.000)
$NEGRET * RETURN_DT (\beta_3)$	0.044*** (0.000)	0.022* (0.089)	0.270** (0.018)	0.009 (0.505)	0.011 (0.408)	-0.009 (0.951)
$NEGRET * RETURN_NONDT (\beta_4)$	0.028*** (0.000)	0.009*** (0.010)	0.160*** (0.000)	0.021*** (0.000)	0.005*** (0.001)	0.019 (0.252)
Constant	-0.013*** (0.000)	-0.008*** (0.000)	-0.140*** (0.000)	-0.007*** (0.000)	-0.000 (0.903)	-0.038*** (0.001)
Controls	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Observations	7,819	7,819	7,819	22,239	22,239	22,239
R-squared	0.149	0.252	0.373	0.096	0.164	0.213
F-test p value: $\beta_3 = \beta_4$	0.134	0.312	0.333	0.388	0.675	0.844

Panel B. Earnings persistence

	Young				Mature			
	$ARO A_{t+1}$		$\Delta ARO A_{t+1}$		$ARO A_{t+1}$		$\Delta ARO A_{t+1}$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	0.325*** (0.000)		-0.383*** (0.000)		0.613*** (0.000)		0.083 (0.554)	
$(\Delta) ARO A_NONDT_t (\beta_2)$	0.465*** (0.000)		-0.317*** (0.000)		0.463*** (0.000)		-0.443*** (0.000)	
$(\Delta) INCROA * ARO A_DT_t (\beta_3)$		0.628*** (0.000)		0.180*** (0.001)		0.774*** (0.000)		0.196 (0.306)
$(\Delta) INCCROA * ARO A_NONDT_t (\beta_4)$		0.682*** (0.000)		-0.085*** (0.000)		0.706*** (0.000)		-0.033*** (0.000)
$(\Delta) DECROA * ARO A_DT_t (\beta_5)$		0.251*** (0.000)		-0.812*** (0.000)		0.517*** (0.000)		-0.052 (0.762)
$(\Delta) DECROA * ARO A_NONDT_t (\beta_6)$		0.414*** (0.000)		-0.481*** (0.000)		0.369*** (0.000)		-0.739*** (0.000)
Constant	-0.062*** (0.003)	-0.066*** (0.001)	-0.064*** (0.005)	-0.051** (0.021)	0.002 (0.763)	-0.003 (0.728)	-0.024*** (0.007)	-0.026*** (0.001)
Controls	Y	Y	Y	Y	Y	Y	Y	Y
Industry fixed effect	Y	Y	Y	Y	Y	Y	Y	Y
Year fixed effect	Y	Y	Y	Y	Y	Y	Y	Y
Observations	7,819	7,819	7,819	7,819	22,239	22,239	22,239	22,239
R-squared	0.261	0.272	0.124	0.184	0.361	0.386	0.185	0.326
F-test p value: $\beta_1 = \beta_2$	<0.001		0.120		0.040		<0.001	
F-test p value: $\beta_3 = \beta_4$		0.549		<0.001		0.459		0.233
F-test p value: $\beta_5 = \beta_6$		<0.001		<0.001		0.184		<0.001

Panel C. Analysts' price forecast revision

VARIABLES	Young		Mature	
	(1)	(2)	(3)	(4)
	$\Delta PTGFORECAST$	$\Delta EPSFORECAST$	$\Delta PTGFORECAST$	$\Delta EPSFORECAST$
$\Delta ROA (\beta_1)$	0.949*** (0.001)	0.021 (0.729)	0.695** (0.048)	-0.023 (0.137)
$DT (\beta_2)$	0.011** (0.011)	-0.000 (0.770)	0.015*** (0.000)	0.000 (0.981)
$\Delta ROA * DT (\beta_3)$	0.177 (0.198)	0.002 (0.751)	0.262* (0.086)	0.007 (0.323)
$DECROA * \Delta ROA (\beta_4)$	0.185*** (0.002)	0.009*** (0.000)	0.205*** (0.000)	0.012*** (0.000)
$DECROA * \Delta ROA * DT (\beta_5)$	-0.464* (0.058)	-0.008 (0.384)	-0.335 (0.149)	-0.018* (0.070)
Constant	0.061 (0.134)	-0.001* (0.071)	0.041*** (0.000)	0.002*** (0.000)
Controls	Y	Y	Y	Y
Controls * ΔROA	Y	Y	Y	Y
Industry fixed effect	Y	Y	Y	Y
Year fixed effect	Y	Y	Y	Y
Industry Dummies * ΔROA	Y	Y	Y	Y
Year Dummies * ΔROA	Y	Y	Y	Y
Observations	19,300	19,148	90,230	89,705
R-squared	0.090	0.069	0.079	0.092

Table 8. High versus low sales-growth firms

This table reports cross-sectional analysis based on sales growth. Our full samples are divided to high sales growth (at or above median sales growth rate) and low sales growth (below median sales growth rate) subsamples. Panel A repeats the analysis in Table 3 for each subsample. Panel B repeats the analysis in Table 4 for each subsample. Panel C repeats the analysis in Table 6 for each subsample. All variables are defined in Appendix. Numbers in parentheses are p-values. ***, **, * correspond to statistically significant difference between DT firms and non-DT firms at 1%, 5%, and 10%, respectively, for two-tailed tests.

Panel A. Investment decision

	High sales growth			Low sales growth		
	(1) $\Delta CAPX$	(2) ΔRD	(3) ΔDAT	(4) $\Delta CAPX$	(5) ΔRD	(6) ΔDAT
$RETURN_DT (\beta_1)$	0.003 (0.257)	0.001 (0.671)	-0.006 (0.848)	0.003 (0.592)	0.008 (0.135)	0.024 (0.617)
$RETURN_NONDT (\beta_2)$	0.008*** (0.000)	0.003*** (0.000)	0.060*** (0.000)	0.007*** (0.000)	-0.000 (0.567)	0.024*** (0.000)
$NEGRET * RETURN_DT (\beta_3)$	0.037*** (0.000)	0.038*** (0.000)	0.260** (0.010)	0.028** (0.046)	-0.027* (0.062)	0.041 (0.757)
$NEGRET * RETURN_NONDT (\beta_4)$	0.033*** (0.000)	0.015*** (0.000)	0.123*** (0.000)	0.019*** (0.000)	0.008*** (0.000)	0.108*** (0.000)
Constant	-0.015*** (0.000)	-0.008*** (0.000)	-0.161*** (0.000)	-0.005*** (0.000)	0.001 (0.598)	0.022* (0.063)
Controls	Y	Y		Y	Y	
Year FE	Y	Y		Y	Y	
Observations	15,882	15,882	15,882	15,889	15,889	15,889
R-squared	0.152	0.247	0.314	0.082	0.205	0.261
F-test p value: $\beta_3 = \beta_4$	0.648	0.020	0.179	0.514	0.016	0.610

Panel B. Earnings persistence

	High sales growth				Low sales growth			
	$ARO A_{t+1}$		$\Delta ARO A_{t+1}$		$ARO A_{t+1}$		$\Delta ARO A_{t+1}$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$(\Delta)ARO A_DT_t (\beta_1)$	0.371*** (0.000)		-0.647*** (0.000)		0.442*** (0.000)		0.115** (0.019)	
$(\Delta)ARO A_NONDT_t (\beta_2)$	0.556*** (0.000)		-0.310*** (0.000)		0.374*** (0.000)		-0.434*** (0.000)	
$(\Delta) INCRO A * ARO A_DT_t (\beta_3)$		0.760*** (0.000)		0.279*** (0.000)		0.307** (0.025)		0.173*** (0.000)
$(\Delta) INCRO A * ARO A_NONDT_t (\beta_4)$		0.741*** (0.000)		-0.030*** (0.007)		0.657*** (0.000)		-0.039*** (0.000)
$(\Delta) DECRO A * ARO A_DT_t (\beta_5)$		0.264*** (0.000)		-0.802*** (0.000)		0.618*** (0.000)		-0.723*** (0.001)
$(\Delta) DECRO A * ARO A_NONDT_t (\beta_6)$		0.476*** (0.000)		-0.617*** (0.000)		0.324*** (0.000)		-0.652*** (0.000)
Constant	-0.009 (0.439)	-0.010 (0.388)	-0.019 (0.128)	-0.016 (0.191)	-0.016 (0.200)	-0.024** (0.048)	-0.060*** (0.000)	-0.044*** (0.001)
Controls	Y	Y	Y	Y	Y	Y	Y	Y
Industry fixed effect	Y	Y	Y	Y	Y	Y	Y	Y
Year fixed effect	Y	Y	Y	Y	Y	Y	Y	Y
Observations	15,882	15,882	15,882	15,882	15,889	15,889	15,889	15,889
R-squared	0.391	0.404	0.130	0.200	0.275	0.292	0.189	0.311
F-test p value: $\beta_1 = \beta_2$	<0.001		<0.001		0.484		<0.001	
F-test p value: $\beta_3 = \beta_4$		0.763		<0.001		0.012		<0.001
F-test p value: $\beta_5 = \beta_6$		<0.001		<0.001		0.028		0.734

Panel C. Analysts' price forecast revision

VARIABLES	High sales growth		Low sales growth	
	(1)	(2)	(3)	(4)
	$\Delta PTGFORECAST$	$\Delta EPSFORECAST$	$\Delta PTGFORECAST$	$\Delta EPSFORECAST$
$\Delta ROA (\beta_1)$	0.706 (0.310)	0.016 (0.522)	0.575 (0.162)	-0.023 (0.258)
$DT (\beta_2)$	0.015*** (0.000)	0.000 (0.661)	0.008 (0.115)	-0.000 (0.899)
$\Delta ROA * DT (\beta_3)$	0.213** (0.020)	-0.002 (0.499)	-0.052 (0.820)	0.022* (0.054)
$DECROA * \Delta ROA (\beta_4)$	0.235*** (0.000)	0.004*** (0.002)	0.219*** (0.000)	0.015*** (0.000)
$DECROA * \Delta ROA * DT (\beta_5)$	-0.298* (0.074)	-0.004 (0.521)	-0.320 (0.278)	-0.034** (0.019)
Constant	0.084*** (0.000)	0.000 (0.731)	0.009 (0.424)	0.002*** (0.000)
Controls	Y	Y	Y	Y
Controls * ΔROA	Y	Y	Y	Y
Industry fixed effect	Y	Y	Y	Y
Year fixed effect	Y	Y	Y	Y
Industry Dummies * ΔROA	Y	Y	Y	Y
Year Dummies * ΔROA	Y	Y	Y	Y
Observations	58,868	58,518	62,921	62,505
R-squared	0.080	0.053	0.088	0.085