

Louvain School of Management

How had the COVID-19 pandemic modified investors' reactions and perceptions of news ?

Focus on the Post Earnings Announcement Drift

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Academic year 2022-2023
Dissertation for the Master of Management (GEST2MS/GE)
Corporate finance
Daytime schedule

Abstract

This paper investigates the behavior of investors toward news during the pandemic. Previous research found that COVID-19 increased uncertainty making investors and analysts unsure about news value and implications (Brennan, Edgar, & Power, 2022; Xu, Chen, Zhang, & Zhao, 2021). Consequently, the accuracy of their forecasts decreased, reducing their confidence regarding their decision-making abilities (Hao et al., 2022; Wang & Wang, 2020). This lack of consensus among financial actors could potentially impact the overall market stability. Therefore, understanding investors' perceptions and reactions may help in mitigating some adverse consequences observed in past crises (Arner, 2009). This is why this study initially examined the reaction of investors to global news during the pandemic using the prospect theory. As various reactions were observed, we focused on the analysis of earnings news announcements and their following reactions. This was conducted through the study of potential variations in the magnitude and sign of the post-earnings announcement drift (PEAD) during the COVID crisis. We have based our paper on 41266 quarterly earnings news announcements of listed US companies from 2010 to 2021, covering both pre and pandemic periods.

Our main findings indicate that the positive pre-COVID PEAD significantly declined during the pandemic, ultimately disappearing by the first quarter of 2021. Surprisingly, in our attempt to provide an explanation for this outcome, we found that unexpected earnings have a positive impact on PEAD. This suggests an increased investor sensitivity to earnings announcements during the pandemic, which contradicts our prior findings. More specifically, based on prospect theory, investors reacted more strongly to positive earnings news while showing no reaction to negative news. Additionally, we investigated the influence of firm size and analyst coverage on this result. Unexpected earnings for small firms had a positive influence on the PEAD, confirming the inverse relationship between firm size and this anomaly. Conversely, in the scenario with low analyst coverage, the error median had a significant negative impact. Overall, our conclusion highlights the significant influence of the COVID-19 pandemic on investors' perceptions and reactions, specifically regarding earnings news. Whilst we do not provide a complete explanation for the market anomaly of PEAD, our findings offer valuable insights and observations about its evolution and dynamics.

Acknowledgment

First, I would like to warmly thank my thesis supervisor, James Thewissen, professor of Finance at UCLouvain, for his guidance and support throughout the realization of this thesis. Despite his demanding schedule, he made time for me and our constructive meetings were instrumental in positively shaping my research. His insightful feedback and valuable advice were crucial in enhancing the quality of my work. Moreover, I would also like to warmly thank him for providing me with the database I needed for this research.

Last but not least, I want to express my gratitude for my family and friends' constant support and encouragement during the challenging period of conducting this research. They played an integral role in my personal growth and development, and without their help and support, I would not have been able to reach this point. These past five years at UCLouvain would not have been as fulfilling and rewarding without their continual presence.

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1 Introduction

COVID-19 has disrupted society as a whole; restrictions on businesses, and social activities, as well as the lockdown, have changed how people live worldwide. Indeed, to avoid the spread of the disease, a lot of institutions (schools, theatres, restaurants,...) had to close leading to job losses. Moreover, teleworking was required in companies, and social distancing was mandatory for everyone. All these actions created a climate of concern and stress affecting all individuals (Jaspreet & Jaspreet, 2020). More generally, this disease increased uncertainty and negatively impacted the global economy. In fact, no country was spared; even the world's greatest powers, such as the US, saw their stock market prices plummet when the pandemic struck (Jones, 2021).

Actors, including the overall financial market, had to deal with this new uncertainty and the impact of governmental restrictions (Scherf, Matschke, & Rieger, 2022). These mobility restrictions affected the quality of analysts' forecasts by making them more diffuse and less accurate (Gao, Wen, & Yu, 2021; Hao, & Pham, 2022). In addition, the beliefs of analysts alternated during the pandemic between positive and very negative thoughts about the future before realizing that they may have overestimated the impact of COVID-19 (Hao et al., 2022). This lack of accuracy along with this macroeconomic crisis should have consequences on the investors' behaviors and perceptions.

These investors' behaviors and reactions were studied for a long-time giving birth to the prospect theory which allows an understanding of their decision-making in times of uncertainty. The latter states that depending on the way information is given, the outcome of the decision may differ (Kahneman & Tversky, 1979). Based on this theory, academics tried to explain over the last two years different behaviors that were observed during this pandemic. The main conclusion is that these behaviors were diverse as investors had to adapt to the rapid change in the environment. In fact, some of them shifted their position toward safety asset portfolios and reduced their investment due to increased risk aversion (Huber, Huber, & Kirchler, 2021; Singh, 2020). Others raised their equity holdings and adopted risky behavior driven by a change of frame where losing hurt less than before (Ikeda, Yamamura, & Tsutsui, 2020; Priem, 2021). Finally, some of them maintained

their position by continuing their trading activities without moving toward risky (or not) alternatives (Angrisani, Cipriani, Guarino, Kendall, & de Zarate Pina, 2020; Pelster & Wengerek, 2020). This diverse range of behaviors observed highlights the complex and individual nature of investors' decision-making processes in uncertain times. Given these researches and based on prospect theory, it can be concluded that there is no definitive answer to how investors react to the news during COVID-19.

Therefore, the phenomenon known as Post Earning Announcement Drift (PEAD) is a suitable laboratory in order to study investor reactions toward company financial information in this crisis environment. Indeed, this pandemic has not only affected the financial results of companies but also influenced how investors evaluate them (Xu et al., 2021). Studies have namely demonstrated that investors' perception of earnings news is stronger in times of uncertainty (Kyaw, Olugbode, & Petracci, 2022). Hence this thesis aims to examine how COVID-19 has influenced investors' behaviors regarding earnings news in the US market. This is achieved by comparing their reactions before and during the pandemic, with a particular focus on analyzing the Post-Earnings Announcement Drift to identify any potential changes in their responses.

This paper puts forth research objectives. We investigated, based on the prospect theory, whether after earnings announcements investors reacted less negatively to bad news and more positively to good news or the other way around as reflected in the PEAD. In other words, we studied the relationship between the pre-pandemic as well as pandemic periods and the overall market reaction to corporate earnings announcements. With this approach, we gained insights into how the pandemic has affected investors' perception of earnings news.

Our key results are that the positive pre-COVID Post-Earnings Announcement Drift (PEAD) had undergone a significant decline during the pandemic leading to its disappearance in the first quarter of 2021. Thanks to linear regressions, we thus tried to find an explanation for this result during the pandemic. However, contrary to our expectations, we discovered that the analyst forecast error had a significant positive effect on the PEAD.

This suggests that during the COVID-19 period, investors demonstrated a higher sensitivity to earnings announcements. To account for the varying frames in which investors find themselves, we specifically examined positive and negative unexpected earnings separately, considering the principles outlined by the prospect theory. Our analysis revealed that investors displayed a stronger response to positive earnings news while showing no significant reaction to negative news, thereby explaining the overall positive outcome observed. We then investigated the influence of firm size and analyst coverage on this global result. The unexpected earnings of small firms have a higher positive and significant impact on the PEAD, confirming the inverse relationship between firm size and this anomaly. Conversely, when focusing on analyst coverage, we observed a significant negative effect of the error median when the number of analysts is low. For the big and high analyst coverage firms, these effects are non-significant over the entire period. However, our regression model accounted for only fifty percent of the variance in the PEAD, indicating the potential influence of other unexplored factors on this unexplained market anomaly as well as its decline.

Thereby, the main contributions of this study are, firstly, to extend the literature on this pandemic environment and its consequences on the market (Ambros, Frenkel, Huynh & Kilinc, 2020; Ftiti, Ameer, & Louhichi, 2020; Xu et al., 2021). Indeed, our study is one of the first to investigate the impact of COVID on earnings news. Secondly, this thesis contributes to the field of behavioral finance by providing a quantitative method for understanding investors' responses to uncertainty. Previous research by authors such as Singh (2020), Huber et al. (2021), Ikeda et al. (2020), Priem (2021), Pelster et al. (2020), Angrisani et al. (2020) have already noted diverse and even conflicting investor attitudes towards news. Yet, none of these researchers have combined all their reactions to observe an overall long-term result which is the objective of our study. Thirdly, analyzing an anomaly such as the PEAD in this ever-changing environment is a challenge that few authors (D'Augusta & Grossetti, 2023; Ma'aji & Hi, 2021) have undertaken. Thus, by studying PEAD over an extended period, we add to this limited body of literature a "longer-term" perspective on the pandemic impacts. Fourthly, investigating the investors' behaviors in the context of COVID-19 can have wider implications. It could help in understanding some economic events' consequences as well as helping leaders and

decision-makers in government and industry to draw lessons from this unexpected crisis and make informed decisions for the future.

Lastly, to carry out this thesis, we will proceed as follows. We will first review the previous literature that studied the impact of COVID news on market participants with a focus on analysts and investors and understand it through prospect theory. This will help us to formulate our research question in a PEAD context as well as our hypothesis. Next, we will present our initial database and our methodology. Finally, we will expose our empirical analysis and results as well as provide our interpretations.

2 Literature review

2.1 COVID 19 : An upheaval for businesses and financial markets actors

COVID-19 is one of the most unexpected and exogenous events that the financial market has ever encountered. The effects of the pandemic have varied among market participants. Banks, for example, experienced an increase in deposits due to people's fears (Ding, Levine, Lin, & Xie, 2020). The impact on businesses is another. Taking a sample of firms across different economies, Ding and al. (2021) found that firms' resilience varied depending on their pre-pandemic financial strength. Stronger financial firms were less affected by the pandemic as they were able to meet debt obligations even with a drop in sales during lockdown restrictions.

The entire financial market was also mainly impacted by governmental restrictions to prevent the spread of the disease such as the introduction of a lockdown or the restriction of activities (Scherf et al, 2022). Scherf et al. (2021) study the impact of the announcement of restrictions on the index of national countries included in OECD and BRICS between January and March 2020. They found that, although the overall reaction toward new restrictions is negative, the indexes tended to underreact to the latter at the beginning of the pandemic. Then, as COVID intensified, countries tended to overreact to these new measures. Phan et Narayan (2020) went in the same direction by studying the stock price response toward countries' policy governments during the pandemic. They found that among the 25 most affected countries, most countries were slow to react to the COVID news announcements.

Then, this pandemic also increased market uncertainty, making it difficult for analysts to provide qualitative forecasts for stock prices or earnings. Indeed, Gao et al. (2021) analyzed their forecasts' dispersion in China to find that these were more diluted due to mobility restrictions. It is important to highlight the significant role that analyst forecasts play in the market, serving as a fundamental basis for investors' investment decisions (Hao et al., 2022). Notably, during times of uncertainty, the demand for data from investors tended to increase (Hao et al., 2022). In response, stock analysts prioritized providing

up-to-date information and setting aside forecast accuracy. Specifically, Hao et al. (2022) studied the reaction of analysts in a sample of US firms from February 2019 to March 2021. They found that prior to the crisis, analysts had an optimistic outlook, which turned to be defeatist at the onset of the pandemic to then gradually become positive by the end of 2020. In other words, Hao et al. (2022) showed that the informativeness of the prediction is lower during the pandemic probably due to the overestimation of the COVID-19 impact. This contrasted with prior studies that claimed that analysts tend to underestimate macroeconomic news (Hugon, Kumar, & Lin, 2016).

Therefore, as the analysts' forecasts are a benchmark for investors, their attitudes are likely to be impacted. Their reactions have been previously studied through prospect theory which helps explain decision-making under uncertainty. Kahneman et Tversky (1979) have shown that investors tend to avoid losses because a loss hurts significantly more than a comparable gain. From a financial point of view, this means that the value function of investors varies depending on the frame that they are in. On the one hand, when people face losing frame alternatives, they are willing to take more risks. In this case, the value function is more strongly convex, indicating a preference for a high probable loss over a low sure loss situation (Kahneman & Tversky, 1979). On the other hand, when the alternatives are presented from a gain perspective, investors are likely to become more risk averse, and their value function turns out to be concave. In other words, they prefer a low certain gain over a probable high gain (Kahneman & Tversky, 1979).

For these reasons, observing the reactions of investors' COVID-19 situation will allow us to analyze how the prospect theory is applied and what the resulting behaviors are. First, the pandemic has triggered more risk aversion leading to a shift toward safety asset portfolios such as ESG (Environmental, Social, and Governance) and EAFE (Europe, Australasia, and Far East) portfolios. Singh (2020) found that during the pandemic investors tended to allocate their capital to ESG portfolios because of their long-term focus strategies which made them less affected by these shocks. Huber et al. (2021) analyze the perception and the behavior of finance professionals toward risk before and during the crisis by subjecting them to experimental investment situations. Their findings revealed that their risk aversion rose, resulting in decreased investment activity without a corresponding adjustment of their expectations.

On the contrary, Ikeda et al.(2020) found that people's feelings about loss were altered during the pandemic. Indeed, losing considerable amounts of money hurt less than before, hence investors being more willing to adopt risky behavior. This observation was also supported by a study conducted in Belgium, which analyzed 6.5 million individual investor transactions. The research found that investors increased their equity holdings and continued to purchase shares even when stock prices plummeted during the first wave of the pandemic (Priem, 2021).

Finally, investor behaviors in response to the pandemic were not significantly impacted. In fact, Pelster et al. (2020) conducted a regression analysis at the transactional level and discovered a positive relationship between investors' trading activities and the number of COVID-19 cases during the beginning of the pandemic. The main point is that investors did not significantly alter their investment preferences towards safer or riskier assets. Similarly, Angrisani et al. (2020) conducted a study to examine the stability of risk preferences by comparing participants' questionnaire responses before and after the pandemic. They concluded that risk aversion remained stable and could not solely account for the observed risk premium during the pandemic.

As there is no definitive answer to the overall reaction of investors toward news in the COVID environment, it is interesting to further explore and investigate what their reactions are regarding earnings news in this context.

2.2 The laboratory: Post earnings announcement drift

Previous studies have highlighted that investors also rely on earnings news to make their forecasts, especially when the environment is uncertain (Brennan et al., 2022; Kyaw et al. 2022). Kyaw et al. (2022) actually conclude that when there is uncertainty in the overall market, the investors' perception and reaction to earnings news are stronger than in other situations. Moreover, we know that the earnings announcement is the most important event for a company as it contains valuable information for the firm's stakeholders (Kyaw et al., 2022; Landsman & Maydew, 2022). In fact, these announcements allow investors to assess whether the company has met, beaten, or on the contrary, fallen short of expectations. When a company performs better than expected by the benchmark

(usually given by analysts over a quarter), it tends to have a positive impact on the stock price (Thewissen, 2021). Conversely, if the company fails to meet expectations, this effect is reversed and accentuated in times of high uncertainty (Kyaw et al., 2022). This price adjustment, in line with the prospect theory, is expected to occur directly in accordance with the efficient market theory (Fama, 1970).

However, some authors (e.g., Ball & Brown, 1968; Bernard & Thomas, 1989; Foster, Olsen, & Shevlin, 1984; Freeman & Tse, 1989) contradicted this theory by showing that abnormal stock returns take time to drift in the direction of the earnings surprise after the earnings announcement. In other words, the stock price tends to exhibit a behavior where investors are constantly anticipating positive or negative outcomes, even though the results have already been disclosed (Jegadeesh & Livnat, 2006). This mispricing called the Post Earning Announcement Drift is one of the clearest examples of unexplained stock market anomalies.

This phenomenon has been studied extensively around the world, such as in the U.S. stock market. Foster et al. (1984) found that the abnormal post-announcement return is directly related to the magnitude and the sign of the unexpected earning change providing a trading opportunity around 60 days. Bernard et Thomas (1989) went in the same direction and stated that using a long-short investment strategy based on standard unexpected earnings can generate a positive return with zero-portfolio investment. All these studies and others (e.g. Bernard & Abarbanell, 1992; Freeman & Tse 1989) drew the same conclusion: new information takes more time to be fully incorporated into the stock price indicating the market's underreaction to this announcement. Consequently, there is a potential for trading opportunities based on this anomaly.

Following this result, numerous attempts have been made to find out why this anomaly still exists. For example, Foster et al. (1984) tried to explain the PEAD with the firm's size. They hypothesized that since small firms deliver less information on the stock market, they tend to be more inefficient, and the information takes longer to be incorporated. Bernard et Thomas (1989) add three main reasons: transaction costs, difficulty in interpreting available information, and the potential misspecification of the CAPM (Capital Asset Pricing Model). Other studies, such as Campbell, Ramadorai et Schwartz (2007),

focused on the role of institutional investors. However, despite these attempts, none of them was able to explain the PEAD phenomenon in its entirety.

Nevertheless, more recent studies have shown that the PEAD's magnitude may decrease. Chordia, Subrahmanyam et Tong (2014) showed that certain anomalies, including the post-earnings announcement drift, tended to decrease in the actual environment of high liquidity and high trading activity. Martineau (2021) and Millian (2015) agreed and concluded that market participants have improved their ability to process earnings information, thereby reducing the potential for post-earnings-announcement drift.

Therefore, given the fact that COVID-19 increases uncertainty leading to lower quality of the analysts' forecast and various reactions from investors toward news, it is obvious to study what impact COVID-19 will have on PEAD as its magnitude depends on these two factors.

3 Research question and contributions

This paper aims to investigate the impact of COVID on investors' reactions toward news, specifically focusing on comparing their behaviors around the quarterly earnings announcement days before and during the pandemic. Thanks to the analysis of the changes in the magnitude and sign of the Post Earning Announcement Drift (PEAD) during this period, we will gain insights into the effects of COVID-19 on investor behavior.

This thesis provides significant contributions to the literature in many different ways. First, it contributes to the increasing number of studies on how COVID-19 is impacting the financial market. Previous studies have actually shown that COVID-related news, such as the number of cases, increased volatility and diminished the level of liquidity in the market, leading to a higher level of overall risk (Ambros et al. 2020, Ftiti et al. 2020). In our case, our main interest lies in understanding how the pandemic affects the usual company information published. Focusing on firm-related specific information, Brennan et al. (2022) and Xu et al. (2021) have shown that COVID-19 complicates the firm information environment and alters the way in which these pieces of information are evaluated. This thesis adds to this field of research a focus on the earnings news released by US companies in this pandemic framework.

Second, this paper also contributes to the behavioral finance literature by providing a valuable and quantifiable understanding of how market participants respond to uncertainty and shifting conditions. Indeed, during the pandemic, participants react in different ways whether by increasing their risk aversion (Huber et al., 2021; Singh, 2020), rising their love for risk (Ikeda et al., 2020; Priem 2021), or not changing their behavior (Angrisani et al., 2020; Pelster et al., 2020). Thus, our research brings a novel perspective by exploring the collective long-term impact of individual reactions in the context of PEAD and prospect theory.

Third, our work is among the first to explore the post-announcement drift, one of the most well-known unresolved market inefficiencies, in the pandemic circumstances in the US. Whilst D'Augusta et Grossetti (2023) have studied the annual earnings news and the post-announcement return in the US market to find a negative relationship during COVID-19, our work is the first to investigate quarterly earnings announcements (instead

of yearly ones) over a longer post announcement window (180 days) as well as over longer pandemic period. This will provide a broader perspective on this anomaly in this pandemic context.

Finally, more generally, examining changes in investors' reactions due to the pandemic may help to understand the underlying economic outcomes and to draw relevant conclusions. In fact, this thesis might allow policymakers and business leaders to learn how to communicate effectively with investors and manage expectations during a crisis. It highlights the importance of considering the influence of the external environment and the way information is provided to individuals (such as investors and analysts) when forming their expectations (Hameleers, 2021).

4 Hypothesis

As noted in the literature review, the COVID-19 pandemic has had a significant impact on the global economy, causing widespread uncertainty. This made it challenging for businesses to plan for the future and has caused significant volatility in financial markets.

On the one hand, this uncertainty growth led to a higher probability of earnings manipulation by companies. Indeed, Yan, Liu, Wang, Zhang, et Zheng (2022) suggested that the negative signals from the financial market due to the pandemic have prompted companies to engage in earnings management practices. The objective was to avoid disappointing their investors and the related negative consequences such as a decline in stock price. This practice of earnings management is a contributing factor to the delayed market response to earnings news, leading to an increase in the PEAD (Louis & Sun, 2008). In addition, other researchers (Fink, 2020; Wang & Wang, 2020), have revealed that under conditions of information uncertainty, investors may exhibit an underreaction to earnings news. Wang et Wang (2020) specifically found that during times of negative signals from the financial market, investors tended to be more conservative and may be less confident in their investment decisions. As a result, they were more likely to hold on to their existing positions, even if there was new information that suggested a change in the underlying fundamentals of the company. This led to a stronger post-earnings announcement drift.

Basing ourselves on these findings, we thus formulated the following first hypothesis:

Hypothesis 1 :The Post Earnings Announcement Drift which has constantly been positive before the pandemic, became increasingly stronger during the COVID crisis due to the overall investor's reaction toward earnings news.

On the other hand, a common method for dealing with uncertainty is to assume that investors, when faced with uncertainty, become more pessimistic (Bird & Yeung, 2012; Kyaw, 2022). In other words, they put more weight on negative information than on positive one. Bird et al. (2012) found the market tended to react to bad news and completely ignored the good ones, which resulted in a negative post-announcement drift for firms reporting (bad and good) news. In addition, D'Augusta et Grossetti (2023) put forth the argument that the uncertainty surrounding the COVID-19 pandemic has led to an increase in skepticism among investors toward earnings news. They argue that some earnings announcements were based on pre-crisis assumptions and projections that did not take into account the pandemic's impact. Therefore, this concern of investors about the credibility of the company's reported earnings has resulted in an inverse relationship between earnings news and abnormal returns after the announcement. According to their research, investors tended to react negatively regardless of whether the earnings news are positive or negative. Moreover, their reactions were negatively and significantly stronger for good news than for bad. Hence, after analyzing the results, we formulated this second hypothesis as the post-earnings announcement drift is the difference between cumulative abnormal returns of positive and negative earnings news in a larger announcement window.

Hypothesis 2 : The previously positive Post-Earnings Announcement Drift observed before the pandemic undergoes a shift, resulting in a null or even negative PEAD during the COVID-19 crisis due to the overall investor's reaction toward earnings news.

Given the literature's divergent opinions on how investors respond to this increase of uncertainty, our empirical study will investigate whether these opposing hypotheses can be confirmed or rejected using a linear regression analysis of available data. Specifically, to quantify the impact of COVID-19, we will look at the magnitude and sign of the post-earnings announcement drift (PEAD) before and during the pandemic.

5 Data and Methodology

We now explain the quarterly earnings press release we used, outline the variables we are interested in, and describe the methodology we employed. The main variables are summarized in Table 2.

5.1 Sample selection

Before analyzing the data collected, we first look at the contribution that has already been written on our topic. The result of this research is that only a few existing pieces of literature dealt with the impact of COVID on PEAD. The present thesis stands out from the existing literature as it covers a longer time frame and involves a larger sample size of companies. Indeed, we study the significance of the PEAD in the US market, before and during this pandemic. The choice to focus on the US market was motivated by the desire to investigate how a disease can affect one of the world's greatest economies.

Then, to answer our research question, we had 92975 quarterly earnings announcements of listed companies on the US market between 2004 and 2021 thanks to the US4 database. The first step was to divide the data into two periods: pre- and pandemic. For the pre-COVID period, we started in the first quarter of 2010, to avoid the impact of the 2008 crisis, until the fourth quarter of 2019. The COVID period began in the first quarter of 2020, as the first COVID case was detected in the US on the 22nd of January 2020 (Statista, 2023), and continued until the latest available data (first quarter of 2021). We filtered the data to the required period and obtained 69,660 observations for our analysis.

To ensure its accuracy, we employed the winsorizing method used by Boudt, De Goeij, Thewissen et Van Campenhout (2015) to minimize the impact of outliers. Their approach, inspired by Gelper, Fried et Croux (2010), involves replacing outlying forecast errors with more probable values. Moreover, we excluded all missing data (NA) from our database to ensure a smooth coding process. This resulted in a final dataset consisting of 41266 observations, as depicted in Table 3.

Our database relied on a diverse range of data sources allowing us to have all the variables of interest at our disposal. Each of them provides insights into the financial

performance of the companies being examined. For instance, accounting data, such as earnings announcements, was obtained from Compustat, which is recognized for its comprehensive and accurate financial information. Meanwhile, stock information (e.g. share price, returns, share outstanding,...) was gathered from the Center for Research in Security Prices (CRSP), a trusted source for historical stock data. In addition to these sources, the Institutional Brokerage Estimate System (I/B/E/S) provided us key performance indicators (such as Earnings per share) as well as every analyst data.

5.2 Methodology and data description

In the upcoming section, we will examine the various variables used in our regression model and the methodologies implemented to obtain them. This will ensure that the variables included in the model are relevant and reliable as well as the results obtained are robust.

5.2.1 PEAD and analyst forecast error variables

A commonly followed practice by most investment research services is to release the consensus analyst forecast as an estimate for a company's earnings per share (Boudt et al., 2015). Substantial evidence supports that there exists a positive correlation between the magnitude of the analysts' forecast error and the stock returns observed on the day of the earnings announcement (Boudt et al., 2015; Martineau, 2021). Therefore, to calculate the Post-Earnings-Announcement-Drift (PEAD) phenomenon, we applied the method introduced by Abarbanell et Bernard (1992). We used winsorized data, as previously discussed, to minimize the impact of outliers. Our first step was to use the *werrormedian* variable (shown in Table 1) which represents the winsorized analyst forecast error. This standardized unexpected earnings (or analyst forecast error) was calculated by subtracting, from the actual Earnings per Share, the consensus analyst forecast scaled by the stock price on the day before the forecast date.

$$\text{Analyst forecast error} = \frac{\text{Actual EPS} - \text{Consensus EPS}}{\text{Stock price}}$$

Then, we grouped observations into deciles based on the magnitude of the analyst forecast errors. The categories were ranked from decile 1 (the most negative forecast error) to decile 10 (the most positive). Decile 1 indicates bad news for investors because the portfolio has underperformed, while decile 10 suggests good news as the firm has performed better than expected. We chose to split the sample in this way because we hypothesized that the stock price reaction will be stronger as the magnitude of forecast error rises.

Following this, we took the mean of the cumulative abnormal returns, which measures how the stock performed (its actual return) in comparison to the expected return (based on market benchmark) over a specific period. It has been observed that the majority of the drift takes place within the initial 60 days of trading subsequent to the announcement, and there is little statistical evidence to support any significant drift beyond 180 days (Bernard & Thomas, 1989). Therefore, the 180-day period was selected to encompass the entire drift.

Finally, to calculate the PEAD, we subtracted the mean of the cumulative abnormal return for Category 1 from the mean of the cumulative abnormal return for Category 10. This calculation provides us a measure of the magnitude of the drift.

$$PEAD = \text{Mean CAR 180 (decile 10)} - \text{Mean CAR 180 (decile 1)}$$

By following these steps, we were able to accurately assess the PEAD phenomenon and its implications. We will be using this variable (*PEAD*) as our dependent variable for all of our regression analyses.

5.2.2 Control variables

Moving onto our control variables next, we initially consider those related to the companies themselves. Firstly, to account for seasonal trends and long-term variations in financial data, as well as the autocorrelation of financial returns, we include the previous year's return as a control variable. Indeed, this variable helps us clarify the relationship between the current year's return and the return from the previous year as proven by

Elgers et Lo's (1994) research. We also incorporate the Return On Asset (*EARN_TA*) in order to regulate the overall financial performance of the company impact as well as its volatility thanks to the *sd* variable. In addition, we included the size of the company as a control variable since we are aware that the post-earnings announcement drift is affected by the latter (Bernard et Thomas, 1989). We followed the Bhushan (1989) approach by taking the logarithm of the firm's market value. Regarding the market data, we factored the stock return volatility which is measured by the standard deviation of monthly return over the past year (*risk_monthly*).

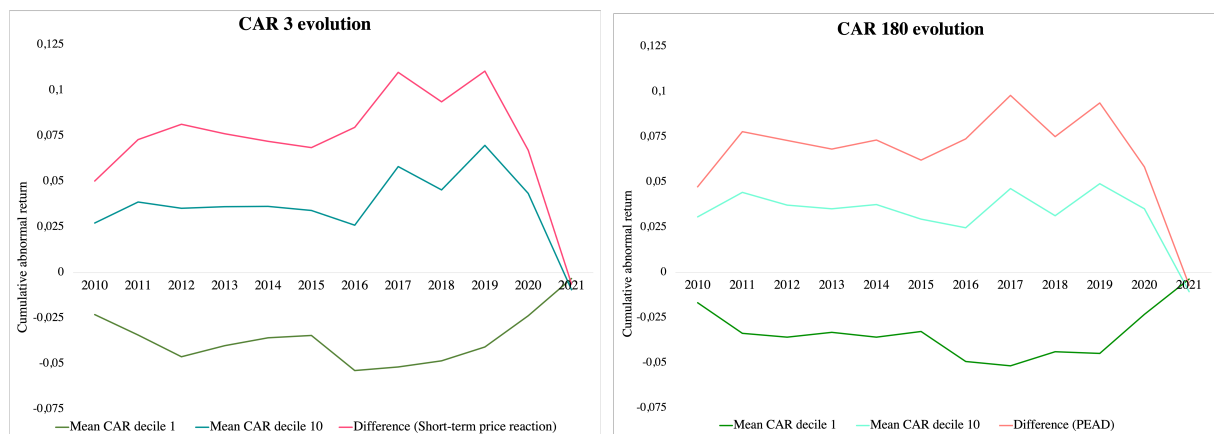
Then, in order to capture the influence of analysts on the PEAD, we include two control variables: the number of analysts and the standard deviation of the analyst consensus. The former is a measure of analyst coverage. We control this variable because Bhushan (1989) showed that there is a positive correlation between firm size and analyst coverage. It also takes into account the potential impact of this variable on analysts' forecasting behavior and the calculation of the error median. We also control the standard deviation of the analyst consensus (*sd_consensus*) as a proxy for information uncertainty, as suggested by Boudt et al. (2015). Indeed, by considering the consensus forecast, which incorporates both public and private insights from analysts covering a specific stock, we seize the most readily available metric to investors. Therefore, by controlling the standard deviation, which reflects the uncertainty risk associated with the company's future performance, we better isolate the effect of the analyst forecast error on the PEAD.

Finally, it is a well-established fact that qualitative information, such as the tone of earnings press releases, has a wide influence on the investor's reaction toward news (Boudt et al., 2015). Therefore, to measure the tone, we adopt the same approach as Boudt et al. (2015) by calculating the difference between the proportion of positive (*PositiveHenry*) and negative (*NegativeHenry*) words used scaled by the number of words (*NumberOfWord*) of earnings press released. The lists of positive and negative words are based on Henry's work (Henry, 2008). Additionally, we regulated the impact of the language complexity on the PEAD, by adding the Gunning Fog Index (*FOG*) as a control variable. Indeed, Young (2020) has found that this variable influences PEAD. This index takes into account factors such as the average sentence length and the frequency of long words in relation to the total number of words (Young, 2020). It provides insight into the readability of the text, indicating the level of education required to understand it (Li, 2008).

6 Empirical results

In this section, we present our empirical results that confirm the existence of a PEAD in our sample data. First, we looked at the evolution of cumulative abnormal returns in the short and long term in order to analyze the overall impact of earnings releases on stock prices. Then, we tested our hypothesis thanks to linear regression models with several control variables. As mentioned before, we included a large number of control variables to avoid bias in our analysis as well as to prevent endogeneity concerns as much as possible. Finally, we investigated the different variables that could have an influence on the observed results, ensuring a full analysis of factors that may contribute to the PEAD.

6.1 Cumulative abnormal return and PEAD analysis



These graphs present a broad overview of the evolution of the Cumulative Abnormal Return (CAR) before and during the COVID-19 pandemic across different event windows. In order to analyze the stock price reaction, we took the difference between the mean of CAR when included within the highest decile and lowest decile. These deciles were determined based on the magnitude of the forecast error, as explained previously.

In our short-term analysis, we focus on CAR 3, which captures the three-day period surrounding the earnings announcement to evaluate the short-term impact of the earnings announcement on stock prices. Similarly, to measure the long-term price reaction, we computed the cumulative abnormal return around 180 days after the earnings announcement.

The difference in these long-term CAR provides insights into how the market continues to react and adjust to the earnings news over an extended timeframe, thus measuring the PEAD.

Overall, the stock price reactions exhibited a similar trend. Specifically, during the pandemic, we observed a decrease in positive abnormal returns for positive earnings surprise, indicating a decline in the market's positive reaction to better-than-expected earnings. Additionally, the magnitude of unexpected negative returns gradually decreased, suggesting a diminishing impact of negative earnings surprises on stock prices over time. This trend reversal could be attributed to the unprecedented market conditions mentioned in the literature review (e.g. increase of uncertainty, volatility in the market, the impact of lockdown restrictions, and economic slowdown) which changed investor sentiment during the pandemic. Moreover, we could hypothesize that the short-term reaction is slightly higher because it may be more sensitive to immediate news and events related to the pandemic, while the long-term one may be influenced by a wider range of factors such as the overall performance and outlook of the company.

To further investigate the PEAD phenomenon, which is the primary focus of our research, we conducted a t-test (as detailed in Table 4) to examine its significance. The results indicated that the p-values for the difference in CAR 180 between the two deciles were statistically significant for all years except 2021. This implies that the PEAD's existence has been confirmed from 2010 to 2020, demonstrating persistent abnormal returns beyond the initial earnings announcement period. However, we could not gather enough evidence to support the presence of this phenomenon in the first quarter of 2021. A potential explanation could be attributed to the learning effect of COVID. As the pandemic progressed in waves, investors and analysts may have gained a better understanding of its impact on companies and economies, leading to adjustments in stock prices. This hypothesis is supported by the trend observed in the mean of the *standard_consensus* variable, which measures the level of agreement among analysts. Specifically, the mean increased from 0.0633 in 2019 to 0.24 in 2020 and decreased to 0.126 in 2021, indicating a diminution in uncertainty regarding the future performance of companies.

This analysis thus confirms our second hypothesis, which suggests that the positive Post-Earnings Announcement Drift experienced a shift by declining during the COVID

pandemic and disappeared by the end of the studied period. We will try to explain this downward trend thanks to several regressions with the analyst forecast error as a primary dependent variable.

6.2 Factors influencing the PEAD

Before interpreting the regression outcomes, we provide descriptive statistics for the variables used in our analysis (as shown in Table 2). The latter presents an overview of their central trend (such as mean and median) and dispersion (such as standard deviation). Then, the correlation matrix (shown in Table 5) allows us to understand the strength and the sign of their relationships. Overall, we can clearly notice that correlations were significant and consistent with our expectations. For instance, the number of analysts necessary to reach the consensus is positively correlated with the size of the company aligning with the notion that larger firms tend to attract a higher analyst coverage.

In this section, we will begin by examining the individual impact of COVID as an independent variable on the PEAD. Subsequently, we will analyze the combined influence of the pandemic and the error median on this phenomenon. Furthermore, based on the prospect theory, we will investigate the impact when the error median is exclusively positive or exclusively negative. Finally, we will explore the firm size and analyst coverage's effects on our findings.

6.2.1 Model without interaction variable

$$PEAD = \beta_0 + \beta_1 Werrormedian + \beta_2 Covid_dummy + \beta_3 Controls + \epsilon$$

The purpose of this regression is to assess the independent contributions of the variables and their significance in influencing the PEAD. Previously, we explained that the magnitude of analyst forecast error and the subsequent stock price reactions are interconnected variables. By observing the result shown in Table 6, we can note that the error median has a significant negative impact ($-1,186e^{-14***}$) on the PEAD at a 99% level for the overall period. It can be deduced that, throughout the entire period regardless of the presence or absence of COVID-19, investors generally exhibit a diminished reaction to

unexpected earnings. This relationship has been supported by Patton et Timmerman's (2010) research which confirmed that there is a monotonically decreasing relationship between cumulative abnormal returns (CAR) and forecast errors.

Another notable finding is that the coefficient of the COVID-19 variable is negative and statistically insignificant ($-3.108e^{-17}$). This suggests that even if this negative sign goes in line with our graph and our second hypothesis, we cannot conclude that the sole presence of Covid has a significant impact on the PEAD.

6.2.2 Model with interaction variable

We will now investigate if due to the pandemic, individuals increased or decreased their sensitivity toward earnings news. The following regression assesses the influence of COVID-19 on both the magnitude and sign of the effect of the earnings forecast error on the Post-Earnings Announcement Drift (PEAD).

$$PEAD = \beta_0 + \beta_1 Covid_dummy * Werrormedian + \beta_2 Werrormedian + \beta_3 Covid_dummy + \beta_4 Controls + \epsilon$$

Based on our analysis of the coefficients in Table 7, we found a significant positive coefficient ($1,203e^{-14*}$) at a 90% confidence level for the pandemic period. This means that there has been an increased sensitivity among investors toward news, amplifying the effect of earnings surprises on stock prices. This higher reactivity has resulted in a larger post-earnings announcement drift (PEAD) compared to the previous period. In other words, investors are more responsive to earnings news during the pandemic, leading to a stronger impact on stock prices and a more pronounced PEAD. This outcome contradicts our earlier results but is consistent with some findings reported in previous literature (Ball et Brown, 1968, Hoa et al., Kyaw et al., 2021). Indeed, Kyaw et al. (2021) have found that the heightened market-wide uncertainty implied a stronger reaction from investors to earnings news.

On the contrary, during the pre-pandemic period, we have a negative and significant coefficient at a 99% level between the analyst forecast error and the PEAD ($-1,369e^{-14***}$),

meaning that the higher the forecast error is, the lower PEAD will be. This relationship is higher than if we take the regression without the interaction variable. A possible reason could be because, in addition to the findings of Patton et Timmerman (2010), earnings forecasts may generally be considered more credible in a non-pandemic economy. During normal periods with less uncertainty and volatility, Ng, Tuna et Verdi (2013) demonstrated that using distinct measures of forecast credibility, higher levels of forecast credibility are associated with a stronger short-term reaction and a smaller long-term drift.

In order to explain further the overall positive sign during the pandemic, we will now investigate whether people react more strongly to negative or positive earnings news. In fact, we know that based on prospect theory, investors respond differently to positive and negative announcements depending on the frame in which they are.

6.2.3 Positive and negative analyst forecast errors

As previously discussed, there is a divergence in the market's response to earnings announcements that beat expectations compared to those that fall short (Thewissen, 2021). Therefore, based on the prospect theory, we could hypothesize that when the earnings announcement exceeds expectations (indicated by a positive error median), investors may interpret it as a signal of potential profitability. Consequently, they could be likely to react positively, but with a cautious approach due to risk aversion. On the other hand, when the earnings announcement falls short of expectations (indicated by a negative error median), it may be perceived as a potential loss, leading to negative reactions and a willingness to take more risks. To examine the overall investors' reactions in this uncertain environment, we conducted the same regression on two subsets of the database (results are shown in Table 7).

In the subset of observations where the error median is positive (indicating good news), we found that during the pandemic, the analyst forecast error has a significant and positive impact ($5,067e^{-15**}$ at a 95% level of confidence) on the PEAD. This implies that when the earnings announcement exceeds the analyst's expectations, investors react positively and the stock experiences an upward drift during the subsequent period, which is consistent with prior literature (e.g. Thewissen, 2021).

Focusing next on the negative error median sample, we observe, during COVID, a non-significant negative coefficient ($-2,394e^{-15}$) in relation to PEAD. This suggests that, despite the negative sign which is consistent with our previous graphs, investors did not exhibit a significant reaction to negative news during the COVID crisis. This result can be interpreted as investors being less sensitive to negative unexpected earnings during the pandemic, aligning with the findings of Ikeda et al. (2020).

These two results contrast with the non-pandemic period outcomes. Indeed, when investors receive positive news, their reaction tends to be significantly negative ($-4,980e^{-15***}$) at 99% of confidence, leading to a decrease in the Post-Earnings Announcement Drift. Conversely, their reaction tends to be significantly positive ($2,400e^{-15***}$) at a 99% confidence when investors receive negative news, resulting in an increase in the PEAD. This suggests that in normal market conditions, investors exhibit an opposite response to earnings news.

This analysis allows us to understand how the interaction between COVID and the error median influences the PEAD differently depending on the direction of the earnings surprise. After comparing the results, we can conclude that the high positive significant coefficient of the overall regression during the pandemic is due to investors reacting strongly to positive news and not to negative news. We will now investigate whether this overall positive effect is amplified or not, by considering the size of the company and the analyst coverage.

6.2.4 The impact of firm size on the PEAD

As previously mentioned, the size of the firm has an inverted relationship with the post-earnings announcement drift (Bernard & Thomas, 1989; Foster et al., 1984). Thus, we divided the database into two subsets: small firms with a market capitalization below the median of the *mkvaltq* variable and big firms with a market capitalization above the median. We then run the same regression model as previously described. The outcomes of this analysis are shown in Table 8.

For small firms, during the pandemic, the analyst forecast error has a higher impact ($3,636e^{-15*}$ at a confidence level of 90%) on the PEAD compared to the overall sample,

which coincides with Foster et al. findings (1984). However, before the pandemic, the effect is inversely related. We can see that the value is $-4,416e^{-15***}$ which is significant at a 99% level. Therefore, in the small firm's pre-covid sample, if the unexpected earnings increase, the impact of the forecast error is negative on the post-earnings announcement drift.

Concerning the big firms, the lack of significance of the coefficient, in the COVID and non-COVID period, does not allow us to assert a relationship between the error median and the PEAD. This non-significance could be explained by Martineau (2019) who found that in recent years, the strength of the relationship between analyst earnings surprises and the post-earnings announcement drifts has significantly decreased over time. This suggests that the main process of price discovery occurs primarily during the earnings announcement itself.

6.2.5 The impact of NoA on the PEAD

We took into account the analyst coverage (*NoA*) which is positively correlated with firm size as shown in our correlation matrix (refer to Table 9) but also proved by Bhushan (1989). Indeed, the number of analysts required to make a consensus forecast depends on several other factors, including size, the complexity of the company, media coverage, volatility of its financial results, and availability of financial data.

Moreover, according to Bhushan's (1989) findings, the higher the number of analysts needed to make the consensus, the lower the information uncertainty for a firm. In fact, a greater number of analysts can lead to a reduction in information asymmetry among market participants, ultimately resulting in a decrease in uncertainty. Consequently, we can expect that the impact on the post-earnings announcement drift (PEAD) will be less severe for firms that have a higher level of analyst coverage, and conversely, more pronounced for firms with lower analyst coverage. We followed the same methodology as before which involved dividing the dataset into two using the median value of *NoA*: 8 analysts. This resulted in two distinct datasets: one with a large number of analysts ranging up to 48, containing 21,720 observations, and another with a small number of analysts from 0 to 8, containing 19,544 observations.

By observing the Table 9, during the non-pandemic period, the positive coefficient of the errormedian variable is statistically significant ($6,718e^{-15***}$), indicating that a low number of analysts (high information asymmetry) leads to a higher impact of unexpected earnings on the drift. However, during the COVID crisis, the impact is weakened and reverted with a significant coefficient ($-5,421e^{-15*}$ at the 90% level). One possible explanation is that as uncertainty increases, having fewer analysts covering the companies may amplify the negative reaction of investors to earnings news (Bird, Choi, & Yeung, 2014; Kyaw, 2022). This is the only situation where, during the pandemic, the Post-Earnings Announcement Drift is negatively affected by unexpected earnings, which is aligned with our initial expectation of a negative trend.

Looking at the firm where the number of analysts is high, the significance of the coefficient of the errormedian variable disappears. This suggests that a higher number of analysts could have a moderating effect on the relationship between the unexpected earnings variable and the PEAD.

7 Limits

As we have seen in the literature, explaining the magnitude of the Post-Earnings Announcement Drift (PEAD) and its underlying influencing factors remains a challenging task. This has been confirmed in our empirical result as we are unable to entirely explain why we observe a declining shift during the COVID. Therefore, assessing the quality of our model is a mandatory step.

The adjusted R-squared value for the general model is 0.5, indicating that 50% of the PEAD variance can be explained by the number of independent variables in the model. We could suppose that other factors that are contained in the error term should have been taken into consideration or that the model may suffer from endogeneity. Based on our findings, we suggest that additional research be conducted to examine the overall impact of COVID on the Post Earnings Announcement Drift. This could be achieved by incorporating pandemic-related variables into the analysis to increase the R-squared adjusted value.

However, we stay confident in the quality of our model because the Fisher statistic for the model is big with a p-value of less than 0.01. This implies that the relationship between the independent variables and the PEAD is statistically significant meaning that our model is reliable to assert the link between the variables under consideration. Furthermore, the model has small residuals with a median of 0, showing that the latter is appropriate for the data. Indeed, the low residuals indicate that the model's predictions are close to the actual values, demonstrating the model's accuracy.

8 Conclusion

The COVID-19 pandemic challenged market efficiency by being an unforeseen shock that led to a significant increase in global market uncertainty, shaking the foundations of investors' beliefs and expectations. Previous studies have shown that there are several reactions to global news during COVID that we explained based on prospect theory. In this study, we chose to highlight earnings news within the US market. Our objective was to examine how the COVID-19 crisis affected the interpretation of these news and the subsequent reactions of investors. More specifically, we analyzed the post-earnings announcement drift magnitude and sign to carry out this investigation.

The main conclusion of this research is that the previously positive Post-Earnings Announcement Drift (PEAD) experienced a significant shift and declined towards its lowest point, ultimately disappearing by the end of the first quarter of 2021. In order to understand this result, we conducted regression analyses to examine the impact of unexpected earnings on the PEAD.

Interestingly, we observed that investors became more sensitive to earnings announcements during the pandemic. Specifically, based on prospect theory, investors are reacting more strongly to positive news while showing no reaction to negative news. This overall positive impact on the PEAD contradicts the initial result, highlighting the difficulties of explaining the causes of this anomaly. Furthermore, we investigated the influence of firm size and analyst coverage on this positive dynamic during the pandemic. Our findings demonstrated a significant and stronger impact for small firms, confirming the inverse relationship between firm size and PEAD. However, when we examined the ana-

lyst coverage, we discovered a significant negative impact on the error median when the number of analysts was low. This finding represents the only example where the impact of unexpected earnings aligns with our expectation of a negative effect.

To conclude, our study contributes to the existing literature by expanding the understanding of the impact of the pandemic on the financial market, as well as on the investor's perception and behavior after news announcements in times of uncertainty. Additionally, we are among the first to investigate the well-known anomaly of PEAD in such an uncertain environment. From a broader perspective, since the pandemic, uncertainty has become the norm for the global economy. Therefore, by studying the investor's reaction in the COVID environment, our study can help managers and analysts to adapt their models to try and reduce unwanted investors' behaviors. Nonetheless, it is important to note that our regression model only explained 50% of the variance in the PEAD, indicating the existence of other unaccounted factors contributing to this market anomaly as well as its decline. Whilst this research provides valuable insights into the evolution of the PEAD, it is crucial to acknowledge that the objective of this study was not to provide a definitive explanation of this phenomenon but rather to observe its variations due to the pandemic.

By combining all of our findings together, we have proven that COVID impacted the investors' perceptions and reactions toward news, especially earnings ones, leading to a decrease in PEAD. Therefore, as our study only relies on figures and cannot explain the underlying reasons for this downward trend, we could ask ourselves the following: *To what extent have investors used qualitative information as a basis for their decisions in response to the heightened uncertainty caused by the pandemic? In a broader context and in light of the current events, could we expect the same impact of the war in Ukraine and inflation on investors' reactions, or is there a potential learning effect from the experience of the pandemic?* These questions will be left for future research endeavors.

9 References

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10 Appendixes

Table 1: Variable Description

Dependent variables	
<i>PEAD</i>	Difference between the cumulative abnormal return from decile 10 and the cumulative abnormal return decile 1 over 180-day period (<i>car180</i>).
Independent variable	
<i>Werrormedian</i>	Winsorized analyst forecast error : difference between the consensus EPS forecast (<i>Consensus_median</i>) and reported EPS (<i>Actual</i>) scaled by the closing price on the day preceding the forecast date. This consensus is calculated as the median value obtained from the latest analysts' earnings forecasts
<i>Covid_dummy</i>	Dummy variable that take a value of one if the announcement was made during the year 2020 and 2021, and zero otherwise
Control variables	
<i>Return</i>	Stock price return of the previous year
<i>EARNTA</i>	Earnings on total asset (ROA)
<i>Loss</i>	Dummy variable that takes the value of one if the ROA is negative, and zero otherwise
<i>Sd</i>	Standard deviation of Return on Asset over the the five last periods
<i>Log (1+Mkvaltq)</i>	Size of the company : logarithm of market capitalization at the end of the quarter
<i>Sd_consensus</i>	Standard Deviation of analyst forecast error included in the consensus
<i>Log (1+NoA)</i>	Analyst coverage : logarithm of the number of analysts' forecasts needed to make the consensus forecast
<i>FOG</i>	Gunning Fog Index : measure of the education level required to easily understand the document
<i>Standardized sentiment</i>	Number of positive words (<i>PositiveHenry</i>) minus negative words (<i>NegativeHenry</i>) divided by the number of words based on the Henry library
<i>factor (year)</i>	Year between 2010 to 2021

Table 2: Summary Statistics

Variable	N	Mean	Std. Dev.	Min	Pctl. 25	Pctl. 75	Max
US4.PEAD	41266	-0.007	0	-0.007	-0.007	-0.007	-0.007
US4.werrormedian_covid	41266	0.00031	0.0055	-0.083	0	0	0.07
US4.werrormedian	41266	0.00086	0.014	-0.083	-0.00022	0.0023	0.07
US4.return	41266	0.089	0.055	0.013	0.055	0.11	1.1
US4.EARNTA	41266	0.0075	0.034	-1.2	0.002	0.017	0.67
US4.loss	41266	0.14	0.35	0	0	0	1
US4.sd	41264	0.0088	0.023	0.0000019	0.00081	0.0084	1.4
US4.STD_consensus	41266	0.57	47	0	0.012	0.061	6627
US4.FOG	41266	24	24	0.8	20	24	815
US4.logmkvaltq	41266	8.2	2.1	1.6	6.7	9.5	15
US4.standardized_sentiment	41266	0.011	0.0097	-0.028	0.0045	0.017	0.09
US4.logNoA	41266	2.2	0.76	0.69	1.6	2.8	3.9
US4.risk_monthly	41266	0.099	0.38	-0.98	-0.083	0.23	15

Table 3: Sample breakdown by year

Year	Number of observations
2010	3232
2011	3350
2012	3284
2013	3800
2014	4101
2015	4008
2016	3835
2017	3681
2018	3703
2019	3965
2020	3747
2021	560

Table 4: Statistical significance of the PEAD : Result of the t-test

Year	Meandecile1	Meandecile10	Difference (PEAD)	Pvalue
2010	-0.016680983	0.03079082	0.047471805	2.853969e-15
2011	-0.033624137	0.04432801	0.077952149	5.863825e-40
2012	-0.035762423	0.03734229	0.073104710	1.048907e-22
2013	-0.033054349	0.03529600	0.068350352	7.644372e-20
2014	-0.035759143	0.03759216	0.073351300	3.143433e-29
2015	-0.032632511	0.02954773	0.062180238	4.881425e-16
2016	-0.049168459	0.02477363	0.073942085	1.500442e-17
2017	-0.051600420	0.04644770	0.098048123	3.159861e-19
2018	-0.043757653	0.03142628	0.075183928	4.349024e-12
2019	-0.044704653	0.04913354	0.093838198	5.173861e-22
2020	-0.023135973	0.03528745	0.058423421	7.475995e-24
2021	-0.003592168	-0.01058940	-0.006997229	8.037784e-01

Table 5: Correlation matrix of variables

	US4.werrormedian	US4.return	US4.EARNTA	US4.loss	US4.sd	US4.STD_consensus	US4.FOG	US4.logmkvltq	US4.standardized_sentiment	US4.logNoA	US4.risk_monthly
US4.werrormedian	1										
<i>pvalue</i>		0.023	0.117	-0.155	0.001	-0.038	-0.001	0.032	0.011	0.042	0.014
US4.return	0.023	1	<0.001	<0.001	(0.8310)	<0.001	(0.8575)	<0.001	(0.0214)	<0.001	<0.041
<i>pvalue</i>	<0.001		<0.001	<0.001	0.268	0.009	0.029	<0.001	-0.111	-0.112	0.116
US4.EARNTA	0.117	-0.244	1	-0.485	<0.001	(0.0682)	<0.001	<0.001	<0.001	<0.001	<0.001
<i>pvalue</i>	<0.001	<0.001		<0.001	-0.251	-0.048	-0.032	0.210	0.134	0.119	0.091
US4.loss	-0.155	0.320	-0.485	1	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001
<i>pvalue</i>	<0.001	<0.001	<0.001	<0.001	0.261	0.026	0.007	-0.232	-0.143	-0.117	-0.088
US4.sd	0.001	0.268	-0.251	0.261	1	<0.001	0.008	-0.163	<0.001	<0.001	<0.001
<i>pvalue</i>	(0.8310)	<0.001	<0.001	<0.001	<0.001	(0.0214)	(0.1062)	<0.001	<0.001	<0.001	<0.001
US4.STD_consensus	-0.038	0.009	-0.048	0.026	0.011	1	-0.002	-0.017	-0.056	-0.084	-0.004
<i>pvalue</i>	<0.001	(0.0682)	<0.001	<0.001	(0.0214)	<0.001	(0.7479)	(0.005)	(0.7023)	(0.1009)	(0.3633)
US4.FOG	-0.001	0.029	-0.032	0.007	0.008	-0.002	1	-0.038	0.116	-0.030	-0.008
<i>pvalue</i>	(0.8575)	<0.001	<0.001	(0.1584)	(0.1062)	(0.7479)	<0.001	<0.001	(0.7023)	<0.001	(0.0980)
US4.logmkvltq	0.032	-0.283	0.210	-0.232	-0.163	-0.017	-0.038	1	0.116	0.762	<0.001
<i>pvalue</i>	<0.001	<0.001	<0.001	<0.001	<0.001	(0.0005)	<0.001	<0.001	<0.001	<0.001	<0.001
US4.standardized_sentiment	0.011	-0.111	0.134	-0.143	-0.056	-0.002	0.116	0.007	0.1816	-0.014	0.057
<i>pvalue</i>	(0.0214)	<0.001	<0.001	<0.001	<0.001	(0.7023)	<0.001	(0.1816)	1	<0.001	<0.001
US4.logNoA	0.042	-0.112	0.119	-0.117	-0.084	-0.008	-0.030	0.762	0.0045	1	-0.005
<i>pvalue</i>	<0.001	<0.001	<0.001	<0.001	<0.001	(0.1009)	<0.001	<0.001	(0.0045)	<0.001	(0.2880)
US4.risk_monthly	0.014	0.116	0.091	-0.088	-0.004	-0.008	-0.032	0.057	0.138	-0.005	1
<i>pvalue</i>	(0.0041)	<0.001	<0.001	<0.001	(0.3633)	(0.0980)	<0.001	<0.001	<0.001	(0.2880)	<0.001

Note: The table presents the correlation matrix for the variables identified in Table 1. The Pearson correlation coefficients are displayed below the diagonal, while the Spearman one are displayed above. The coefficient in parentheses indicate *p*-values corresponding to the significance levels of the correlations.

Table 6: Model without interaction variable

	<i>Dependent variable:</i>
	PEAD
werrormedian	-1.186e-14*** (2.039e-15)
covid_dummy	-3.108e-17 (2.596e-16)
return	3.822e-16 (6.305e-16)
EARNTA	6.687e-15*** (9.465e-16)
loss	8.908e-17 (9.626e-17)
sd	-3.522e-15*** (1.276e-15)
STD_consensus	-1.006e-19 (5.885e-19)
as.numeric(FOG)	8.624e-20 (1.181e-18)
log(1 + mkvaltq)	-6.803e-18 (2.296e-17)
standardized_sentiment	-1.160e-15 (2.970e-15)
log(1 + NoA)	2.379e-17 (5.840e-17)
risk_monthly	1.240e-16 (8.088e-17)
Constant	-0.007*** (1.862e-16)
Observations	41,264
R ²	0.500
Adjusted R ²	0.500
Residual Std. Error	5.593e-15 (df = 41241)
F Statistic	1,874.591*** (df = 22; 41241)

The variables in the parentheses are the sd_error

*p<0.1; **p<0.05; ***p<0.01

Table 7: Model with interaction variable

	<i>Dependent variable:</i>		
		PEAD	
	All errormedian	Errormedian positive	Errormedian negative
werrormedian_covid	1.203e-14* (5.586e-15)	5.067e-15** (2.053e-15)	-2.394e-15 (1.639e-15)
werrormedian	-1.369e-14*** (5.586e-15)	-4.980e-15*** (9.354e-16)	2.400e-15*** (6.449e-16)
covid_dummy	-8.236e-17 (2.607e-16)	-4.709e-17 (6.685e-17)	-2.400e-17 (1.334e-16)
return	2.964e-16 (6.318e-16)	2.981e-16 (1.969e-16)	3.491e-16* (1.895e-16)
EARNTA	6.646e-15*** (9.466e-16)	2.393e-15*** (3.019e-16)	7.222e-17 (2.620e-16)
loss	9.123e-17 (9.626e-17)	7.386e-17** (3.047e-17)	2.685e-17 (2.656e-17)
sd	-3.519e-15 *** (1.276e-15)	-1.296e-15*** (3.812e-16)	-2.756e-15*** (3.830e-16)
STD_consensus	-1.177e-19 (5.885e-19)	-5.142e-19 (8.628e-19)	-1.278e-21 (1.046e-19)
as.numeric(FOG)	9.335e-20 (1.181e-18)	8.200e-21 (3.336e-19)	-7.866e-20 (3.876e-19)
log(1 + mkvaltq)	-6.649e-18 (2.296e-17)	-1.989e-18 (6.528e-18)	-1.483e-18 (7.348e-18)
standardized_sentiment	-1.137e-15 (2.970e-15)	- 8.903e-16 (8.346e-16)	1.113e-16 (9.945e-16)
log(1 + NoA)	2.521e-17 (5.840e-17)	2.599e-18 (1.696e-17)	-2.380e-18 (1.823e-17)
risk_monthly	1.293e-16 (2.410e-17)	1.346e-17 (2.452e-17)	-2.655e-17
Constant	-0.007*** (1.862e-16)	-0.007*** (-6.997e-03)	-0.007*** (6.015e-17)
Observations	41,264	28,388	12,111
R ²	0.500	0.500	0.500
Adjusted R ²	0.500	0.500	0.499
Residual Std. Error	5.593e-15 (df = 41240)	1.304e-15 (df = 28364)	9.783e-16 (df = 12087)
F Statistic	1,793.044*** (df = 23; 41240)	1,233.218*** (df = 23; 28364)	525.524*** (df = 23; 12087)

The variables in the parentheses are the sd_error

*p<0.1; **p<0.05; ***p<0.01

Table 8: Size comparison

	<i>Dependent variable:</i>	
	PEAD	
	Big firms	Small firms
werrormedian_covid	1.239e-15 (8.235e-15)	3.636e-15* (2.172e-15)
werrormedian	3.637e-17 (2.917e-15)	-4.416e-15*** (8.802e-16)
covid_dummy	1.389e-17 (1.907e-16)	-1.404e-18 (1.496e-16)
return	-1.000e-15 (6.608e-16)	2.052e-16 (2.638e-16)
EARNTA	1.015e-15 (1.142e-15)	2.185e-15*** (3.978e-16)
loss	8.172e-17 (9.704e-17)	2.418e-17 (4.233e-17)
sd	-2.560e-16 (1.719e-15)	-7.980e-16 (5.156e-16)
STD_consensus	-1.213e-17 (6.664e-17)	-2.559e-20 (2.109e-19)
as.numeric(FOG)	4.204e-19 (1.333e-18)	-1.683e-20 (4.896e-19)
log(1 + mkvaltq)	6.132e-18 (2.033e-17)	4.728e-18 (1.633e-17)
standardized_sentiment	-2.521e-15 (2.304e-15)	1.571e-16 (1.545e-15)
log(1 + NoA)	6.558e-17 (4.914e-17)	1.579e-18 (2.841e-17)
Constant	-6.997e-03*** (2.066e-16)	-6.997e-03 *** (1.092e-16)
Observations	20,631	20,633
R ²	0.5	0.5
Adjusted R ²	0.499	0.499
Residual Std. Error	3.134e-15 (df = 20608)	2.003e-15(df = 20610)
F Statistic	936.72*** (df = 22; 20608)	936.8*** (df = 22; 20610)

The variables in the parentheses are the sd_error

*p<0.1; **p<0.05; ***p<0.01

Table 9: Comparison analyst coverage

	<i>Dependent variable:</i>	
	PEAD	
	High Number of Analysts	Low Number of Analysts
werrormedian_covid	-7.295e-16 (4.836e-15)	-5.421e-15* (3.231e-15)
werrormedian	-1.533e-16 (2.041e-15)	6.718e-15*** (1.247e-15)
covid_dummy	1.413e-16 (1.729e-16)	3.177e-17 (1.886e-16)
return	5.213e-16 (4.899e-16)	-1.555e-16 (3.948e-16)
EARN_TA	-9.484e-16 (8.974e-16)	-2.993e-15*** (5.380e-16)
loss	-2.396e-16*** (7.598e-17)	-2.451e-17 (5.968e-17)
sd	1.193e-15 (1.236e-15)	1.305e-15* (7.095e-16)
STD_consensus	1.307e-17 (3.427e-17)	3.419e-20 (2.768e-19)
as.numeric(FOG)	1.784e-19 (9.430e-19)	-1.966e-20 (7.129e-19)
log(1 + mkvaltq)	1.014e-17 (1.646e-17)	5.021e-18 (1.656e-17)
standardized_sentiment	3.008e-16 (2.027e-15)	1.116e-16 (2.087e-15)
log(1 + NoA)	3.600e-17 (7.047e-17)	9.492e-18 (4.760e-17)
risk_monthly	1.411e-16** (6.688e-17)	-7.296e-17 (4.823e-17)
Constant	-6.997e-03*** (1.771e-16)	-6.997e-03*** (1.397e-16)
Observations	21,720	19,544
R ²	0.4999	0.499
Adjusted R ²	0.4994	0.4994
Residual Std. Error	2.792e-15 (df = 21696)	2.628e-15 (df = 19520)
F Statistic	943.30*** (df = 23; 21696)	848.694*** (df = 23; 19520)

The variables in the parentheses are the sd_error

*p<0.1; **p<0.05; ***p<0.01

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