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Distracted Analysts: Who bears the consequences?

The direct and indirect consequences of the limited attention bias in analyst forecasting

Master Thesis Financial Economics

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Abstract

Previous literature finds the limited attention bias to affect the analyst forecasting performance. The question remains, who bears the consequences? A measure based on exogenous shocks to the analyst portfolio shows that several parties suffer from the distraction of analysts. The examination of earnings forecasts discovers a vast decrease in accuracy for distracted analysts, posing a serious threat to analysts' career perspectives. Moreover, the bias hurts long-term investment strategies based on analyst sell recommendations. Next to these direct impacts, the bias has a negative indirect effect. The examination of portfolio firms finds analyst distraction to hurt firm shareholders. In periods of analyst distraction, CEOs use firm resources to conduct value-destroying mergers.

Keywords: Behavioral finance, corporate finance, analyst, limited attention, forecasts, mergers and acquisitions

Table of contents

1. Introduction

Surely at some point in your life, you have played the game memory. The game asks you to memorize a set of cards to find the matching pairs. At the start of the game, the players have not seen any of the cards, as they are all closed. Every turn, a player reveals two cards in an attempt to match the cards. If the two cards are not matching, the player closes the cards again. In small card sets, you easily recall and match the cards, but the opposite is true for larger sets. Large sets induce short-term memory loss due to the limited attention bias. Similarly, the bias deteriorates the performance of economic agents. Finance literature suggests effects for market participants with large information inflows, such as hedge fund managers, institutional shareholders and retail investors (Barber and Odean, 2008; Fang, Peress, and Zheng, 2014; Kempf, Manconi, and Spalt, 2017). In the same logic, sell-side analysts suffer from the phenomenon. They experience daily pressure from the market to issue accurate firm evaluations. Nonetheless, simple human biases negatively impact their work (Hirshleifer and Teoh, 2003). Shocks to their information environment cause distraction and thus deteriorate the forecasting performance. This deterioration hurts the investment strategies of brokerage clients and consequently the career perspectives and remuneration of the analyst (Harford, Jiang, Wang, and Xie, 2019). Besides, poor forecasting indirectly damages another group of economic agents, namely the shareholders. An externality of analyst forecasting is the alignment of management and shareholders through analyst firm monitoring. Analysts discipline managers that waste firm resources on personally beneficial strategies (Jensen and Meckling, 1976). Hence, analyst distraction fosters the misalignment of management and shareholders. This study analyzes the effect of the limited attention bias on the analyst forecasting performance and subsequently on the performance of their clients and portfolio firms. The external distraction measure sheds new light on the consequences to the analyst careers and clients returns. Furthermore, thorough studies on the portfolio firm effects are absent. Examinations on the probability of detrimental mergers and the market performance of acquirers around mergers provide a basis for future research. All outcomes of this study are relevant to a wide range of economic agents. First, small errors in forecasting due to limited attention have large consequences to analysts, as they negatively impact their career paths. Second, analyst limited attention presents a threat to clients that heavily rely on analyst output. Without considering the circumstances of the analyst and other market signals, the output of the analyst may not yield value. In the scope of the whole financial market, estimations from accredited sources of company valuations also require context. Finally, the study on firm value assesses market inefficiencies and provides essential information to their solutions. In the case of analyst distraction, monitoring effects may explain deviations from shareholder value maximization. Data on this inefficiency may guide corporate governance in their attempts to reduce agency costs.

The study of the analyst limited attention bias consequences encounters three main challenges. First, the data used in the research stems from six different vendors and an even larger number of databases. Most of these sources unfortunately do not share identification variables. Hence, the aggregation of the data involved thorough manual proceedings and checks. Second, the construction of the exogenous measure poses a challenge. No verified source publishes complete analyst portfolios and therefore studies must construct analyst portfolios with data from the I/B/E/S database. Also, the measure includes the in-portfolio stock preference of the analyst, which no previous mechanisms regarded yet. A final challenge, four separate regressions on analyst distraction yield little explanatory value. All analyses, despite the focus on different economic agents, must also serve as building blocks. Results on the forecasting accuracy show in a detailed manner that limited attention deteriorates the forecasting performance. Also, the examination of analyst recommendations suggests that analyst distraction induces poor client performance. These two inquiries credibly support the notion of analysts exerting maximum effort to reduce errors in their forecasts. Based on this assumption, the final analysis on merger strategies finds an indirect effect on the value of portfolio firms.

Literature finds accurate analysts to experience preferable career paths, which is a strong incentive to minimize their inaccuracy (Harford et al., 2019). The impact of the inaccuracy varies between different stocks due to the stocks' popularity amongst investors. Analysts focus more on stocks with higher market capitalization and institutional following in an attempt to increase their reputation. Limited attention bias hinders analysts in these attempts. This paper examines the effects of analyst distraction by constructing a portfolio shock measure. The measure marks the industry with the maximum and the industry with the minimum return in a quarter as shock industries. If the analyst portfolio contains a great share of firms in these industries, the distraction is larger for all non-shock firms in the portfolio. Also, the mechanism weights stocks based on analyst stock preference, proxied by market capitalization and institutional following. Several arguments support the rationale behind this construction. Since industry shocks induce volatility, trader attention for an industry rises and thus draws analyst attention. Also, larger volatility requires increased analyst effort to correctly evaluate the stock. Besides that, the media attention for extreme performers raises the pressure on the stock estimations, which require more analyst attention. All analyses control for fixed effects on the $industry \times quarter$ and $broker \times quarter$ to prevent variation between industry quarters and broker quarters from impacting the results. The first regression tests the effect of the limited attention bias on the earnings forecast accuracy. It regresses the proportional mean absolute forecast error, developed by Clement (1999), on the distraction proxy. Results show that a one-standard deviation increase in distraction results in a 24 basis points less accurate EPS forecast. The magnitude of the effect is equal to more than eight quarters of general analyst experience. This deterioration of the forecasting performance should caution analysts in consideration of their career perspectives but also all economic agents using earnings forecasts.

The study of EPS estimates shows the detrimental effect of analyst distraction on the forecasts of a company performance ratio. In comparison to EPS estimates, analyst recommendations convey a larger analyst sentiment regarding the mispricing of a stock. Economic agents use the recommendations due to their significant yield (Womack, 1996). The short-run returns of investment strategies based on analyst recommendations potentially arise from the effect of the recommendation on investor sentiment (Green, 2006; Jegadeesh and Kim, 2006; Moshirian, Ng, and Wu, 2009). Nonetheless, analyst recommendations address the fundamental value of a stock, as they evaluate capital budgeting decisions (Jegadeesh, Kim, Krische, and Lee, 2004). Therefore, this study examines the long-term returns of investment strategies based on analyst recommendations in periods of analyst distraction. If analyst recommendations yield value, the distraction measure must decrease the stock returns for buy recommendations and increase the stock returns for sell recommendations. This analysis only considers the effects for STRONGBUY and STRONGSELL recommendations (i.e., the extreme recommendations), as they relate to the most rigorous decisions of the analyst. Results on STRONGBUY issues suggest no significant effects for 91-day and 365-day holding periods. Next, STRONGSELL data implies no impact for the 91-day holding period, but an inferior return of 4.9 percentage points for the 365-day holding period. The results partially confirm the prediction of inferior returns in periods of analyst distraction. An analyst optimism bias may explain the insignificant effect for the STRONGBUY recommendations, as buy recommendations may already incorporate this bias (Hong and Kubik, 2003). Additionally, short-term trader sentiment rationalizes the insignificance of the 91-day period for the STRONGSELL sample. Overall, the results serve as a warning to investors to not solely depend on analyst recommendations in their investment strategies.

In a perfectly efficient capital market, both the shareholders and firm managers strive for shareholder maximization. Nonetheless, firm management theory states that CEOs seek to misappropriate firm resources for individual benefit (Jensen and Meckling, 1976). They attempt to reduce their personal portfolio risk by conducting diversifying mergers (Amihud and Lev, 1981). Analyst monitoring offers a solution to the misalignment of shareholders and firm managers (Chung and Jo, 1996; Knyazeva, 2007; Yu, 2008). Inherently, the distraction of analysts results in the pursuance of value-destroying activities for CEOs. The analysis of the impact of relaxed analyst monitoring on firm value maximization occurs in an M&A setting. Takeover data offers several advantages, as firms separately disclose merger information, CEOs authorize the deals and takeover investments are not sticky. The hypothesis states that CEOs destroy value through conducting diversifying mergers in times of analyst distraction. A first evaluation tests the probability of general, diversifying and non-diversifying mergers in times of analyst inattention. A one-standard deviation increase in distraction results in 5.1% and 17.3% rises in respectively general and diversifying mergers. Results of non-diversifying mergers offer no significant outcomes. All merger probability results confirm the hypothesis and support the literature on empire building. However, an increased merger likelihood is not inherent to value destruction. An analysis of the cumulative abnormal announcement returns explores the exact value destruction. Past literature theorizes the analyst distraction to negatively impact the announcement returns. The event period $[-1, +5]$ shows a return decrease of 49 basis points for a one-standard deviation increase in analyst distraction. A consideration of four extra days previously finds a 58 basis points lower return. The results agree with the expectation of lowered announcement returns due to analyst distraction and should caution corporate governing bodies.

This study contributes to the current analyst literature on three different aspects. First, the distraction measure sheds new light on the source of a limited attention bias for analysts. Literature agrees on the notion that the presentation of information correlates with such biases (Tversky and Kahneman, 1973; Hirshleifer and Teoh, 2003). Analysts perceive predominantly available information in the media as salient. Recent papers construct novel proxies for analyst distraction based on this notion. Driskill, Kirk and Tucker (2020) and Bourveau, Garel, Joos and Petit-Romec (2020) choose external shock mechanisms to quantify analyst inattention. This study improves the measure of Bourveau et al. (2020) by incorporating the analyst career concerns discussed in Harford et al. (2019).

Second, the contribution to the literature on the effect of limited attention on the analyst performance. General literature indicates declines in accuracy and timeliness of the estimates (Truong, 2018; Pisciotta, 2020). The inquiries of this paper investigate the effect of analyst distraction on forecast accuracy and additionally offer evidence of the effect on analyst recommendations. Central research by Womack (1996) argues recommendations to offer long-term yields due to fundamental company evaluation. This paper studies the implication of analyst distraction on this notion. Similar to Zhang (2017), the analyses are based on data of extreme recommendations (i.e., STRONGBUY and STRONGSELL). The addition of the limited attention bias to the analyst performance literature provides further detail on the value of analyst-produced information.

Third, the evidence on the effect of analyst inattention on corporate actions extends the current literature. Renowned studies on overinvestment by Jensen and Meckling (1976) and Fama (1980) provide a fundament in this area. These studies theorize an effect of monitoring bodies, such as analysts, on firm performance. Subsequent studies confirm this theory by finding a negative effect of analyst monitoring on overinvestment (Moyer, Chatfield, and Sisneros, 1989; Chung and Jo, 1996; Knyazeva, 2007; Yu, 2008). In specific, managers overinvest in attempts to diversify their personal portfolios (Amihud and Lev, 1981). This paper augments the literature by examining the implications for analysts suffering from the limited attention bias. The two-step approach reviews the source and the size of the value destruction by firm managers in times of analyst distraction.

The remainder of this paper is structured as follows. First, the theoretical framework, which reflects on the empirical background of the study. It touches upon the psychological theory, provides a broad perspective of the finance literature and zooms in on the implications for analysts. Next is the introduction of the three hypotheses of the study: the Reduced Forecast Accuracy, the Inferior Returns and the Firm Value Destruction Hypothesis. Afterward, the data and methodology sections explain the set-up of the analyses, followed by the presentation of the results. The results section contains the tables of all main regressions and their interpretations. After the concluding remarks, the limitations and further research implications conclude the study.

2. Theoretical framework

The literature on the limited attention bias comprises perspectives from different academic fields. This section reviews contributions on the psychological explanation, the general financial market implications and the direct and indirect consequences.

2.1 Limited attention in psychology

Early psychological literature discovered that people cannot process every piece of information they encounter. The field suggests a selection procedure, first examined in 1958 by Broadbent. His research argues that an individual-specific limit truncates the inflow of information before the information processing (i.e., the memory only considers incoming data until the limit is reached). The limit in the theory of Broadbent can be compared to the memory limit of a computer, which uses a set limit disregarding the content of the files. Subsequent literature offers two criticisms to his notion, namely the disregard of the data compression mechanism and the neglect of the content. The model by Broadbent addresses the first criticism by arguing that the memory fully evaluates all information. This implies that the brain only processes a few data points at once. Treisman (1964) improves the mechanism of Broadbent by introducing her Attenuation model. In the model, the brain compresses the incoming data to process all information in a simplified manner. We call this procedure *encoding* and it allows all incoming information to be presented in an easily interpretable format (Stevens and Fiske, 1995). Furthermore, Broadbent's disregard of the content does not seem rational, as people often perceive salient information more vividly. Evidence by Stevens and Fiske suggests that the encoding process prioritizes information that is salient to the individual. In further examinations of information processing, studies focus on the moment of the information selection. Logic assumes early selection, as it eases the pressure on the processing capacity. However, a large body of literature suggests thorough and late selection (Deutsch and Deutsch, 1963; Shiffrin and Gardner, 1972; Shiffrin, 1975). This hypothesis of late selection potentially explains the strong selection process that filters non-salient information. In general, the psychological literature agrees on a limited capacity of the memory, reflected in the limited attention bias. The debate continues on the exact place and mechanism of the non-salient information filter.

Schneider and Shiffrin (1977) investigate information processing of people by looking at the short-term store and the long-term store of the memory. The short-term store easily reaches its capacity limit and contains a range of new information. The long-term store has a large capacity and comprises of thoroughly studied information that the memory recalls automatically. If information does not transfer from the short-term store to the long-term store by studying it, the information disappears from the memory. The model by Schneider and Shiffrin processes information in two manners, automatic processing and controlled processing. On the one hand, automatic processing uses the information in the long-term store to perform an automated task, such as unlocking your phone. On the other hand, controlled processing refers to the processing of new information and requires active attention. An example is learning how to use a new application on your phone. The job of sell-side analysts mostly comprises repetitive tasks, which trigger the automatic processing. Analysts often use similar data to perform similar analyses to evaluate a company. However, in the case of a shock to one of their portfolio companies, the new information requires controlled processing.

The research of Schneider and Shiffrin defines two types of tasks we perform using the processed information: attention and search tasks. The attention tasks simply use the long-term store and relate to the division of attention, limited by the processing power of a person. In these tasks, two causes of performance deterioration show. First, a larger number of tasks induces worse average performance per task. Next to that, the inclusion of tasks that require relatively more focus induces *selective attention*. In this case, the limited attention capacity of a person results in overall declining performance for all other tasks. Whereas the attention tasks simply demand the attention of the analyst, search tasks additionally use the short-term memory to recall information. For these tasks, Sternberg (1966) notes an interesting link between information pool size and reaction time. He finds larger amounts of information to increase reaction time. The larger pool of information induces a more complex encoding process of data points, as they appear in a more complex environment. In response, articles by Swanson and Briggs (1969) and Simpson (1972) suggest that studying the perceived information counters the increase in reaction time. The framework by Schneider and Shiffrin argues several potential deteriorations to the analyst performance. In specific, the size of the portfolio and misperceived incoming news may impair the performance.

Later research on information processing focuses on digital information, which embodies most of the information supply to analysts. Lang (2000) proposes two reasons for the limited attention bias in mediated information. First, the subject does not possess the right resources. This occurs when a person cannot correctly process the message. For instance, you cannot follow a news report due to deficient background knowledge. Second, the subject decides to allocate too few resources due to underestimation. For example, you wrongfully perceive a television news report as very simple and therefore focus on people appearing in the background instead. Lang argues that subjects focus on information that satisfies either of two conditions: a) the information is relevant to individual goals b) the information is novel, unexpected or environment-changing. Furthermore, literature by Kruschke and Johansen (1999) suggests that people often do not correctly identify the first type of important information due to the concept of cue competition. They incorrectly identify new clues as salient and switch our focus from essential cues to irrelevant cues. The belief that the irrelevant cues are salient stems in many cases from individual overconfidence. People often believe that new information can benefit them. However, in line with Lang (2000), the lack of appropriate skills or resources prevents them from translating the information into personal benefits. Literature by Langer (1975) refers to this concept as the illusion of control. This theory supports the notion of the limited attention bias to analysts, as they process data that suffices the two conditions of Lang. Furthermore, the number of cues is high to analysts, easily resulting in a focus on non-salient cues.

2.2 Limited attention in finance

In the behavioral finance literature, the effect of the limited attention bias on different economic agents receives great attention. The first economist to highlight the limits of human attention capacity and information processing was Simon (1955). He argues that economic agents have limited processing power and adjust their attention accordingly. In the light of general economic theory, a conflict with the strong form of the Efficient Market Hypothesis (EMH) appears. The strong EMH states that all past and present information is already incorporated in stock prices, which predicts all stock prices to equal fundamental value (Malkiel, 1989). Consequently, the limited attention bias cannot be the sole cause of abnormal returns in the market. However, research indicates several deviations from the EMH due to the limited attention bias. Huberman and Regev (2001) study the effect that media attention has on company performance. In a single case, a news article in the *New York Times*, which solely discloses published information, results in a 400% increase for the stock. A subsequent study by Engelberg and Parsons (2011) provides evidence on attention effects in local areas. They examine the effect of earnings announcements for S&P500 companies and find that the media coverage of these events impacts local trading.

The effects of limited attention on company performance in behavioral finance studies mostly stem from individual traders (Barber and Odean, 2008). An example of this limited attention shows during the tech bubble of the late 1990s (Shiller, 2000). Many individual investors engaged in trades of tech shares based on the belief in the media that tech firms held growth opportunities. This trading due to the limited attention bias caused prices to rise exorbitantly before the market crash, in which many individual investors suffered great losses. Furthermore, the limited attention bias to retail investors also shows on a more regular basis in the paper of DellaVigna and Pollet (2009). They suggest lower attention on Fridays compared to other trading days. The immediate response to announcements on that day is 15% lower. However, the limited attention bias does not only apply to retail investors. Fang, Peress and Zheng (2014) focus on the effect on hedge fund managers and find increased buys for stocks highlighted in the media. Moreover, these buys resulted in poor fund performance. Also, institutional investors suffer from the bias. Kempf, Manconi and Spalt (2017) find institutional shareholders to relax their firm monitoring constraints in times of shocks to their stock portfolios.

Behavioral finance research on the limited attention bias uses psychological studies to explain their findings. Research by Peng and Xiong (2006) suggests that the scarcity of the cognitive resources results in category-learning behavior (i.e., increasing memory efficiency through assigning datapoints to different categories). Investors appear to better process broad information spectra, such as data on the industry and the total market, than firm-specific data. Peng and Xiong, Van Nieuwerburgh and Veldkamp (2009) examine the relationship between cognitive learning and the Home bias. According to them, investors choose to study information on domestic firms, as they seek a learning advantage in this familiar category. In accordance, the paper of Libby, Bloomfield and Nelson (2002) argues that, for the optimal processing of information, the presentation must be adjusted to the recipient. Presenting information in a non-familiar way increases the required processing power of the memory. Consequently, the recipient incorrectly absorbs a share of the information.

2.3 Limited attention to analysts

Analyst estimations and recommendations convey a strong message on company valuation. The estimates mitigate the information asymmetry between investors and the company management (Kelly and Ljungqvist, 2012). Information asymmetry disappears as the stock price mirrors more information on the company earnings (Francis and Soffer, 1997; Ayers and Freeman, 2003; Piotroski and Roulstone, 2004). Empirical evidence even suggests that analyst predictions have a greater influence on stock prices than growth rates based on past company performance (Stanley, Lewellen, and Schlarbaum, 1981; Linke, 1982; Cragg and Malkiel, 1982). Further research on this topic investigates the effect of analyst information on investor decisions. A large share of investors uses the information in their decision-making (Givoly and Lakonishok, 1979; Elton, Gruber and Gultekin, 1981). Thence, a substantial share of the market views analysts as an established authority in the evaluation of firm performances. Later research by Bradshaw, Ertimur and O'Brien (2017) and Loh and Stulz (2019) supports the hypothesis that capital market fluctuations highly depend on analyst-produced information. They argue that the dependency is the result of high accuracy in analyst predictions. In comparison with univariate times-series models, which provide the strongest predictive modeling, analyst predictions result in higher accuracy (Givoly and Lakonishok, 1979; Armstrong, 1983; O'Brien, 1990).

Womack (1996) argues that analyst recommendations convey a strong company evaluation and a degree of analyst sentiment. He discovers that analyst recommendations yield returns in the short-run and the long-run. In the short-run, the returns are partially the result of the changed market sentiment towards a stock after the release of the recommendation (Green, 2006; Jegadeesh and Kim, 2006; Moshirian, Ng, and Wu, 2009). In the long run, analyst recommendations relate to the underlying company fundamentals. The shock to the market sentiment disappears and returns remain (Jegadeesh et al., 2004). Womack (1996) separates the buy recommendations from the sell recommendations and finds that especially sell recommendations yield a substantial return in the long run. All findings imply that analyst recommendations are very powerful instruments. However, analysts refrain from manipulation through recommendations, as analysts with higher relative forecast accuracy experience more favorable future career opportunities and a lower probability of turnover (Mikhail, Walther, and Willis, 1999; Hong and Kubik, 2003; Ljungqvist et al., 2006).

Analysts suffer from the limited attention bias by wrongly perceiving the importance of information (Hirshleifer and Teoh, 2003). The availability bias of Tversky and Kahneman (1973) explains this focus of analysts on non-salient information. Prominently available information, often through media attention, dominates the memory of analysts. The high presence of the information mentally overweighs the likelihood (Pennington and Hastie, 1988). Consequently, the probability of an unexpected event happening is underweighted and the occurrence attracts attention (Fischhoff, Slovic, and Lichtenstein, 1978). Empirical evidence of various studies reflects the notion of an availability bias in analyst performance. A shock to an analyst portfolio company results in an increased interest in the shocked portfolio company (Truong, 2018; Bourveau et al., 2020; Pisciotta, 2020). The combination of these findings and evidence on optimal corporate decision-making creates a theoretical basis to analyze the effect on corporate actions. The OECD (1999) defines optimal corporate decision-making as the maximization of shareholder value. Jensen and Meckling (1976) agree and outline a theoretical framework on corporate decision-making in the *Theory of the firm*. They focus on the inefficiency of empire building, which implies overinvestment of available funds by managers. A theory that Fama (1980) later supports.

Finance literature on overinvestment positions corporate social responsibility (CSR) projects as a prominent overinvestment cause. Evidence on CSR projects provides two opposing views: the conflict-resolution hypothesis and the overinvestment hypothesis. The conflict-resolution hypothesis states that firms undertake CSR projects to invest in the relationship between executives and non-investing stakeholders (Calton and Payne, 2003; Freeman, Harrison, Wicks, Parmar, and De Colle, 2010; Jo and Harjoto, 2011). Consequently, for projects that reduce such conflicts, analyst coverage is positively related to CSR investments. The rationale is that the monitoring role of an analyst reveals the CSR engagement of the executives to the public, which results in the resolution of the conflict. Next, the overinvestment hypothesis argues that CSR projects are wasting limited resources and therefore induce agency costs (Barnea and Rubin, 2010; Adhikari, 2016). The overinvestment explanation suggests that executives abuse CSR projects to improve their personal reputation. This implicates a negative relationship between analyst coverage and CSR engagement, as the attention of analysts disciplines executives.

The literature on acquirer returns to mergers shows an ambiguous picture with sign swapping values for cumulative abnormal returns (Neely, 1987; Higson and Elliott, 1998). However, the returns often appear negative when empire-building serves as the motive of the merger (Jensen, 1986; Titman, Wei and Xie, 2003; Hope and Thomas, 2008). Empire building is especially present in deal firms with high levels of cash (Richardson, 2006). Also, Doukas (1995) finds a negative relationship between the free cash flow and bidder returns, as managers misappropriate firm resources. Mergers allow managers to diversify their personal portfolio risk (Jensen and Meckling, 1976; Murphy, 1985; Kanniainen, 2000; Denis and McConnell, 2003). The risk reduction strategy aims to reduce the risk incorporated in an executives’ personal portfolio (Amihud and Lev, 1981). Personal risk of the executive is closely related to the firm risk, as firms tie key performance indicators to the compensation of the CEO. Through business income diversification, executives create stable cash flows (May, 1995). In this strategy, the executive undertakes a diversifying merger to partially hedge firm-specific risk (Murphy, 1985). Morck, Shleifer and Vishny (1990) find these diversifying mergers to be detrimental to the shareholder value of the acquirer. The negative impact on the firm value results from an exogenous shift in the diversity and environment of the firm (Lamont and Polk, 2002). Capital market theory suggests that the risk reduction cannot be beneficial to shareholders, as they can personally diversify their portfolio. Moreover, the transaction costs induced by the risk reduction strategy surpass the transaction costs of personal portfolio diversification by the shareholder (Alberts, 1966; Levy and Sarnat, 1970).

Unfortunately, managers experience no repercussions by the market for empire building (Harford and Li, 2007). If corporate governance is not sufficient, third-party involvement may reduce the value destruction. Analyst monitors offer a potential solution to the misalignment of shareholders and firm management (Moyer, Chatfield, and Sisneros, 1989; Chen and Steiner, 2000). Analyst following bounds the misconduct of managers and increases firm value (Chung and Jo, 1996; Knyazeva, 2007; Yu, 2008). The monitoring role puts pressure on the attentiveness of analysts, since distraction may result in negative externalities.

3. Hypotheses

This study assumes that analysts strive for maximum accuracy in their recommendations and estimates. Two steps rationalize that belief. First, the clientele of brokerage firms expects new analyst estimates and recommendations to contain valuable information that exposes potential stock mispricing. Moreover, the same clientele evaluates the professional activities of the analyst. Thus, analyst career concerns drive the demand for correctness in their work. This correctness should particularly be reflected in earnings forecasts, as they require a more precise estimation. Although analysts care about the accuracy of earnings forecasts, it may deteriorate in the presence of distracting circumstances. Analysts are prone to the availability bias, which causes them to focus on a particular firm or industry due to its temporary prominence in their information environment. In the case of distraction to an analyst portfolio, the limited attention bias may deteriorate the accuracy of earnings forecasts.

Reduced Forecast Accuracy Hypothesis: The distraction of analysts, in the situation of external shocks to their portfolio companies, results generally in lower forecast accuracy for non-shock portfolio firms.

The Reduced Forecast Accuracy Hypothesis assumes worse quality analyst earnings estimates during periods of distraction. These forecasts often play an important role in the investment decisions of investors, as the forecasts are market-widely used in investment strategies. Though, these forecasts estimate only one important firm ratio. Buy and sell recommendations offer an opportunity to grasp the full sentiment of the analyst towards a stock. Investment strategies based on these recommendations yield significant returns in the short-run and long-run, as the recommendations carry fundamental company information. Similar to the earnings forecasts, the market often uses recommendations to evaluate the performance of analysts. Analysts must therefore issue their recommendations with care, which offers a basis to examine a personal bias. As beforementioned, many investors trade based on these recommendations, due to their added value. In the short term, the yields contain noise due to the market sentiment brought along by the recommendations. However, the stock evaluation relates to the underlying firm fundamentals, offering a yield in the long run. Thus, the effect of analyst distraction on long-term buy-and-hold strategies is evident. Extreme recommendations of STRONGBUY and STRONGSELL convey the most analyst sentiment towards a stock and therefore provide a fundament to the analysis of an association. A distracted analyst may issue recommendations less carefully, which results in lower long-term returns to recommendation-based investment strategies.

Inferior Returns Hypothesis: The distraction of analysts, in the situation of external shocks to one of their portfolio companies, results in inferior returns to their buy and sell recommendations in a long-term buy-and-hold strategy.

The primary profession of an analyst is to provide accurate estimates and recommendations to their customers. However, analyzed firms also benefit from the analyst activities. In the examination of firm benefits, the *Theory of the Firm* by Jensen and Meckling (1976) serves as a fundament. This theory states that agency costs arise when firm managers use company resources to their personal benefit in periods of loosened monitoring. Managers specifically focus on diversifying mergers in an attempt to reduce their personal portfolio risk. Since the managers' portfolio risk highly depends on the firm they manage, they diversify the firm risk to create stable personal cashflows. Jensen and Meckling argue that diversifying mergers merely result in the misalignment of shareholders and CEOs, as the mergers destroy shareholder value. The involvement of third parties, such as analyst monitors, disciplines firm managers. However, times of analyst distraction allow managers to pursue personal strategies with reduced negative consequences.

Firm Value Destruction Hypothesis: The distraction of analysts, in the situation of external shocks to one of their portfolio companies, and subsequent loosened monitoring results in the destruction of firm value through diversifying mergers.

4. Data

The data in the studied sample spans over a time range of 26 years (1992-2017). The lower bound of the range ensures complete data for all variables used in this study. The upper bound relates to a recent change in the I/B/E/S reporting standards. In 2018, I/B/E/S swapped the values of some of the analyst identification variables, which distorts inquiries. All data is on the analyst-firm-quarter level to maximize the variation in the data.

The data originates from a variety of sources. All data on the analyst[1] is from the I/B/E/S current year earnings-per-share (EPS) file, appended by the I/B/E/S recommendations file. Analyst codes identify the different analysts in the sample. These codes remain with the analysts even if they switch brokerage firms. Analysts codes do not distinguish between individuals and teams of analysts. However,

[1] All observations with missing values and zero values for the analyst ID are deleted. Similarly, all observations with missing values for all EPS-related variables are deleted.

team leaders must keep a full overview and therefore suffer from a similar bias as the individual analyst. All stock-related data, except for the extreme returns industry indicator, stems from CRSP and all company financials from Compustat[2]. The Fama and French classification divides all firms into 12 industries based on their SIC codes. Furthermore, the data on mergers stems from ThomsonOne[3]. Again, the Fama and French definition classifies all target firm industries and specifies diversifying and non-diversifying mergers. The main variable in this study relies on stock data from the website of Kenneth R. French and the I/B/E/S current-year earnings per share file. Data on the industry shock component stems from the website of French, where he publishes industry-based returns according to the 12-industry framework. This data is added to the analyst portfolios constructed with data from the I/B/E/S database. Finally, the institutional shareholder information used for the stock preference weight stems from the institutional shareholder database of Thomson Reuters.

Several adjustments prepare the data for the analyses. First, a minimum forecast horizon of zero for all EPS estimates eliminates all late estimates (i.e., estimates after the forecast period end date). Next, the maximum forecast horizon is one year according to prior literature (Clement, Koonce, and Lopez, 2007; Harford et al., 2019). Besides, only the latest forecast per analyst-firm-quarter observation remains. All analysts with fewer than six estimations in the complete time range are excluded to allow for a better comparison. The same logic excludes all analysts covering fewer than two firms[4] and all firms covered by fewer than two analysts[5].

The dataset contains a total of 2,132,473 EPS estimations and 410,868 buy-and-sell recommendations spread over 104 quarters. Those estimations are issued by 13,216 analysts, which belong to 953 different brokerage firms. Furthermore, the estimations cover 12,021 distinct US-listed firms, which conduct a total of 13,753 unique mergers.

Table 1 provides a complete overview of all descriptive statistics[6], with several notable values. The Distraction variable shows a low mean of 0.038 and median of 0.000, which can be explained by non-distraction values for 83.2% of its data. The values are mainly the result of the absence of shocks in the analyst portfolios, as many portfolios cover few different industries. The PMAFE measure shows a large maximum value of 32.747. However, further scaling may incur the loss of important explanatory value. Furthermore, to conduct a solid analysis on the effect of analyst distraction, the construction of portfolios must be accurate. If all data in the I/B/E/S regarding the identification of firms and analysts are correct, only the completeness of the portfolios can be questioned. In the dataset, the average analyst portfolio size is 13.8. Considering the portfolio size of 12.6 in a similar study by Bourveau et al. (2020), the constructed portfolios appear correct.

[2] All observations with missing values and zero values for the SIC codes are deleted.
[3] All mergers where Acquirer CUSIP is equal to Target CUSIP are deleted.
[4] A single company portfolio per definition results in a zero-distraction portfolio.
[5] Companies covered by a single analyst distort the PMAFE measure, as it compares individual forecast accuracy to firm-wide accuracy.
[6] All variables continuous variables with skewed distributions are winsorized.

Table 1 Summarization statistics

Variables	N	Mean	Median	STDV	Min	Max
Dependent variables						
PMAFE	2,132,473	0.009	-0.025	0.680	-1.000	32.747
91-day Return | S BUY	89,706	0.012	-0.001	0.283	-0.697	1.243
91-day Return | S SELL	7,961	-0.008	-0.033	0.281	-0.697	1.243
365-day Return | S BUY	89,706	0.015	-0.060	0.642	-0.974	3.652
365-day Return | S SELL	7,961	-0.002	-0.087	0.669	-0.974	3.652
Merger	2,132,473	0.033	0.000	0.179	0.000	1.000
Diversifying Merger	2,132,473	0.008	0.000	0.089	0.000	1.000
Non-diversifying Merger	2,132,473	0.025	0.000	0.156	0.000	1.000
CAR [-5,+1]	42,232	-0.008	-0.005	0.072	-0.771	0.730
CAR [-1,+5]	42,232	-0.009	-0.005	0.071	-0.554	0.473
CAR [-5,+5]	42,232	-0.009	-0.006	0.082	-0.788	0.545
Interest variable						
Distraction	2,132,473	0.038	0.000	0.122	0.000	0.988
Control variables						
Analyst						
Horizon	2,132,473	176.654	162.000	99.105	0.000	365.000
Firm Experience	2,132,473	10.494	6.000	12.298	0.000	103.000
General Experience	2,132,473	29.055	23.000	23.061	0.000	103.000
Portfolio Size	2,132,473	13.676	13.000	8.179	2.000	151.000
Different Industries	2,132,473	2.544	2.000	1.471	1.000	12.000
Firm						
Return on Assets	2,132,473	0.013	0.038	0.163	-1.138	0.299
Book to Market	2,132,473	0.856	0.507	1.568	-0.594	15.862
Cash to Assets	2,132,473	0.112	0.062	0.133	0.000	0.764
Leverage	2,132,473	0.566	0.565	0.252	0.060	1.428
Total Assets	2,132,473	7.851	7.805	1.987	0.140	15.936
Stock Volatility	2,132,473	0.224	0.183	0.181	0.058	1.751
Stock Turnover	2,132,473	1.318	0.299	2.601	0.000	15.993
Deal						
Stock Swap	42,232	0.336	0.000	0.473	0.000	1.000
Tender	42,232	0.144	0.000	0.351	0.000	1.000
Hostile	42,232	0.017	0.000	0.131	0.000	1.000
New Economy	42,232	0.224	0.000	0.417	0.000	1.000
Competing Bid	42,232	0.055	0.000	0.229	0.000	1.000
Relative Size	42,232	0.026	0.007	0.042	0.000	0.152
Target						
Target Sales Growth	42,232	0.214	0.104	0.468	-0.441	3.966
Target Book to Market	42,232	3.062	0.897	5.697	0.109	23.866
Target Return on Assets	42,232	0.087	0.070	0.080	0.000	0.563

Table 1 shows the descriptive statistics of all variables used in the main regressions. Further definitions of the variables can be found in Table A.2 of the Appendix.

5. Methods

The following section discusses the construction of the distraction variable, the methods per analysis and defines the control variables. Table A.2 in the Appendix provides a complete overview of all variables and their definitions. All company financial variables are at book value unless mentioned otherwise. Furthermore, all regressions include fixed effects on the industry, broker and 104 quarters[7]. These effects prevent the variation from being explained by differences between the industry, broker or time period of the observations. The standard errors are clustered on the analyst and firm-level to counter potential heterogeneity in the sample. Additionally, the results section reports the distraction coefficients multiplied by the distraction standard deviation. The distraction variable requires this interpretation since it does not allow an interpretation of one-unit changes[8].

5.1.1 Distraction measurement

A study of analyst limited attention requires a variable that registers temporary attention deficits of analysts. The distraction proxy is on the analyst-firm level in a given quarter and comprises of three components, namely the occurrence of an industry shock, the analyst portfolio impacted by the industry shock and the stock importance to the analyst. The industry shock (IS) component identifies shock and non-shock firms. Barber and Odean (2008) introduced the IS measure, which is further used in several studies on limited attention (Kempf, Manconi and Spalt, 2017; Bourveau et al., 2020). Next, the constructed analyst portfolios extend the measure. The distraction caused by shock firms applies equally to all non-shock firms in the analyst portfolio in a given quarter. Finally, the distraction proxy includes a weight on the relative firm importance in the portfolio. Studies on analyst attention agree that certain types of firms within a portfolio receive greater attention. Analysts prefer stocks based on career perspectives and compensation incentives. The career perspectives of analysts depend on their market-wide reputation, which heavily relies on the evaluations of institutional investors (O'Brien and Bhushan, 1990; Groysberg, Healy, and Maber, 2011). Additionally, the evaluation of institutional investors also impacts the analyst remuneration, as the evaluations guide the choice of a brokerage firm by investors (Ljungqvist et al., 2007; Maber, Groysberg, and Healy, 2014). Consequently, stocks with high institutional following receive a stronger analyst focus. Next to the interest of institutional investors, shares have another significant predictor of analyst preference, namely the market capitalization (Chung and Jo, 1996; Harford et al., 2019). By closely following larger firms, analysts gain publicity and recognition (Hong and Kubik, 2003). Thus, the distraction measure includes weights for institutional following and market capitalization. Finally, a correlation check between the analyst measure and the shareholder measure of Kempf, Manconi and Spalt (2017) ensures that the results are not driven by the

[7] The low variation in the distraction variable does not allow for stricter fixed effects.
[8] Due to the upper bound of the limit to one, further explained in section 5.1.

distraction of another important monitor, namely the shareholders. The resulting cross-correlation of 0.048 indicates that shareholder distraction does not drive the results.

In this study, the distraction variable explains the consequences of the limited attention bias. Larger values of the interest variable D indicate a larger distraction for the analyst with regards to the firm-quarter observation. The distraction proxy takes a value in the range of zero to the limit of one[9], with zero distraction for shocked firms and firms in non-shocked portfolios. Furthermore, the distraction level rises with the number of distracting firms in the analyst portfolio. All non-shock companies within a portfolio share the similar level of distraction. Equation (1) calculates D for every analyst a, firm f and calendar quarter q through:

$$(1) \qquad D_{afq} = \sum_{IND \neq IND_f} w_{aq}^{IND} \times w_{afq} \times IS_q^{IND}$$

Where *IND* represents the industry of extreme returns, following the 12 industries of Fama and French. The second term IND_f denotes the Fama and French industry of firm f. Next, w_{aq}^{IND} corresponds to the relative size of the industry IND in the portfolio of the analyst, and w_{afq} considers the level of institutional following and market capitalization of firm f. Finally, the indicator variable IS_q^{IND} equals one if an industry shock occurs in the Fama and French industry IND within a given quarter q and zero otherwise.

Equation (1) contains several carefully constructed components. Fama and French label the 12 industries for the IND and IND_f. This approach clusters the large number of industries defined by other industry classifications as DIC, NAICS and GICS, allowing for a stronger comparison. Furthermore, the condition of non-similar industries assures no link between the industry shock and company fundamentals, as it excludes the industry of the shocked firm. Next, the w_{aq}^{IND} factor divides the number of portfolio firms belonging to shock industries by the total number of firms in the portfolio, and w_{afq} represents the relative importance of the firm in the portfolio. The weighting factor does not largely affect the distraction variable, but simply puts more emphasis on certain companies within the portfolio. Equation (2) calculates the weight relative to the rest of the portfolio with the following formula:

$$(2) \qquad w_{afq} = \frac{\sum(quint.\ inst_{afq} + quint.\ cap_{afq}) + (quin.\ inst_{afq} + quint.\ cap_{afq})}{2 * \sum(quint.\ inst_{afq} + quint.\ cap_{afq})}$$

Where $inst$ (i.e., institutional following) and cap (i.e., market capitalization) represent quintiles with small value firms placed in the first quintile and large value firms placed in the fifth quintile. The values of $quint.\ inst_{afq}$ and $quint.\ cap_{afq}$ refer to the number of the quintile for a firm-analyst pair in each quarter. The numerator adds the total for the portfolio to the individual firm numbers. Next, the denominator is equal to twice the sum of the values for the total portfolio. By adding the sum of the total

[9] The distraction variable equals zero for all distracting firms. Therefore, non-zero distraction in portfolios always requires at least one non-shock firm, which limits the D from a value of exactly one.

portfolio to the numerator and the denominator, the weight does not have an extreme impact on the proxy.

5.1.2 Industry Shock measure

In line with Barber and Odean (2008), a shock industry is defined as an industry that yields either the minimum or the maximum return in a given quarter of all twelve industries. The use of this definition is rational to the research of analyst distraction because of three reasons. First, the occurrence of an industry shock increases the volatility in that industry and therefore provides potential returns to traders. In their following stock-picking decisions, traders value analyst predictions (Givoly and Lakonishok, 1979; Elton, Gruber, and Gultekin, 1981). Hence, the rising volatility offers the analyst an incentive to focus on the specific industry. Second, stocks with higher volatility require more investigation for an analyst to produce a precise estimate. Moreover, the analyst forecast dispersion is higher in these periods (Athanassakos and Kalimipalli, 2003). Thus, an analyst cannot simply rely on peer forecasts and must exert more effort to produce an estimate (Trueman, 1994). Third, behavioral finance predicts the market to focus on extreme performers due to their increased attention in the media. This shift of the focus puts higher pressure on the predictions of extreme performers. Consequently, analysts have an incentive to shift their interest to the share of extreme performers in their portfolio.

The IS variable poses a constant measure for attention-grabbing events in different industries. Examples of these events are changes in the competitive nature of the industry, such as the tech bubble of 2000 and the banking crisis of 2007 (Kempf, Manconi, and Spalt, 2017). These events result in distraction to analyst portfolios. Table A.1 shows an overview of all extreme return industries across the 104 different quarters. Industries 6 (Business Equipment) and 7 (Telephone and Television Transmission) closely relate to the tech bubble of 2000, showing extreme maximum returns until the bubble bursts and extreme minimum returns afterward. Additionally, industry 11 (Finance) shows extreme minimum returns as the financial crisis commences in the final quarter of 2007.

5.2 Forecast accuracy

The first analysis tests whether a higher distraction level results in lower forecast accuracy. The dependent variable was developed by Clement (1999) and used in various studies (Green, Jame, Markov and Subasi, 2014; Bourveau et al., 2020). The measure, called the proportional mean absolute forecast error *($PMAFE_{afq}$)*, accounts for differences in companies and time and thus allows for a comparison between different analysts (Ke and Yu, 2006). The $PMAFE_{afq}$ measures forecast accuracy relative to other analysts following the same firm in that quarter based on EPS estimates. It measures the difference between the absolute forecast error (AFE_{afq}) and the mean absolute forecast error of all analysts following the company in a given quarter ($MAFE_{fq}$). Furthermore, equation (3) scales the difference by the $MAFE_{fq}$ to prevent a large impact of heteroskedasticity. Equations (3) and (4) have the following structure:

(3) $AFE_{afq} = Absolute\ (Estimate\ EPS_{afq} - Actual\ EPS_{afq})$

(4) $PMAFE_{afq} = \left(AFE_{afq} - MAFE_{fq}\right) / MAFE_{fq}$

Where AFE_{afq} corresponds to the absolute value of the forecast error for analyst a of firm f in quarter q. $MAFE_{fq}$ equals the mean of the AFE_{afq} for all analysts covering the firm in the given quarter. Furthermore, $PMAFE_{afq}$ covers the proportional difference between the estimate of analyst a and the firm-quarter average. From equation (4) follows that lower values of $PMAFE_{afq}$ relate to higher forecast accuracy of the analyst with -1 as its lower bound. The $PMAFE_{afq}$ functions as the independent variable in a multivariate linear regression model:

(5) $PMAFE_{afq} = \beta_1 + \beta_2 D_{afq} + \beta_3 Controls\ Analyst_{afq} + \gamma + \varepsilon_{afq}$

Model (5) uses a set of control variables associated with the forecasting ability of the analyst and adds fixed effects γ[10]. The first control variable *Forecast Horizon* considers the difference between the estimates' time of issuance and the forecast period end date. The extra time and information available in the horizon period generally improve analyst accuracy (Bandyopadhyay, Brown, and Richardson, 1995; Jacob, Lys, and Neale, 1997). Next, two measures of learning by the analyst, based on psychological studies. Learning improves the reaction time of people when regarding large doses of information (Swanson and Briggs, 1969; Simpson, 1972). Clement (1999) supports this argument and suggests that the experience of the analyst positively impacts the forecasting ability. The variable *General Experience*, introduced by Mikhail, Walther, and Willis (1997), reflects the overall experience the analyst has by the number of quarters since their first issued estimate. In further research, Mikhail, Walther and Willis (2003) review firm-specific learning by the analyst and find it to positively impact the preciseness of forecasts through less underreaction. Therefore, the regression contains the control variable *Firm Experience*, equal to the number of quarters forego since the first estimate of the firm by the analyst. As beforementioned in section 2.1, the complexity of the analyst portfolio affects the analyst performance. The control variable *Portfolio Size,* counting the number of unique firms in an analyst portfolio, originates from an influential article by Clement (1999). He agrees with the work of Sternberg (1966), which argues an increase in the information inflow of people to result in slower processing and reaction time. In specific, Clement (1999) finds that the analyst portfolio size is negatively associated with the forecast ability of the analyst. In the same study, he argues the number of different industries in the analyst portfolio to be negatively related to the forecasting performance. Consequently, the final

[10] The general fixed effects throughout the study are on the industry, broker and quarter.

control variable in the forecast accuracy analysis is *Different Industries*, which reflects the number of different industries in an analyst portfolio according to the Fama and French classification.

5.3 Analyst recommendations

The market-adjusted (defined in section 5.4) buy-and-hold returns operate as the response variable in the analysis of returns to investment strategies based on analyst recommendations. Similar to Zhang (2017), separate analyses explore the effect of the buy and sell recommendations of analysts. The range of possible analyst recommendations is as follows, STRONGBUY, BUY, HOLD, SELL and STRONGSELL. Only STRONGBUY and STRONGSELL recommendations serve as response variables in this study, as convey the most information on the analyst sentiment regarding a stock. Thus, these returns experience the largest impact in times of distraction. Equations (6) and (7) define the following multivariate linear regression models:

(6) $$Return \mid STRONGBUY_{afq} = \beta_1 + \beta_2 D_{afq} + \beta_3 Controls\ Analyst_{afq} + \beta_4 Controls\ Firm_{afq} + \gamma + \varepsilon_{afq}$$

(7) $$Return \mid STRONGSELL_{afq} = \beta_1 + \beta_2 D_{afq} + \beta_3 Controls\ Analyst_{afq} + \beta_4 Controls\ Firm_{afq} + \gamma + \varepsilon_{afq}$$

In model (6), the dependent variable represents the market-adjusted buy-and-hold returns of the *STRONGBUY* recommendations of analyst a for firm f in quarter q. The model regresses 91-day returns and 365-day returns on the distraction measure along with sets of control variables on the analyst and the firm and. Similarly, model (7) regresses the 91-day returns and 365-day returns of *STRONGSELL* recommendations on the distraction proxy. Both models (6) and (7) add the standard fixed effects γ. The set of analyst control variables in models (6) and (7) is equal to model (5). Furthermore, regarding the firm controls, the profitability of a firm is commonly known to be a predictor of firm stock returns (Pástor and Pietro, 2003; Akbas, Jiang, and Koch, 2017). Therefore, *Return on Assets* divides the net income by the total asset base. Next, the book-to-market ratio of a firm indicates the under and overvaluation of the stock. *Book to Market* considers this ratio in the regression. Besides, firms need to possess cash reserves for uncertainty and investment opportunities. Greater levels of cash holdings potentially unlock large returns (Autukaite and Molay, 2011; Im, Park, and Zhao, 2017). *Cash to Assets* scales the cash holdings by the total assets base. Additionally, the literature argues a large effect of firm size, often reflected by the total asset base, on stock returns (Schwert, 1983; Barber and Lyon, 1997). Due to the right skewness of the variable, *Total Assets* is equal to the logarithm of the total asset base. The firm's financial structure impacts stock returns based on the present investment opportunities (Gomes and Schmid, 2010). *Leverage* measures the ratio of total debt to total assets. Finally, two variables control for differences in share characteristics. Stock liquidity relates to the supply and demand of stocks and thus the stock price variation (Datar, Naik, and Radcliffe, 1998; Amihud, 2002). Therefore, *Stock Turnover*¸ estimated by the quarterly stock trades divided by market capitalization considers the liquidity. Also, *Stock Volatility*, equal to the quarterly stock volatility, accounts for the explanatory value of volatility in predicting stock returns (French, Schwert, and Stambaugh, 1987).

5.4 Mergers

This section describes the examination of analyst distraction and corporate actions in an M&A setting. Merger data offers several advantages in the study of CEO actions. The high discretion of takeovers results in the publication of the exact announcement dates. Also, the characteristics of the deal are often separately registered and takeover investments do not embody constant expenditures of the firm. The latter makes it reasonable to argue that the investment is a result of the circumstances. Finally, the CEO is ultimately responsible for the finalization of a merger, rationalizing the link between CEO actions and analyst inattention.

5.4.1 Merger probability

Three different response variables on mergers explain the differences between diversifying and non-diversifying mergers. The adopted three linear probability models look as follows:

(8) $$Merger_{afq} = \beta_1 + \beta_2 D_{afq} + \beta_3 Controls\ Firm_{afq} + \gamma + \varepsilon_{afq}$$

(9) $$Diversifying\ \ Merger_{afq} = \beta_1 + \beta_2 D_{afq} + \beta_3 Controls\ Firm_{afq} + \gamma + \varepsilon_{afq}$$

(10) $$Non - diversifying\ Merger_{afq} = \beta_1 + \beta_2 D_{afq} + \beta_3 Controls\ Firm_{afq} + \gamma + \varepsilon_{afq}$$

The dependent variable in models (8), (9) and (10) is a binary factor on the analyst-firm level that equals one in the case of respectively a general, diversifying or non-diversifying merger in the calendar quarter. All three models use several general control variables on firm financials and standard fixed effects γ. Although the firm controls are repeated, the remainder of this paragraph provides a rationale for the context of mergers. First, the variable *Return on Assets* considers the profitability of the acquirer. High profitability permits managers of bidder firms to conduct more financial investments, such as mergers (Malmendier and Tate, 2008). Next, *Book to Market* controls for firms that conduct mergers to benefit from stock overvaluation. A relatively high market valuation of company stock drives firms to takeover companies with a lower relative valuation (Rhodes–Kropf, Robinson, and Viswanathan, 2005; Ismail, Abdou, and Annis, 2011). Furthermore, many finance articles argue mergers to be valuable in times of cash abundance (Jensen, 1986; Malmendier and Tate, 2008). *Cash-to-*Assets accounts for the level of cash, scaling the cash holdings by the total assets base. Kempf, Manconi and Spalt (2017) argue that firm size positively links to merger probability. Merger strategies arise from greater resources at larger firms, but also defense mechanisms against takeovers from other firms (Gorton, Kahl, and Rosen, 2009). *Total Assets* serves as a proxy of firm size. Last, *Leverage* considers the financial structure of the firm.

Kaplan and Zingales (1997) argue the financial structure to impose restrictions on firm investments, such as mergers.

5.4.2 Merger performance

An increased chance of a diversifying merger is not strictly inherent to value destruction. Therefore, the final analysis is on the effect of the mergers on firm value. Specifically, the cumulative abnormal returns (CARs) around the announcement of the merger. The CARs are estimated with the market-adjusted approach, preferred by MacKinlay (1997) and Cable and Holland (1999) in an examination of event study techniques (Leij, 2019). An estimation period of $[-180, -30]$ determines the normal returns. The event itself is not included in this window, since this may result in distorted normal returns (Binder, 1998). The abnormal returns result from subtracting the normal return from realized returns. Three CAR_{ft} event windows $[-5, +1]$, $[-1, +5]$, $[-5, +5]$ serve as the dependent variable in the multivariate linear regressions:

(11) $CAR_{ft[-5,+1]} = \beta_1 + \beta_2 D_{afq} + \beta_3 Controls\ Firm_{afq} + \beta_4 Controls\ Deal_{afq} + \beta_5 Controls\ Target_{afq} + \gamma + \varepsilon_{afq}$

(12) $CAR_{ft[-1,+5]} = \beta_1 + \beta_2 D_{afq} + \beta_3 Controls\ Firm_{afq} + \beta_4 Controls\ Deal_{afq} + \beta_5 Controls\ Target_{afq} + \gamma + \varepsilon_{afq}$

(13) $CAR_{ft[-5,+5]} = \beta_1 + \beta_2 D_{afq} + \beta_3 Controls\ Firm_{afq} + \beta_4 Controls\ Deal_{afq} + \beta_5 Controls\ Target_{afq} + \gamma + \varepsilon_{afq}$

Where the CAR_{ft} is on the firm-level f and in different time windows t. The three models control for characteristics of the acquiring firm, target firm and deal, next to the standard fixed effects γ. Controls on the acquirer are similar to the firm controls used in the linear probability models. Furthermore, target and deal controls stem from merger returns literature (Moeller, Schlingemann and Stulz 2004; Ben-David, Graham, and Harvey, 2007; Baker, Pan and Wurgler, 2012). The controls on the deal characteristics include the dummy variables *Stock Payment*, equal to one for stock-financed payments, *Tender*, equal to one for tender offers, *Hostile*, equal to one for a hostile takeover, *Competing Bid*, equal to one in the case of competing offers, and *Diversifying Merger*, equal to one for diversifying mergers. Also, *Relative Size* considers the size of the deal scaled by the firm size (i.e., the total asset base) of the acquirer. Next, three variables control for the effect of target firm characteristics on returns. Large sales growth of a target firm induces poor announcement period returns (Morck, Shleifer, and Vishny, 1990). Therefore, *Target Sales Growth* corresponds to the sales growth over the past 5 years. Also, *Target Book to Market* considers potential stock mispricing and *Target Return on Assets* accounts for effects of the profitability.

6. Results

The following section discusses the main results of the study[11]. First, a test with regards to the Reduced Forecast Accuracy Hypothesis. Forecasting errors in the EPS estimations view the effect of analyst distraction in detail. The hypothesis predicts analysts to deliver lower quality forecasts for larger distraction levels. Next, an examination of the returns to an investment strategy following analyst recommendations checks the Inferior Returns Hypothesis. The hypothesis argues limited attention to result in lower yields. Finally, two analyses discuss merger probability and merger performance in periods of analyst distraction. The Firm Value Destruction Hypothesis suggests the reduced monitoring of the firm to allow value destruction through diversifying mergers by CEOs.

6.1 Forecast accuracy

The limited attention bias explains deteriorating analyst forecasting performances. The next section investigates this theory by exploring the analyst limited attention bias impact on the measure of forecast performance, the proportional mean absolute forecast error (PMAFE).

A linear multivariate model regresses the PMAFE on the analyst distraction proxy, where the response variable takes a value of -1 when no error occurs. In the case of an error, the measure increases relatively to the errors of other analysts covering the same firm in a quarter. The Reduced Forecast Accuracy Hypothesis expects a positive association between analyst distraction and the PMAFE. The model controls for several analyst-level variables, discussed in section 5.2. The standard fixed effects account for the variation caused by differences in broker, industry and quarter and standard errors are clustered on the analyst and firm-level. Additionally, Table A.3 in the Appendix presents a robustness check including the analyst controls mentioned in Table A.2. The results point in the same direction.

Table 2 shows the results of the linear multivariate analysis, where the first and second columns display the results from the regressions with solely broker fixed effects. The positive relationship between analyst distraction and forecast errors supports the results in the following column. Model (3) shows a positive significant relationship between Distraction and the PMAFE. The correlation of 1.986 is significant on the 5% level. This finding implies that a one-standard deviation increase from the mean results in 24 basis points ($= 0.12 * 1.986$) less accurate forecasts.

The results in Table 2 accept the Reduced Forecast Accuracy Hypothesis, as the earnings forecasts deteriorate in times of distraction. Although the deterioration is not large, these small differences matter in the finance environment of analysts. Mikhail, Walther and Willis (1999) find a 3.35% higher chance of analyst turnover for a one-standard deviation decrease in relative forecast

[11] The research design requires measurement of economic effects in one-standard deviation increases, further explained in section 5.

accuracy. In further perspective, the forecast error resulting from a one-standard deviation increase in distraction is equal to more than eight quarters of general analyst experience.

Table 2. Analyst forecast accuracy

	(1)	(2)	(3)
Distraction	1.894[a] (3.12)	2.143[a] (3.16)	1.986[b] (2.73)
Horizon	0.011[a] (14.06)	0.023[a] (18.84)	0.023[a] (18.81)
Firm Experience	-0.039[a] (-5.04)	-0.034[a] (-4.56)	-0.035[a] (-4.63)
General Experience	0.020[a] (2.58)	0.023[b] (2.74)	0.023[b] (2.79)
Portfolio Size	0.035 (1.66)	0.018 (0.96)	0.017 (0.87)
Different Industries	0.003 (0.20)	0.094 (0.94)	0.114 (1.11)
Industry FE	No	No	Yes
Broker FE	Yes	Yes	Yes
Industry-quarter FE	No	No	Yes
Broker-quarter FE	No	Yes	Yes
Quarter FE	No	Yes	Yes
N	2,093,047	2,092,491	2,092,491
R^2	0.012	0.030	0.031

Table 2 shows the results of linear multivariate models, where the dependent variable is the Proportional Mean Absolute Forecast Error (PMAFE) from Clement (1999). Negative values of the Relative Forecast Error indicate a smaller relative forecast error. The significance of the coefficients is displayed by *a (<0.01), b (<0.05)* and *c (<0.010),* with the exact t-values presented underneath the coefficients. Differences in the N-term stem from the linear model dropping singleton observations. All models are robust to double-clustering standard errors on the firm and analyst level. The variables are further defined in Table A.2 of the Appendix.

6.2 Analyst recommendations

The previous section reviewed earnings estimates, which serve as an instrument to many investment strategies. However, since they only evaluate the earnings management of a company, this section switches towards a broader view, namely analyst recommendations. The correctness of the recommendations highly matters to analysts, as many important investors follow the advice in their strategies. The inquiries only include STRONGBUY and STRONGSELL recommendations, as they convey the strongest message on mispricing.

The study of analyst recommendations builds on the assumption that recommendations yield value. STRONGBUY recommendations should therefore outperform STRONGSELL recommendations in the studied sample. Statistics in Table 1 show the buy-and-hold returns calculated by the market-adjusted model for two different holding periods. The STRONGBUY group denotes a 91-day return of 0.012 and a 365-day return of 0.015, next to negative returns for both holding periods of the STRONGSELL group. These statistics confirm the assumption of predictive skills. All median values appear negative, implying fewer positive returns in total. Overall, Table 1 validates the theory that analyst recommendations yield value to investors.

Table 3. Analyst recommendations

	91-day Return | S BUY	91-day Return | S SELL	91-day Return | S BUY	91-day Return | S SELL	365-day Return | S BUY	365-day Return | S SELL	365-day Return | S BUY	365-day Return | S SELL
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Distraction	0.011	0.008	-0.005	0.109	-0.051	0.247[c]	-0.010	0.412[b]
	(0.84)	(0.14)	(-0.35)	(1.42)	(-1.60)	(1.71)	(-0.30)	(2.34)
Return on Assets	0.274[a]	0.213[a]	0.262[a]	0.208[a]	0.525[a]	0.301[a]	0.497[a]	0.304[a]
	(41.83)	(9.84)	(40.39)	(8.97)	(35.21)	(5.85)	(33.30)	(4.61)
Book to Market	0.009[a]	0.008[b]	0.009[a]	0.011[a]	0.049[a]	0.037[a]	0.047[a]	0.042[a]
	(13.75)	(2.01)	(13.35)	(4.64)	(31.98)	(7.42)	(30.70)	(8.14)
Cash to Assets	0.176[a]	0.186[a]	0.175[a]	0.171[a]	0.425[a]	0.487[a]	0.370[a]	0.484[a]
	(23.98)	(5.58)	(21.92)	(4.85)	(23.06)	(5.43)	(20.19)	(5.73)
Total Assets	-0.004[a]	0.002	-0.003[a]	0.002	-0.010[a]	-0.004	-0.009[a]	0.001
	(-5.24)	(0.62)	(-4.66)	(0.81)	(-6.67)	(-0.52)	(-5.56)	(0.52)
Leverage	0.047[a]	0.014	0.046[a]	0.055[b]	0.162[a]	0.185[a]	0.157[a]	0.176[a]
	(10.05)	(0.79)	(9.66)	(2.40)	(15.09)	(3.94)	(14.27)	(3.94)
Stock Turnover	-0.002[c]	-0.002[c]	-0.001	-0.000	-0.004[a]	0.001	-0.005[b]	0.001
	(-3.99)	(-1.79)	(-0.59)	(-0.89)	(-5.65)	(0.58)	(-2.02)	(0.58)
Stock Volatility	-0.003	0.006	0.004	0.001	-0.001	0.001	-0.015[a]	0.218[b]
	(-0.70)	(0.64)	(0.61)	(1.03)	(-0.51)	(0.10)	(-3.00)	(2.00)
Firm Experience	0.001	0.001	0.001[c]	0.001	0.001[a]	0.001	0.001[a]	0.001
	(1.17)	(0.67)	(1.84)	(1.46)	(3.33)	(0.98)	(3.16)	(1.05)
General Experience	-0.001	-0.001[a]	-0.000	-0.001[c]	-0.001	0.001	-0.001	0.000
	(-0.82)	(-3.58)	(-1.27)	(-1.84)	(-0.77)	(0.25)	(-1.51)	(0.11)
Portfolio Size	0.001[b]	0.001	0.001[b]	0.001	0.001[a]	-0.003	0.001[a]	-0.002
	(2.56)	(0.10)	(2.51)	(0.72)	(2.69)	(-1.16)	(3.55)	(-1.06)
Different Industries	-0.001	0.001	-0.001	-0.005	-0.001	-0.009	-0.001	-0.009
	(-0.89)	(0.33)	(-0.34)	(-1.15)	(-0.23)	(-0.94)	(-0.51)	(-0.90)
Industry FE	No	No	Yes	Yes	No	No	Yes	Yes
Broker FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-quarter FE	No	No	Yes	Yes	No	No	Yes	Yes
Broker-quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	86,407	6,298	86,407	6,074	86,407	6,298	86,407	6,074
R^2	0.1807	0.322	0.2536	0.448	0.185	0.352	0.262	0.4821

Table 3 shows the results of linear multivariate models, where the dependent variables are the buy-and-hold returns for either a 91-day or 365-day holding period. Furthermore, the data is separated into two samples, one comprises STRONGBUY (i.e., S BUY) recommendations and another of STRONGSELL recommendations (i.e. S SELL). The significance of the coefficients is displayed by *a (<0.01), b (<0.05)* and *c (<0.010)*, with the exact t-values presented underneath the coefficients. Differences in the N-term stem from the linear model dropping singleton observations. All models are robust to double-clustering standard errors on the firm and analyst level. The variables are further defined in Table A.2 of the Appendix.

The results on analyst recommendations stem from four multivariate linear regressions. In these regressions, buy-and-hold returns serve as the dependent variable. The regressions separate the STRONGBUY and STRONGSELL recommendations and also distinctly view the 91-day and 365-day buy-and-hold returns. Furthermore, the sample of STRONGBUY recommendations is larger than the sample of STRONGSELL recommendations, which is in line with the average market growth over the years and the analyst optimism bias (Cowen, Groysberg, and Healy, 2006; Mola and Guidolin, 2009). The Inferior Returns Hypothesis predicts the investment strategies to yield inferior returns in times of distraction. This implies a negative coefficient for distraction in the STRONGBUY regressions and a positive coefficient in the STRONGSELL regressions. All regressions include fixed effects on the broker, industry and quarter and cluster standard errors by firm and analyst.

Table 3 displays the results from the different adopted models. The first four columns show the results of the 91-day returns. The two specifications on the STRONGBUY recommendations present insignificant effects, regardless of the fixed effects. Similarly, the distraction coefficients in the STRONGSELL models are not significant but agree on the predicted sign for the distraction variable, and are of greater magnitude. The next four specifications consider the 365-day returns as the response variable. Results on the STRONGBUY data reveal the expected negative coefficient for the distraction variable, which implicates inferior returns. Nonetheless, similar to the first four specifications, the specifications present no significant coefficient. On the contrary, the results for the STRONGSELL data with 365-day returns are significant. The greater magnitude observed for the 91-day returns data translates to a significant positive relationship for the longer holding period. Table 3 displays a coefficient of 0.412 with significance on the 0.05 level for the model with the heaviest fixed effects. A one-standard deviation increase in distraction results in a 4.9 percentage points ($= 0.12 * 0.412$) higher return to a 365-day holding period after a STRONGSELL recommendation. In the light of the sell recommendation, the 4.9 percentage points are viewed as the loss to a shorting strategy.

The results partially accept the Inferior Returns Hypothesis, with only inferior returns for the group of 365-day STRONGSELL recommendations. In the light of an average return of 0.002 to a shorting strategy in Table 1, the 4.9 percentage points inferior return has a substantial economic impact. The insignificance for the 91-day holding period may be the result of the investor sentiment caused by the recommendation, which cancels the distraction effects. In the long-term, the noise does not distort the effects anymore. Though, the long-term STRONGBUY recommendations show no inferior returns. This difference between the effects in the STRONGSELL and the STRONGBUY group is in line with the analyst optimism bias (Cowen, Groysberg, and Healy, 2006; Mola and Guidolin, 2009). Analysts more often wrongfully issue STRONGBUY recommendations, regardless of distraction, due to the optimism bias. Thus, analyst STRONGBUY recommendations in periods of distraction experience a reduced negative effect.

6.3 Mergers

This section documents the effect of analyst inattention on corporate actions. Next to the advising role to their clients, analysts add value by serving as a firm monitor. In general, a CEO strives to maximize the value of the shareholders. However personal incentives, such as empire building, may deviate CEOs from this strategy. The Firm Value Destruction Hypothesis argues that the inattention of analysts results in value-destroying activities by CEOs. Two analyses carefully review this statement. First, linear probability models with binary dependent variables on general, diversifying and non-diversifying merger occurrence examine the link between analyst distraction and different mergers. Next, a multivariate regression uses cumulative abnormal merger returns to establish the magnitude of the value destruction.

6.3.1 Merger probability

Value destruction theories on empire-building argue that managers have individual motives to diverge from shareholder value maximization. CEOs use company resources to diversify the company, granting them diversification of their personal portfolio risk. A first analysis tests the probability of different mergers when analyst monitoring constraints loosen. The Firm Value Destruction Hypothesis predicts a surge in the probability of diversifying mergers in times of analyst distraction.

The analysis describes the impact of analyst distraction on merger occurrence, distinguishing diversifying mergers from non-diversifying mergers. The linear probability model regresses a binary variable, equal to one if a merger occurs, on the distraction variable next to several controls on the acquirer. All analyses include the common fixed effects and the standard errors are clustered at the analyst and firm-level. Finally, Table A.4 in the Appendix contains a robustness check including the analyst controls mentioned in Table A.2. The regression finds similar results.

Table 4 shows the results for the three different types of mergers. The output from the models (1), (2) and (3) serves as a support to the models with the heaviest fixed effects. General merger activity positively correlates with analyst distraction. The coefficient of 0.014 in model (4) implies a 5.1% ($= 0.014 * 0.12/3.33\%$[12]) rise in overall merger activity for a one-standard deviation increase from the distraction mean. Next, the models on diversifying and non-diversifying mergers explain more about the nature of the merger activity. Model (5) indicates a higher probability of diversifying mergers in periods of analyst distraction. The specification including the heaviest fixed effects shows that a one-standard deviation increase, relative to the mean, results in a 17.0% ($= 0.063 * 0.24 * 0.09/0.80\%$[13]) surge in the diversifying merger probability. Model (6), with the non-diversifying merger response variable, shows that a one-standard deviation increase from the distraction mean results in a -0.5% ($= -0.002 * 0.76 * 0.09/2.53\%$[14]) lower likelihood of a non-diversifying merger. Moreover, this value is not significantly different from zero at any level.

The Firm Value Destruction Hypothesis predicts value-destroying merger activities by CEOs as a result of analyst distraction. The section on merger probability finds a higher probability of general mergers and specifically diversifying mergers in periods of distraction. These findings support the hypothesis as finance literature perceives diversifying mergers as value-destroying. The increase in diversifying merger activity potentially suggests a lack of monitoring. However, these findings do not

[12] Conditional on the occurrence of a merger to provide a better comparison
[13] Conditional on the occurrence of a diversifying merger to provide a better comparison
[14] Conditional on the occurrence of a non-diversifying merger to provide a better comparison

necessarily imply value destruction. In order to completely confirm the Firm Value Destruction Hypothesis, the next section analyzes the CARs surrounding the merger announcement.

Table 4. Merger probability

	Merger	Diversifying Merger	Non-diversifying Merger	Merger	Diversifying Merger	Non-diversifying Merger
	(1)	(2)	(3)	(4)	(5)	(6)
Distraction	0.016[a]	0.065[a]	-0.001	0.014[b]	0.063[a]	-0.002
	(2.61)	(3.03)	(-0.17)	(2.28)	(2.88)	(-0.57)
Acquirer ROA	-0.016[a]	-0.033[a]	-0.011[a]	-0.016[a]	-0.032[a]	-0.011[a]
	(-4.75)	(-3.87)	(-2.87)	(-4.49)	(-3.76)	(-2.82)
Book-to-Market	-0.005[a]	-0.004[a]	-0.005[a]	-0.005[a]	-0.004[a]	-0.004[a]
	(-13.08)	(-5.89)	(12.40)	(-12.58)	(-5.50)	(-11.39)
Cash-to-Assets	0.019[a]	0.028[a]	0.016[a]	0.021[a]	0.025[a]	0.019[a]
	(4.12)	(3.02)	(2.94)	(4.51)	(2.97)	(3.41)
Total Assets	0.018[a]	0.024[a]	0.016[a]	0.019[a]	0.021[a]	0.017[a]
	(16.43)	(10.13)	(13.86)	(16.84)	(10.07)	(14.30)
Leverage	-0.021[a]	-0.036[a]	-0.014[a]	-0.021[a]	-0.034[a]	-0.016[a]
	(-5.27)	(-4.89)	(-3.60)	(-5.56)	(-4.78)	(-3.99)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Broker FE	No	No	No	Yes	Yes	Yes
Industry-quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Broker-quarter FE	No	No	No	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
N	2,060,855	2,060,855	2,060,855	2,060,236	2,060,236	2,060,236
R^2	0.051	0.023	0.040	0.061	0.032	0.050

Table 4 shows the results of linear probability models, where the dependent variables are indicator variables equal to one for the occurrence of different mergers (i.e., general, diversifying and non-diversifying merger) and zero for no merger occurrence. The columns on diversifying and non-diversifying mergers are divided by the chance of a diversifying (24%) or non-diversifying merger (76%) under the condition that a general merger occurs. The significance of the coefficients is displayed by *a (<0.01), b (<0.05)* and *c (<0.010)*, with the exact t-values presented underneath the coefficients. All models are robust to double-clustering standard errors on the firm and analyst level. The variables are further defined in Table A.2 of the Appendix.

6.3.2 Merger performance

The Firm Value Destruction Hypothesis expects analyst distraction to result in value destruction by CEOs of portfolio firms. In an efficient market, negative cumulative abnormal announcement returns signal such value destruction.

Three multivariate models analyze the damage of mergers in periods of analyst inattention. In the models, market-adjusted CARs serve as the output variables. The study uses three different event windows: $[-5, +1]$, $[-1, +5]$ and $[-5, +5]$. Furthermore, the regression controls for the acquirer, deal and target. Similar to the other analyses, the fixed effects are on the industry, broker and calendar quarter. All three regressions include standard errors clustered by analyst and firm. Furthermore, Table A.5 in the Appendix presents a robustness check including the analyst controls mentioned in Table A.2. The results of Table A.5 agree with the outcomes in this section.

Table 5. Merger performance

	[-5,+1]	[-1,+5]	[-5,+5]	[-5,+1]	[-1,+5]	[-5,+5]
	(1)	(2)	(3)	(4)	(5)	(6)
Distraction	-0.020	-0.027	-0.041^{c}	-0.023	-0.041^{c}	-0.049^{c}
	(-1.19)	(-1.37)	(-1.76)	(-1.11)	(-1.73)	(-1.71)
Return on Assets	0.027	0.070	0.079	0.027	0.071	0.083
	(0.49)	(1.30)	(1.15)	(0.49)	(1.32)	(1.19)
Book to Market	-0.001	0.003	0.002	-0.002	0.002	0.002
	(-0.44)	(1.20)	(0.76)	(-0.61)	(0.89)	(0.61)
Cash to Assets	0.002	-0.008	0.002	0.002	-0.002	0.011
	(0.11)	(-0.39)	(0.10)	(0.07)	(-0.09)	(0.48)
Total Assets	-0.001	-0.003^{b}	-0.002^{c}	-0.001	-0.003^{a}	-0.002^{c}
	(-0.75)	(-2.54)	(-1.66)	(-0.87)	(-2.89)	(-1.89)
Leverage	0.010	0.030^{b}	0.028^{c}	0.012	0.034^{b}	0.033^{c}
	(0.68)	(2.02)	(1.87)	(0.83)	(2.23)	(1.88)
Stock Swap	-0.025^{a}	-0.026^{a}	-0.028^{a}	-0.024^{a}	-0.026^{a}	-0.027^{a}
	(-5.83)	(-6.50)	(-5.83)	(-5.85)	(-6.33)	(-5.66)
Tender Offer	0.007	0.003	0.010^{c}	0.006	0.003	0.008
	(1.39)	(0.60)	(1.69)	(1.11)	(0.57)	(1.41)
Hostile Takeover	-0.015^{c}	-0.034^{a}	-0.031^{a}	-0.018^{c}	-0.034^{a}	-0.035^{a}
	(-1.65)	(-2.96)	(-2.85)	(-1.93)	(-3.22)	(-3.08)
New Economy	-0.006	-0.010^{c}	-0.009	-0.004	-0.001	-0.009
	(-0.74)	(-1.75)	(-1.11)	(-0.51)	(-1.59)	(-1.06)
Competing Bid	-0.004	-0.005	-0.007	-0.005	-0.005	0.008
	(-0.64)	(-0.68)	(-0.90)	(-0.78)	(0.79)	(1.12)
Diversifying Merger	0.006	0.003	0.001	0.004	0.001	-0.002
	(1.15)	(0.64)	(0.09)	(0.82)	(0.24)	(-0.30)
Target Sales Growth	-0.005	-0.004	-0.007	-0.004	-0.005	-0.006
	(-1.20)	(-1.06)	(-1.39)	(-0.92)	(-1.02)	(-1.07)
Target Book to Market	0.001	0.001	0.001	0.001	0.001	0.001
	(1.09)	(0.04)	(0.45)	(1.37)	(0.27)	(0.69)
Target Return on Assets	-0.014	-0.040	-0.033	-0.015	-0.033	-0.030
	(-0.55)	(-1.51)	(-1.14)	(-0.61)	(-1.29)	(-1.06)
Relative Size	-0.048^{c}	-0.110^{a}	-0.095^{a}	-0.045^{c}	-0.104^{a}	-0.094^{a}
	(-1.95)	(-3.58)	(-3.21)	(-1.85)	(-3.45)	(-3.19)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Broker FE	No	No	No	Yes	Yes	Yes
Industry-quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Broker-quarter FE	No	No	No	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
N	25,174	25,178	25,174	21,824	21,827	21,824
R^2	0.483	0.475	0.456	0.568	0.563	0.549

Table 5 shows the results of linear multivariate models, where the dependent variables are different cumulative abnormal returns surrounding the merger announcement. The significance of the coefficients is displayed by *a (<0.01), b (<0.05)* and *c (<0.010)*, with the exact t-values presented underneath the coefficients. Differences in the N-term stem from the linear model dropping singleton observations. All models are robust to double-clustering standard errors on the firm and analyst level. The variables are further defined in Table A of the Appendix.

Equal to the previous section, the focus is on the output from the models with the largest fixed effects. Although the model with $CAR[-5,+1]$ shows the predicted negative coefficient, the results are insignificantly different from zero. In the next two models, which include more days following the merger, a significant negative coefficient appears. The regression with the event period $[-1,+5]$ finds a one-standard deviation increase from the distraction variable mean to result in a return decline of -49 basis points $(= -0.041 * 0.12)$. The final model examines the largest event window. According to specification (6), a one-standard deviation increase in distraction leads to a -58 basis point ($= -0.049 * 0.12$) lower return.

Specification (4) shows no significant negative effect, which may indicate small leakage of the mergers. Adding subsequent days after $[T + 1]$ (i.e., one day after the merger) to the CARs presents a negative effect for distracted analysts. The average general CARs of $[-1, +5]$ and $[-5, +5]$ in Table 1 are -0.01. In this light, the impacts of respectively -49 and -58 basis points are sizeable. This result, combined with the result on merger probability, confirms the Firm Value Destruction Hypothesis.

7. Concluding remarks

This study examines the consequences of the limited attention bias for sell-side analysts using a firm-analyst-quarter level measure of analyst distraction based on extreme industry shocks in analyst portfolios. The measure tests three hypotheses related to direct and indirect effects of analyst limited attention.

The first analysis tests the Reduced Forecast Accuracy Hypothesis, which states that distracted analysts provide lower accuracy earnings forecasts. The resulting deterioration of 24 basis points for a one-standard deviation increase of distraction confirms the hypothesis. Since small errors have large individual consequences in the analyst profession, the result puts pressure on career-driven analysts. Also, small errors in estimations can result in large negative consequences for investment strategies of the brokerage clientele. Therefore, training analysts to avoid distraction is in the best interest of both the analyst and the broker. In a broader sense, many economic agents suffer from a similar bias. Beforementioned studies by Barber and Odean (2008) and Kempf, Manconi and Spalt (2017) use a similar distraction measure to find equal implications for respectively retail investors and institutional shareholders. Hence, the result on the analyst bias cautions market-wide economic agents to carefully consider whether their evaluations suffer from the bias.

The second test assesses the Inferior Returns Hypothesis. The hypothesis argues analyst distraction to result in inferior yields to their recommendations. This prediction assumes analysts to exert skill in their work, which translates to buy recommendations outperforming sell recommendations. Cumulative average return data confirms the assumption of analyst predictive skill in the recommendations. The main analysis conducts separate tests for 91-day and 365-day holding periods, which show a mixed image. All inquiries on extreme buy recommendations present no significant inferior returns for distracted analysts. Similarly, the extreme sell recommendations with a holding period of 91 days show insignificant results. However, for the 365-day holding period, a one-standard deviation increase in distraction causes a 4.9 percentage points inferior return. This result implies that investors should not solely rely on analyst recommendations in their investment strategies. Without considering the circumstances of the analyst and other evaluations of the asset, biases may hurt investment returns. The implication also applies to the wider financial market. Relying on a single source, despite its accreditation, may hurt investment strategies.

The final tests check the Firm Value Destruction Hypothesis, which states that CEOs destroy value in diversifying merger strategies when analysts are distracted. The two analyses use an M&A setting to assess the effect of analyst distraction on firm value destruction. First, the relationship between analyst distraction and the occurrence of different mergers (i.e., general, diversifying and non-diversifying mergers). A one-standard deviation rise in distraction results in increases for general and diversifying mergers of respectively 5.1% and 17.0%. Especially the effect on diversifying mergers is in line with the Firm Value Destruction Hypothesis. A more complete answer to the hypothesis requires evidence on the value destruction. A regression with the cumulative abnormal announcement returns as the response variable elaborates on the damage to the firm value. The event periods $[-1, +5]$ and $[-5, +5]$ respectively demonstrate return declines of 49 basis points and 58 basis points for a one-standard deviation increase in distraction. These results indicate that deals settled in times of analyst distraction are detrimental to firm value, confirming the Firm Value Destruction Hypothesis. Implications for firm-wide monitors are twofold. The relaxation of analyst monitor constraints results in damages to firm value, implying other monitors do not compensate. Thus, an interacting system of monitors that compensates for relaxed supervision benefits overall firm value. Also, since CEOs abuse periods of loosened monitoring, corporate governance should attempt to minimize the distraction to the monitors. The latter may result in an interfirm agreement since distraction depends on other companies as well.

8. Limitations and implications to further research

The distraction measure serves as a strength to this study but also carries a significant limitation. The current construction of the variable induces distraction for less than 17% of the sample and most of the non-zero distraction values are relatively close to zero. A future study can use a different external shock factor, different industry classification or another weighting scheme to increase the variance. This may result in more significant outcomes and potentially allow for the use of stricter control factors.

This research assessed the correlation between the distraction measure and the measure of Kempf, Manconi and Spalt (2017). The low cross-correlation implies that the results are not explained by similar times of distraction for institutional shareholders. Nonetheless, the interaction of different monitoring bodies is an interesting topic. An implication for further research is to validate the interacting effects between different supervisors, such as analysts and institutional shareholders. Additionally, a future study may also want to consider the current corporate governance structures in place to fully examine the efficiency of different monitors.

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10. Appendix

Table A.1.1 Extreme return industries

Year	Quarter	Minimum Industry	Maximum Industry
1992	1	Healthcare	Consumer Durables
1992	2	Healthcare	Energy
1992	3	Consumer Durables	Energy
1992	4	Energy	Finance
1993	1	Healthcare	Consumer Durables
1993	2	Consumer Non-durables	Consumer Durables
1993	3	Healthcare	Finance
1993	4	Energy	Consumer Durables
1994	1	Healthcare	Business Equipment
1994	2	Consumer Durables	Finance
1994	3	Consumer Durables	Healthcare
1994	4	Shops	Business Equipment
1995	1	Consumer Durables	Finance
1995	2	Energy	Business Equipment
1995	3	Energy	Finance
1995	4	Business Equipment	Healthcare
1996	1	Telecom	Chemicals
1996	2	Chemicals	Consumer Non-durables
1996	3	Telecom	Finance
1996	4	Shops	Energy
1997	1	Business Equipment	Consumer Non-durables
1997	2	Utilities	Healthcare
1997	3	Chemicals	Business Equipment
1997	4	Business Equipment	Telecom
1998	1	Utilities	Consumer Durables
1998	2	Manufacturing	Consumer Durables
1998	3	Finance	Utilities
1998	4	Energy	Business Equipment
1999	1	Utilities	Business Equipment
1999	2	Healthcare	Telecom
1999	3	Finance	Business Equipment
1999	4	Utilities	Business Equipment
2000	1	Chemicals	Business Equipment
2000	2	Consumer Durables	Healthcare
2000	3	Telecom	Utilities
2000	4	Business Equipment	Chemicals
2001	1	Business Equipment	Consumer Durables
2001	2	Telecom	Business Equipment
2001	3	Business Equipment	Consumer Non-durables
2001	4	Telecom	Business Equipment
2002	1	Telecom	Consumer Durables
2002	2	Business Equipment	Consumer Non-durables
2002	3	Business Equipment	Healthcare
2002	4	Shops	Telecom
2003	1	Consumer Durables	Healthcare
2003	2	Chemicals	Consumer Durables
2003	3	Telecom	Business Equipment
2003	4	Shops	Consumer Durables
2004	1	Consumer Durables	Shops
2004	2	Telecom	Energy
2004	3	Business Equipment	Energy
2004	4	Healthcare	Business Equipment
2005	1	Consumer Durables	Energy
2005	2	Chemicals	Utilities
2005	3	Consumer Durables	Energy
2005	4	Energy	Finance

Table A.1.1 shows the extreme return Fama and French industries for the range 1992-2005

Table A.1.2 Extreme return industries

Year	Quarter	Minimum Industry	Maximum Industry
2006	1	Utilities	Manufacturing
2006	2	Business Equipment	Utilities
2006	3	Energy	Healthcare
2006	4	Healthcare	Energy
2007	1	Finance	Utilities
2007	2	Utilities	Energy
2007	3	Consumer Durables	Chemicals
2007	4	Finance	Utilities
2008	1	Finance	Chemicals
2008	2	Finance	Energy
2008	3	Energy	Healthcare
2008	4	Consumer Durables	Healthcare
2009	1	Finance	Business Equipment
2009	2	Shops	Consumer Durables
2009	3	Utilities	Consumer Durables
2009	4	Finance	Consumer Durables
2010	1	Utilities	Consumer Durables
2010	2	Finance	Utilities
2010	3	Finance	Consumer Durables
2010	4	Utilities	Consumer Durables
2011	1	Consumer Durables	Energy
2011	2	Energy	Healthcare
2011	3	Consumer Durables	Utilities
2011	4	Business Equipment	Energy
2012	1	Utilities	Finance
2012	2	Consumer Durables	Telecom
2012	3	Utilities	Telecom
2012	4	Business Equipment	Consumer Durables
2013	1	Business Equipment	Healthcare
2013	2	Utilities	Consumer Durables
2013	3	Consumer Non-durables	Consumer Durables
2013	4	Utilities	Finance
2014	1	Shops	Utilities
2014	2	Finance	Energy
2014	3	Energy	Healthcare
2014	4	Energy	Shops
2015	1	Utilities	Healthcare
2015	2	Utilities	Finance
2015	3	Energy	Consumer Non-durables
2015	4	Utilities	Chemicals
2016	1	Healthcare	Utilities
2016	2	Consumer Durables	Energy
2016	3	Consumer Non-durables	Business Equipment
2016	4	Healthcare	Finance
2017	1	Energy	Business Equipment
2017	2	Energy	Healthcare
2017	3	Consumer Non-durables	Energy
2017	4	Consumer Durables	Shops

Table A.1.2 shows the extreme return Fama and French industries for the range 2006-2017

Table A.2 Variable Descriptions

Variable	Description
Dependent variables	
PMAFE	Proportional Mean Absolute Forecast Error. The proportional difference between the analyst forecast error and firm-wide analyst average
91-day Returns	The market-adjusted returns of a 92 days holding period
365-day Returns	The market-adjusted returns of a 365 days holding period
Merger	Dummy variable equal to one for acquiring firms announcing a majority stake acquisition in quarter q, otherwise zero.
Diversifying merger	Dummy variable equal to one for acquiring firms announcing a majority stake acquisition of a firm in a different industry in quarter q, otherwise zero.
Non-diversifying merger	Dummy variable equal to one for acquiring firms announcing a majority stake acquisition of a firm in the same industry in quarter q, otherwise zero.
CAR [-5,+1]	Cumulative abnormal announcement returns in a seven-day event window to the acquirer, calculated by the market-adjusted model
CAR [-1,+5]	Cumulative abnormal announcement returns in a seven-day event window to the acquirer, calculated by the market-adjusted model
CAR [-5,+5]	Cumulative abnormal announcement returns in an eleven-day event window to the acquirer, calculated by the market-adjusted model
Interest variable	
Distraction	The distraction of the analyst with regards to the firm on a scale of zero to the limit of one
Control variables	
Analyst	
Horizon	Difference between the estimates' time of issuance and the forecast period end date in days
Firm Experience	Firm experience of the analyst since their first estimate, in the number of quarters
General Experience	The overall experience of the analyst since their first estimate, in the number of quarters
Portfolio Size	Number of unique firms in an analyst portfolio
Different industries	Number of different industries in an analyst portfolio according to the Fama and French classification
Firm	
Return on Assets	The net income divided by the total assets
Book to Market	Book value divided by the market value of the firm
Cash to Assets	Cash holdings divided by the total assets
Leverage	The ratio of total debt to total assets
Total Assets	The logarithm of the value of the total asset base
Stock Turnover	Number of stock trades in a quarter, divided by the market capitalization
Stock Volatility	The average stock volatility in a quarter
Deal	
Stock Swap	Dummy variable equal to one for stock financing deals, otherwise zero.
Tender	Dummy variable equal to one for tender offers, otherwise zero.
Hostile	Dummy variable equal to one for hostile offers, otherwise zero.
New Economy	Dummy variable equal to one for new economy target firms defined in Murphy (2003), otherwise zero
Competing Bid	Dummy variable equal to one if competing offers appear, otherwise zero.
Relative Size	The rank value of the deal scaled by the total asset base of the acquiring firm
Target	
Target Sales Growth	The average sales growth in the past five years of the target firm
Target Book to Market	Book value divided by the market value of the target firm
Target Return on Assets	The net income divided by the total assets for the target firm

Table A.2 describes all variables included in the study.

Table A.3. Analyst forecast accuracy with firm controls

	(1)	(2)	(3)
Distraction	1.497[a] (2.45)	1.270[b] (2.04)	1.688[b] (2.31)
Return on Assets	-0.678[b] (-1.85)	-0.564 (-1.46)	-0.432 (-1.19)
Book to Market	-0.133[a] (-4.21)	-0.097[a] (-2.92)	-0.104[a] (-3.19)
Cash to Assets	0.507 (0.90)	-0.004 (-0.01)	-0.256 (-0.71)
Total Assets	-0.302[a] (-6.05)	-0.385[a] (-7.66)	-0.409[a] (-8.40)
Leverage	0.086 (0.24)	0.356 (0.98)	0.364 (1.38)
Horizon	0.011[a] (14.56)	0.023[a] (19.07)	0.023[a] (18.77)
Firm Experience	-0.031[a] (-3.99)	-0.026[a] (-3.41)	-0.025[a] (-3.38)
General Experience	0.021[a] (2.71)	0.023[a] (2.77)	0.023[a] (2.80)
Portfolio Size	0.037[c] (1.76)	0.017 (0.89)	0.010 (0.54)
Different Industries	0.006 (0.59)	0.001 (0.40)	0.066 (0.65)
Industry FE	No	No	Yes
Broker FE	Yes	Yes	Yes
Industry-quarter FE	No	No	Yes
Broker-quarter FE	No	Yes	Yes
Quarter FE	No	Yes	Yes
N	2,058,716	2,058,117	2,058,117
R^2	0.011	0.030	0.031

Table A.3 shows the results of linear multivariate models, where the dependent variable is the Proportional Mean Absolute Forecast Error (PMAFE) from Clement (1999). Negative values of the Relative Forecast Error indicate a smaller relative forecast error. The significance of the coefficients is displayed by *a (<0.01), b (<0.05)* and *c (<0.010),* with the exact t-values presented underneath the coefficients. Differences in the N-term stem from the linear model dropping singleton observations. All models are robust to double-clustering standard errors on the firm and analyst level. The variables are further defined in Table A.2 of the Appendix

Table A.4. Merger probability with analyst controls

	Merger	Diversifying Merger	Non-diversifying Merger	Merger	Diversifying Merger	Non-diversifying Merger
	(1)	(2)	(3)	(4)	(5)	(6)
Distraction	0.012[b]	0.039[c]	-0.002	0.012[b]	0.041[c]	-0.002
	(2.02)	(1.84)	(-0.48)	(2.03)	(1.86)	(-0.40)
Acquirer ROA	-0.017[a]	-0.035[a]	-0.010[a]	-0.016[a]	-0.033[a]	-0.010[a]
	(-4.64)	(-4.12)	(-2.77)	(-4.46)	(-3.96)	(-2.66)
Book-to-Market	-0.005[a]	-0.005[a]	-0.005[a]	-0.005[a]	-0.005[a]	-0.004[a]
	(-13.11)	(-5.92)	(-12.46)	(-12.61)	(-5.52)	(-11.34)
Cash-to-Assets	0.019[a]	0.029[a]	0.015[a]	0.021[a]	0.025[a]	0.018[a]
	(4.17)	(3.35)	(2.83)	(4.53)	(3.24)	(3.29)
Total Assets	0.018[a]	0.022[a]	0.016[a]	0.019[a]	0.021[a]	0.017[a]
	(16.51)	(10.31)	(13.89)	(16.93)	(10.22)	(14.41)
Leverage	-0.021[a]	-0.036[a]	-0.014[a]	-0.021[a]	-0.034[a]	-0.016[a]
	(-5.27)	(-4.95)	(-3.61)	(-5.56)	(-4.85)	(-4.00)
Horizon	0.000	-0.000[a]	0.000[c]	0.000	-0.000[b]	0.000[c]
	(0.45)	(-2.59)	(1.80)	(0.36)	(-2.54)	(1.70)
Firm Experience	-0.001[b]	-0.001[a]	-0.000	-0.000[c]	-0.001[a]	-0.000
	(-2.06)	(-3.20)	(-0.44)	(-1.87)	(-3.04)	(-0.31)
General Experience	-0.000	0.000	-0.000	-0.000	0.000	-0.000[b]
	(-0.08)	(1.07)	(-0.94)	(-1.51)	(0.46)	(-2.35)
Portfolio Size	-0.000	-0.001[a]	0.000	0.000	-0.001[a]	0.000[a]
	(-1.31)	(-5.08)	(1.50)	(0.58)	(-4.95)	(3.98)
Different Industries	0.001[a]	0.008[a]	-0.001[a]	0.001	0.008[a]	-0.002[a]
	(3.13)	(7.60)	(-3.46)	(1.20)	(6.90)	(-5.57)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Broker FE	No	No	No	Yes	Yes	Yes
Industry-quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Broker-quarter FE	No	No	No	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
N	2,060,855	2,060,855	2,060,855	2,060,236	2,060,236	2,060,236
R^2	0.051	0.023	0.040	0.061	0.032	0.050

Table A.4 shows the results of linear probability models, where the dependent variables are indicator variables equal to one for the occurrence of different mergers (i.e., general, diversifying a non-diversifying merger) and zero for no merger occurrence. The columns on diversifying and non-diversifying mergers are divided by the chance of a diversifying (24%) or non-diversifying merger (76%) under the condition that a general merger occurs. The significance of the coefficients is displayed by *a (<0.01)*, *b (<0.05)* and *c (<0.010)*, with the exact t-values presented underneath the coefficients. Differences in the N-term stem from the linear model dropping singleton observations. All models are robust to double-clustering standard errors on the firm and analyst level.

Table A.5. Merger performance with analyst controls

	[-5,+1]	[-1,+5]	[-5,+5]	[-5,+1]	[-1,+5]	[-5,+5]
	(1)	(2)	(3)	(4)	(5)	(6)
Distraction	-0.024	-0.031	-0.045[c]	-0.026	-0.044[c]	-0.051[c]
	(-1.47)	(-1.59)	(-1.95)	(-1.31)	(-1.84)	(-1.82)
Horizon	0.000	-0.000	0.000	0.000	-0.000	-0.000
	(1.05)	(-1.41)	(0.09)	(1.06)	(-1.49)	(-0.13)
Firm Experience	-0.000[a]	0.000	-0.000	-0.000[a]	-0.000	-0.000
	(-2.74)	(0.01)	(-0.92)	(-2.93)	(-0.30)	(-1.10)
General Experience	0.000[a]	0.000	0.000[b]	0.000[c]	0.000	0.000
	(3.34)	(0.77)	(2.56)	(1.87)	(0.55)	(1.47)
Portfolio Size	-0.000	-0.000	-0.000	-0.001	0.000	0.000
	(-1.76)	(-0.83)	(-0.56)	(-0.68)	(0.38)	(0.76)
Different Industries	0.001	0.001	0.001	0.001	0.001	0.001
	(1.67)	(1.41)	(1.25)	(1.17)	(0.52)	(0.58)
Return on Assets	0.029	0.068	0.080	0.030	0.069	0.083
	(0.54)	(1.27)	(1.16)	(0.54)	(1.28)	(1.19)
Book to Market	-0.001	0.003	0.002	-0.002	0.002	0.002
	(-0.42)	(1.24)	(0.78)	(-0.61)	(0.90)	(0.61)
Cash to Assets	0.003	-0.008	0.003	0.002	-0.002	0.012
	(0.16)	(-0.39)	(0.12)	(0.11)	(-0.09)	(0.51)
Total Assets	-0.001	-0.003[b]	-0.002	-0.001	-0.003[a]	-0.002[c]
	(-0.68)	(-2.42)	(-1.62)	(-0.73)	(-2.85)	(-1.80)
Leverage	0.010	0.030[b]	0.030[c]	0.013	0.033[b]	0.033[c]
	(0.77)	(2.00)	(1.79)	(0.89)	(2.18)	(1.88)
Stock Swap	-0.024[a]	-0.027[a]	-0.027[a]	-0.024[a]	-0.026[a]	-0.027[a]
	(-5.79)	(-6.53)	(-5.82)	(-5.80)	(-6.40)	(-5.67)
Tender Offer	0.007	0.003	0.010[c]	-0.006	0.003	0.009
	(1.47)	(0.58)	(1.72)	(1.19)	(0.53)	(1.44)
Hostile Takeover	-0.017[c]	-0.030[a]	-0.032[a]	-0.018[c]	-0.034[a]	-0.035[a]
	(-1.65)	(-2.97)	(-2.85)	(-1.93)	(-3.22)	(-3.08)
New Economy	-0.006	-0.010[c]	-0.009	-0.004	-0.009	-0.008[a]
	(-0.72)	(-1.68)	(-1.08)	(-0.48)	(-1.52)	(-3.08)
Competing Bid	0.005	-0.004	-0.007	-0.006	0.005	0.009
	(0.66)	(0.66)	(0.02)	(0.81)	(0.78)	(1.14)
Diversifying Merger	0.005	0.002	0.001	0.004	0.001	-0.002
	(1.08)	(0.53)	(0.02)	(0.76)	(0.17)	(-0.35)
Target Sales Growth	-0.005	-0.004	-0.007	-0.005	-0.004	-0.006
	(-1.29)	(-1.03)	(-1.41)	(-1.01)	(-0.98)	(-1.08)
Target Book to Market	0.001	0.000	0.000	0.001	0.000	0.001
	(1.08)	(0.03)	(0.45)	(1.33)	(0.28)	(0.68)
Target Return on Assets	-0.015	-0.043	-0.035	-0.015	-0.035	-0.030
	(-0.60)	(-1.60)	(-1.19)	(-0.63)	(-1.36)	(-1.07)
Relative Size	-0.049[b]	-0.109[a]	-0.095[a]	-0.046[c]	-0.104[a]	-0.094[a]
	(-1.99)	(-3.59)	(-3.23)	(-1.90)	(-3.45)	(-3.21)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Broker FE	No	No	No	Yes	Yes	Yes
Industry-quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Broker-quarter FE	No	No	No	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
N	25,174	25,178	25,174	21,824	21,827	21,824
R^2	0.447	0.475	0.456	0.568	0.563	0.549

Table A.5 shows the results of linear multivariate models, where the dependent variables are different cumulative abnormal returns surrounding the merger announcement. The significance of the coefficients is displayed by *a (<0.01), b (<0.05)* and *c (<0.01)*, with the exact t-values presented underneath the coefficients. Differences in the N-term stem from the linear model dropping singleton observations. All models are robust to double-clustering standard errors on the firm and analyst level. The variables are further defined in Table A of the Appendix.